Cargo 200: War, Propaganda, and Russian Fatalities in Ukraine

Ivan Fomichev

Vladimir Zabolotskiy

This version: March 08, 2025

How do military losses impact political behavior and attitudes in autocracies? This paper examines the effects of reports about local soldiers killed in action (KIA) during the ongoing war in Ukraine on online political behavior reflecting patriotic sentiment or regime support. Using more than 20 million posts from 36,000 geo-referenced social media groups, we employ topic-specific engagement metrics as proxies for approval of authorities and patriotism. Leveraging variation in the timing of KIA reports across Russian municipalities and a staggered treatment rollout design, we show that war fatalities lead to a sustained decline in social media engagement with content referencing authorities, with the magnitude of this effect increasing over the course of the war. At the same time, interaction with patriotic and military topics temporarily increases, driven largely by posts referencing the war in Ukraine and fallen soldiers. These effects are stronger in municipalities where local online group administrators actively publish soldiers' obituaries. Analysis of emotional tone further reveals that engagement with propagandistic content — positive in tone and politically relevant — declines after KIA reports, regardless of topical focus. This suggests that direct exposure to war fatalities erodes trust in state-promoted narratives. These findings highlight the critical role

of personal exposure to war casualties in shaping public discourse, with implications for understanding political attitudes in conflict settings.
Keywords: War fatalities, patriotism, regime support, propaganda, social media

1 Introduction

Authoritarian leaders tend to be more militant in their international relations than their democratic counterparts (Rousseau et al. 1996; Benoit 1996). With fewer constraints from public opinion and domestic political pressures, they can engage in longer wars (D. S. Bennett and Stam III 1996) and show less regard for their costs (Siverson 1995), which gives them a strategic advantage over democracies in prolonged conflicts (S. D. Bennett and Stam III 1998). Moreover, because the 'rally-round-the-flag' effect tends to be stronger and more pronounced in autocracies at war (Kizilova and Norris 2024), and international pressure often reinforces domestic support for authoritarian leaders (Hellmeier 2021), they may be tempted to initiate military interventions not for the sake of resolving international disputes, but to consolidate societal support and strengthen their position within the regime.

Wars, however, are costly — and their greatest cost is human lives. Autocrats may initiate wars, but ordinary people pay the ultimate price. At the same time, we know very little about the impact of war fatalities on political opinions and the attitudes of ordinary citizens in autocracies. Studies focusing on democracies suggest a significant relationship between war fatalities and public sentiments, but the size and the direction of the effect largely depends on the duration of the conflict (Kuijpers 2019), media coverage (Gartner 2008a; Baker and Oneal 2001), and framing (Boettcher and Cobb 2009; Berinsky 2007). To what extent these results can be generalized to drastically different political and informational environment typical for authoritarian regimes is unclear.

In autocracies, repression against anti-war dissenters and state control over information shape how citizens perceive military losses. When propaganda stirs up nationalist sentiments and frames interventions as defensive actions against external threats, war fatalities can potentially fuel support for continued aggression rather than calls for peace. In such cases, citizens may adopt a 'don't let them die in vain' mentality, reinforcing militaristic attitudes. Consistent with this, Juan et al. (2024) finds that the revanchist Nazi Party received more votes in German localities that experienced higher soldier mortality rates in the First World War. On the other hand, prolonged wars with high human cost may eventually erode the support for the regime, particularly when state narratives lose credibility. Thus, while the rally-round-the-flag effect can bolster authoritarian resilience in the short term, over time, the realities of war may undermine domestic stability and weaken the very foundations the regime seeks to strengthen. It can also be that war fatalities affect citizens attitudes in both ways, eroding the support for the regime and reinforcing nationalist sentiment at the same time. In this article, we investigate this very question.

Specifically, we explore the dynamic effects of Russian war fatalities in Ukraine on political attitudes in Russia in 2022-2024. In particular, we examine how reports of soldiers killed in action (KIA) influence user engagement with war, patriotic, and regime-related content on social media in their hometowns, using these metrics as proxies for war support, patriotism, and attitudes toward the authorities. To capture social media engagement, we collect over 28 million posts from 36714 geo-referenced online school groups, with users accounting for 12% of Russian adult population, and classify these postings using keyword analysis and a zero-shot large language model (LLM), as well as sentiment analysis. For military losses, we use municipality-level geocoded data from Russian sources (Mediazona and BBC 2023). To measure a more direct exposure to information on fatalities, we also use obituaries posted by the administrators of the school groups in our sample as treatment.

We find a robust and negative effect on engagement with pro-regime content after the first KIA report in a municipality, whereas engagement with patriotic content and content referring to the war in Ukraine increases. Theoretically, the results indicate that war fatalities can erode the legitimacy of the current regime and amplify nationalistic sentiment at the same time.

Additional heterogeneity analysis provides further insights into the mechanism behind these effects. First, we find that the effect is larger in municipalities where obituaries were shared on local school group pages, highlighting the importance of direct exposure to information in shaping attitudes toward the war and the political actors responsible. This finding also underscores the limited spillover of information in autocracies, where state-controlled media and constrained social networks restrict broader dissemination through word-of-mouth or conventional media. Second, by examining the topical content of posts *and* their emotional tone, we show that, following KIA reports, users disproportionately *disengage* with propaganda, i.e., content that is both politically relevant and positive in tone. This is true for both patriotic and pro-government content, suggesting that exposure to information on military losses can undermine the effectiveness of state propaganda.

Importantly, our results are robust to several potential confounding factors: (i) a general decline in social media activity, as the analysis adjusts for engagement with neutral content, such as posts focused solely on education; (ii) the nationwide shifts in attitudes over the course of the invasion, as month fixed effects control for temporal differences; (iii) cross-municipality variation, as municipality-level fixed effects account for time-invariant differences across municipalities. Finally, we show that (iv) the results are not driven by the users shifting their social media consumption towards more positive entertaining content.

Our study makes three main contributions. First, it advances understanding of the separate effects of war casualties on public attitudes toward the conflict, the governing authorities, and nation. We find that war fatalities degrade support for the autocrat — not unlike in settings where leaders are elected democratically (e.g., Althaus, Bramlett, and Gimpel 2012; Getmansky and Weiss 2023) — but also promote an increase in patriotism (Juan et al. 2024; Acemoglu et al. 2022; Carozzi, Pinchbeck, and Repetto 2023). These findings suggest that while war fatalities may decrease support for the ruling elite or the political actors leading the war, they do not necessarily foster anti-war sentiment. Instead, they can amplify patriotic sentiment and, potentially, drive militarism.

Second, our paper contributes to the literature on the effectiveness and limits of propaganda in authoritarian regimes (Geddes and Zaller 1989; Carter and Carter 2023; Gehlbach and Sonin 2014; Yang and Zhu 2024; Alyukov 2023). By looking at how the KIA reports affect users' reaction to a more explicitly propagandistic content, our study contributes to the existing research on public responses to propaganda (Horz 2021; Little and Nasser 2018), particularly during periods of crisis (Rozenas and Stukal 2019; Sirotkina and Zavadskaya 2020) and international instability (Weiss and Dafoe 2019). We show that distressing information, even when framed within a state-promoted narrative, can weaken public support for the regime and its leaders while potentially reducing the effectiveness of subsequent propaganda. Specifically, exposure to reports of soldiers killed in the war in Ukraine prompts more negative reactions to subsequent posts featuring political content with positive tone. In other words, we show that sugarcoating political developments becomes more difficult after people encounter the evidence of the detrimental cost of government actions.

Finally, we contribute to the literature on measuring political attitudes by introducing an innovative approach to track public sentiment with high frequency and granularity through online political behavior. We demonstrate that user engagement metrics, such as likes, reposts, and comments, provide advantages that complement traditional measures of political attitudes, especially in autocratic settings. In such contexts, survey data are often difficult to collect (Libman 2023; Rosenfeld 2023) and may suffer from fear-induced bias (Reisinger, Zaloznaya, and Woo 2023; Yudin 2022) or inflation bias (Frye et al. 2023). Other activities indicative of anti-war and anti-regime sentiment, such as protests (as in Duvanova, Nikolsko-Rzhevskyy, and Zadorozhna (2023)) or information dissemination, are shaped by repression and persecution, which discourage broader participation and restrict involvement to a narrow subset of the politically active population. This is particularly relevant in the case of Russia, where a law criminalizing "public actions aimed at discrediting" the Russian Armed Forces was enacted shortly after the start of the invasion of Ukraine, resulting in the arrest of more than 7,000 individuals for actions allegedly "discrediting the military" (UN 2023). Finally, electoral outcomes are both rare and not consistently reliable due to fraud and voter demobilization (Enikolopov et al. 2013; McAllister and White 2017; The Moscow Times 2022).

The rest of the paper is organized as follows. Sections 2 and 3 provide a brief overview of the literature and the empirical background. Section 4 describes the data employed in the study. Section 4.5 outlines the empirical strategy, and the results are presented in Section 5. Section 7 explores the potential mechanisms behind the effect, and Section 8 concludes.

2 War and political attitudes

War can have profound effects on society and its political landscape. It can help political actors gain support from the public (Hetherington and Nelson 2003; Mesquita and Siverson 1995), foster social cohesion (Bauer et al. 2016), and promote national identity (Acemoglu et al. 2022; Carozzi, Pinchbeck, and Repetto 2023). In this paper, we focus on how one particular aspect of war — its human cost — impacts attitudes towards the authorities, patriotism, and effectiveness of propaganda.

Military losses have been shown to impact public support for the political figures leading the war effort. In the months following the start of a military conflict, wartime leaders frequently experience increased support from the public (e.g., Mueller 1985; Hetherington and Nelson 2003), especially when the public is invested in 'winning the war' (Koch 2011). However, as the conflict unfolds and its costs start to accumulate, the initial 'rally around the flag' dies out, oftentimes leaving these leaders less popular than before the intervention (Voeten and Brewer 2006; Karol and Miguel 2007; Mueller 1985) and giving way to opposing political forces (Kuijpers 2019; Getmansky and Weiss 2023).

In addition, war fatalities can shape public opinion on whether the intervention itself is worth continuing. On one hand, as the casualties pile up, the public might decrease its support for the intervention, considering it too costly to continue (Gartner and Segura 1998; Sullivan 2008; Mueller 1985). Increasing recent casualties, compared to the cumulative total, and rising casualty trends has been shown to have a more pronounced negative effect on the support for war (Gartner 2008a; Gartner and Segura 1998). Additionally, previous studies have found the effect to be larger for local casualties than for the national body count (Gartner, Segura, and Wilkening 1997; Althaus, Bramlett, and Gimpel 2012; Hayes and Myers 2009; Gartner 2008b). On the other hand, if the goals of the intervention have not been achieved, the military losses already incurred may be perceived as in vain, or sunk cost, lending more support to continuing the intervention (Boettcher and Cobb 2009; Veilleux-Lepage 2013).

These countervailing effects are further complicated by the narratives surrounding the intervention. The support for the intervention is conditional on whether there is a consensus regarding the war, both in the elites and among the public (Baker and Oneal 2001; Berinsky 2007). If there is no consensus in the elites, the public might become more polarized, aligning the attitudes towards the intervention along the partisan lines. Essentially, the degree to which the public reacts to the new information on war casualties depends on individual casualty tolerance and the framing of the reports (e.g., reporting only casualties among your own forces or comparing them to enemy losses) (Boettcher and Cobb 2006), the perceived likelihood of the success of the intervention (Gelpi, Feaver, and Reifler 2006; Gelpi 2010) and whether the war is considered just. Ultimately, this can contribute to an increase in polarization, as those who consider the war just are more likely to increase their support for the war as the new information on casualties is revealed (Boettcher and Cobb 2009).

An important caveat regarding the research mentioned above is that it focuses on how the public responds to military interventions and casualties in democratic contexts, whereas authoritarian regimes operate in a substantively different informational and institutional environment. With no free press and silenced opposition, contesting framings and narratives of the war are not allowed to propagate. Alternative information regarding the course of the war — including the number of casualties, the success of military operations, and humanitarian costs costs of the war — is significantly more difficult to access than in democracies. It is therefore not clear how, under these circumstances, people would react to reports of military casualties.

On the one hand, this lack of research can be attributed to the limited role public support has played in the survival of the autocrats of the past. However, it became more relevant in the recent years with the rise of the *informational autocrats*, who rely on the support of the public, mimicking democracy and employing a variety of informational techniques to ensure their stay in the office, without reserving to mass-scale repression (Guriev and Treisman 2019).

On the other hand, studying public opinion in autocracies can be a challenging enterprise even in periods of apparent stability, and even more so in times of crises and international conflicts. The problem is that in authoritarian regimes, the dynamics of political support are often shaped by perceptions of widespread endorsement (Buckley et al. 2024). When individuals believe that a leader or regime enjoys significant public backing, this perception can reinforce support, creating a feedback loop that amplifies the appearance of mass approval. Crises can further intensify this dynamic, as fear and uncertainty may lead individuals to publicly profess greater support for the regime, even as their private trust erodes (Jiang and Yang 2016). This renders traditional surveys significantly less capable of registering shifts in public opinion masked by preference falsification, not to mention practical obstacles to carrying research on such a sensitive topic in autocracy during wartime.

At the same time, understanding it becomes crucial as the world faces increasingly belligerent autocrats. The research has shown that they are more resilient in the aftermath of war, even after defeat (Mesquita and Siverson 1995), and are prone to waging longer (D. S. Bennett and Stam III 1996) and more costly (Siverson 1995) wars. To a large extent, these empirical regularities can be explained by the fact that authoritarian leaders face fewer constraints from public opinion and domestic political pressures, which gives them a strategic advantage over democracies in prolonged conflicts (S. D. Bennett and Stam III 1998). In addition to that, as the 'rally-round-the-flag' effect may be more pronounced and last longer in autocracies during wartime (Kizilova and Norris 2024), and international pressure often reinforces domestic support for authoritarian leaders (Hellmeier 2021), they may be tempted to initiate military interventions not only for the sake of resolving international disputes, but to consolidate societal support and strengthen their position within the regime. Against this background, it is important to understand how ordinary people in autocracies react to the inevitable human cost of war: whether they become disillusioned with the leaders, or, perhaps paradoxically, rally around them even more, and how it affects their views on the conflict and attitudes more generally.

The literature on war casualties and support for incumbents in democracies demonstrates that these effects can be highly context-specific. In the context of the current study, we could reasonably expect any negative effect of the reports of soldiers killed in action on the support for the military actions and the political leadership to be mitigated by state propaganda. While war fatalities can signal incompetence of the leaders and the high costs of war, in the extreme case, government propaganda can be effective enough to weaponize the casualties to promote social cohesion and out-group intolerance, offsetting potential negative effects on the support for the regime. In Russia, where anti-war dissenters are harshly persecuted, and the state narrative of the war dominates everywhere — not only on television that has been under the regime control since 2000s, but also on the streets through billboards advertising military recruitment, and to some extent even in the Russian segment of the internet, where access to opposition websites is blocked, while state-affiliated platforms flood news feeds with propaganda — such an outcome would not be impossible. On the other hand, if propaganda effort is not enough, war fatalities can lead to the erosion of support both for the war and for the regime.

At the same time, inter-state conflicts forge national identities (Hutchinson, Leoussi, and Grosby 2007; see also Kulyk 2024 on the effect of the war on Ukrainian national identity), and, as argued by Juan et al. (2024), war fatalities can foster ingroup favoritism and outgroup distrust, leading to stronger preferences for nationalist parties. Similarly, we also expect information on soldiers killed in action to amplify nationalistic sentiment.

Finally, information on casualties might gain an additional informational dimension in autocracy at war. More specifically, casualty reports can carry information not only about the cost of war and competence of the government, but also about the credibility of propaganda that attempts to portray the invasion as a competent and masterfully executed operation. In such a context, revealing the information on war fatalities might have an extra effect on *how* effective the subsequent propaganda is, in addition to those it has on war and regime support. From this perspective, the research on the effectiveness and framing of propaganda in authoritarian regimes becomes particularly relevant to our research (Horz 2021; Little and Nasser 2018). For example, Horz (2021) present a behavioral model in which the extremeness of propaganda is inversely correlated with the likelihood that the citizen believes it (see also Little and Nasser 2018). Similar to how the Russian regime manipulates economic news to divert blame for policy failures and claim credit for positive developments (Rozenas and Stukal 2019), the regime in Horz's model decides whether to frame a certain event — which might convey information unfavorable to the regime — in a way that casts it in a more or less positive light. The more extreme the propaganda spin is, the more likely citizens are to become skeptical of the message. The analysis presented in the current paper supports this formal intuition.

In this paper, we explore the link between war fatalities and war and regime support in autocracy. Up to this point, the literature has focused primarily on this relation in the context of military interventions performed by democracies. This relation, however, is likely to differ in war-waging autocracies, as the autocrats' control over the media and their repressive potential allow them to shape the narrative to a greater extent along with concealing true information on the cost of the intervention. Given the growing number of military interventions and interstate conflicts involving autocracies in recent years, it is all the more important to understand what shapes public support for such interventions in autocracies.

Arguably, capturing public sentiment in autocracies is challenging, even more so for sensitive topics like war. Survey measures of regime support are subject to biases and limitations, limiting the predictive power their findings can provide. Other indicators of regime and war support are either rare and falsifiable, like elections, or not representative, like protests. In this study, we introduce a novel way to capture public sentiment towards war and regime using social media data that we believe is likely to overcome at least some limitations of the other measures.

3 Background

Since the commencement of the full-scale invasion on February 24, 2022, the Russian government has orchestrated an extensive campaign with the dual purpose of disseminating war propaganda and quashing anti-war dissent. Employing an array of propaganda tools, ranging from prime-time political talk shows to state-controlled telegram channels and troll farms, the government's intention has been to vilify the perceived enemy and legitimize the invasion.

This multifaceted approach combines disinformation tactics with emotional manipulation to sway public opinion, both within the nation and on the international stage. False narratives have been strategically disseminated, portraying the enemy as a direct threat to national security while emphasizing alleged atrocities. This deliberate dehumanization of the enemy serves a dual function: it galvanizes support for the invasion while suppressing any critical voices that challenge the government's actions or motivations. The extensive reliance on war propaganda reflects the government's determination to maintain control over the narrative and present a unified front, even as international criticism and condemnation mount.

The Russian authorities have dedicated substantial efforts to suppress and persecute anti-war protesters. As of October 19, 2023, the impact of these actions has been alarming, with over 19,000 individuals incarcerated for participating in anti-war protests. An additional 748 individuals have been designated as suspects in anti-war criminal proceedings, and 8,122 administrative cases have been initiated against those accused of 'discrediting the Russian military forces' (OVD-Info 2023). Most notably, the majority of administrative actions have targeted individuals who have documented and disseminated information about Russian war crimes in Ukraine.

The broader media landscape in Russia concerning the war now paints a bleak picture, where easily accessible non-governmental sources of information are virtually non-existent, allowing the Russian government to tightly control the narrative surrounding the conflict. Many independent media outlets ceased to exist, while independent journalists and activists face severe repercussions and persecution. This stifling of dissent not only obstructs transparency but also perpetuates a one-sided perspective of the conflict, leaving the Russian public uninformed and oblivious to the atrocities committed in their name. The absence of accessible non-governmental information further reinforces the state's control over public opinion, making it increasingly challenging for the truth to reach the Russian populace.

Local reports of soldiers killed in action (KIA) are a notable exception, as they do not undergo the same level of censorship. Such reports are, in most cases, published by local authorities on social media — e.g., on the official pages of governors, city managers, municipal administrations, etc. — and then disseminated by local newspapers and online news outlets. Usually, each report focuses on the death of one or several soldiers and contains a name, often accompanied by a short biographical note. In principle, KIA reports published by local authorities aim to honor deceased soldiers. Although the federal government could have prohibited the publication of such information, it has generally refrained from doing so, and as of January 2025, KIA reports continue to appear routinely on the websites and social media pages of local authorities and news outlets. One possible explanation for why this practice has not been suppressed is that, given the scale of the war, as well as the existence of

Table 1: Keyword topic frequencies

Topic	Mean
Neutral	0.4556261
War	0.3360837
President	0.0548923
Government	0.0565106
Patriotism	0.1213250
WW2	0.1901032
War in Ukraine (SMO)	0.0135293
Ukraine	0.0145750

the internet and social media, the local dissemination of such information would be impossible to prevent regardless of the authorities' actions. Moreover, an attempt to do so could further undermine the credibility of the regime's narrative.

Importantly, the information on military losses is in stark contrast with the dominant narrative promoted by the federal government since the onset of the invasion (The Current Time 2024). The Ministry of Defense, in particular, has either claimed minimal losses, concealed them, or attributed military casualties to non-military activities, as in the case of the Moskva battleship (TASS, n.d.). This discrepancy between the information from the local and the federal sources, therefore, raises substantial concerns regarding the transparency and credibility of the federal government's narrative regarding the invasion, both among those who support the invasion and those against it. Moreover, comments under the postings about the KIAs on social media appear to be one of the few spaces where the federal narrative is contested (Urman 2019).

4 Data

4.1 Local social media groups

To proxy political attitudes, we use users' reactions — "likes" and derivative engagement metrics discussed in more detail in the next section — to social media posts on specific topics. Previous research has theorized engagement through likes as a multifaceted act, serving different purposes based on the user's attitude toward the content and/or the poster. Most obviously, however, liking reflects an automatic and straightforward response to content the user agrees with or enjoys (Alhabash et al. 2018; Sude, Pearson, and Knobloch-Westerwick 2021), and this is how we interpret it in the current study.

The data on posts and users' reactions to them come from *VK.com*, Russia's most popular social networking site. We gather a universe of posts from official social media accounts of schools, as well as the conventional user interaction metrics — likes, views, shares, and comments — for each post. Our main outcomes of interest are based on the engagement with these posts by the topic of their content in a given municipality.

Using the official social media accounts of schools was a deliberate choice. Fundamentally, we were interested in using social media data to investigate the digital fingerprints of support for the regime and the war in Ukraine. Although there is an abundance of political content on VK.com, analyzing individual users' behavior is problematic for both ethical and technical reasons. An alternative approach is to focus on local, geographically specific online groups that post both political and neutral content and to analyze aggregate engagement metrics for different types of posts. These groups needed to be comparable in size, audience type, and content. Moreover, they had to be numerous — preferably in the thousands or tens of thousands — and geographically dispersed across the country to ensure broad coverage and granularity. School groups satisfied all the aforementioned criteria.

Thus, a significant share of the content published in these communities is, on par with postings about school events, either related to matters of politics or patriotism or mentions the authorities (see examples of posts in Appendix Section A.2). Patriotic posts, e.g., those about military holidays and the Great Patriotic war in particular, comprise a large part of our sample. In addition, some schools have engaged in commemoration of the KIA troops via installing commemorative plaques and hero's desks in the classrooms. Table 1 reports the probabilities of a post falling in a keyword-defined topic.

Second, the school communities are highly similar in terms of content and its timing. As of 2021 Russian government requires all schools to be present online in its attempt to scale up the indoctrination and propaganda among the youth, and a large part of it originates from the Ministry of Education and is sent to the schools simultaneously. Each community in our sample has a Russian government verification mark, and we discard the rest to avoid potential bias in type of content and reduce the noise. We therefore expect the content in our sample to be rather uniform across communities.

Third, we expect school communities to have less partisanship bias than explicitly political online groups, and in general representing a theoretically more relevant population (Appendix Section A.1 provides available socio-demographic characteristics of the groups' subscribers). While online news outlets on the VK social network enjoy relatively high levels of engagement, these communities are largely partisan along the opposition-regime line and serve to a subset of population. Most people do not follow communities with political content (Urman 2019). School communities, not being explicitly political, should overcome the problems associated with selective exposure and polarization in news consumption.

In addition, we expect school communities to be less exposed to paid human commentators and automated bots in comparison to larger communities and social media news outlets that are specifically targeted by bot farms (Shirikov 2022; Meduza 2023). For instance, out of more than 36,000 schools only 84 had more than 1 comment made by a bot (see Supplementary Appendix).

Finally, as of now, almost every school in Russia has a presence on social media. Therefore, online school groups exist in most Russian localities, and most community public pages include address information, allowing us to geolocate them precisely. The only exception is the city of Moscow, where official school groups — i. e. schools groups run by school administrations — do not have government verification marks and rarely post anything political. This is no coincidence, but the reflection of a deliberate approach the regime took to pacify the capital.

4.2 School-community search criteria

We establish specific search criteria for VK school communities. Initially, we focus on communities containing the term *school* or related synonyms in either the community name or description. Next, we refine the list by filtering out communities associated with extracurricular activities, thereby excluding music, art, and sport schools. Subsequently, we eliminate communities referencing specific grades or graduation years, as these typically cater to smaller groups and do not post much content. Finally, we verify the presence of a government verification mark from the *gosuslugi.ru* website on VK school pages and exclude communities that are not verified.

As of September 2022, Russia had 38,549 public schools (Bondarenko et al. 2024). Of these, we collected data from 36,782 official school pages on social media, each representing a specific school. Using data from the official register of legal entities, we linked 36,420 of these social media pages to specific legal entities, along with associated information such as tax numbers, registration numbers, and, most importantly, official addresses, which we used to geo-locate the pages. As shown in Figure A27, by January 2022, the majority of municipalities had at least one school group on social media. The distribution of these groups closely aligned with population density (see Figure A26). By March 2024, however, school groups had spread to cover all of Russia (Figure A28). Given that school groups' coverage was increasing throughout this period, we focus our analysis on 2,040 of Russia's 2,587 municipalities that had at least one school group by January 2022.

Next, we download all the postings made by the school communities, more than 28 million in total. We exclusively consider posts created directly by school group administrators. We exclude reposts, i.e., posts originating from other communities shared on the school community's page, as well as posts with no text. Our final sample amounts to roughly 4 million posts made from February 2022 to February 2023. All posts contain information on how many likes, shares, comments, and views they received from the users, as well as the text of the post.

4.3 Topics of the social media posts

We use multiple techniques to categorize the content of posts, the simplest of which is keyword analysis. In this approach, we identify sets of keywords related to topics such as war and the military, patriotism, the president, and the government. A post is coded as belonging to a certain topic if it contains a keyword associated with that topic. For example, we classify a post as 'patriotic' if it mentions the national anthem, the flag, the Great Patriotic War, patriotic holidays such as Victory Day (9

May) or Defender of the Fatherland Day, and similar themes. We set up all topics except *War in Ukraine* to be not mutually exclusive. This means that if a post is associated with both *Patriotism and Military* and *War in Ukraine*, it is categorized *only* under *War in Ukraine*. However, if a post does not mention the war in Ukraine, it can be categorized under multiple topics, such as both patriotic and related to the authorities. We consider a post *Neutral* if it does not mention any of the keywords from our topics of interest. Topics and their corresponding keywords are detailed in Table A2. A post is categorized into a specific topic if it contains at least one keyword from the predefined set, allowing for a broader selection of relevant posts.

Exploratory keyword analysis confirms that political content makes up a significant share of school postings: More than 30% of the posts in our sample use military vocabulary, with 1% directly related to the ongoing War in Ukraine, or Special military operation (SMO) as the Russian authorities call it, while at least 5% mention either government or president. Patriotic symbols such as the flag, the anthem, or the great patriotic war are mentioned in around 20% of the posts. Only 45% of the posts don't mention these topics.

In addition to keyword analysis, we use zero-shot classification. The difference between zero-shot classification and typical supervised learning is that a model may classify data into numerous classes without requiring particular training samples. In classical supervised learning, a model is trained on a labelled dataset with examples for each category it must classify. In the context of our study, a pre-trained zero-shot categorization provides a scaleable pipeline for estimating the likelihood of a text falling into a topic.

We deploy RuBERT, a Transformer network pre-trained on a multilingual MLM task, on our sample of posts. We focus on longer posts of more than 100 characters as they are likely to be most informative.[1] The model then assigns probabilities that a given post falls into one of several pre-defined topics. For comparability with the keyword analysis, we set the topics to *War, President, Government*, and *Patriotism*. In addition, we select *Education* as a benchmark label, which we expect to be the most prominent topic in local online school groups.[2]

[1] Federal Law of 15.11.1997 N 143-FZ (as amended on 08.08.2024) "On Acts of Civil Status" (as amended and supplemented, entered into force on 19.08.2024)

[2] North.Realities (2022); "Missing in Action: How Mothers and Wives Search in Rostov for Soldiers Who Disappeared on the Front Line" (2024); "Telegram: Contact @Akashevarova" (n.d.)

Table 2: Zero-shot topic probabilities summary statistics

Topic	Mean	SD	Min	Max
Education	0.7445025	0.2771659	0.0010981	0.9979771
War	0.1166711	0.2507715	0.0004749	0.9976617
President	0.0323865	0.1215595	0.0005417	0.9978237
Government	0.1389104	0.2410433	0.0008137	0.9971288
Patriotism	0.2270499	0.2518490	0.0005497	0.9951110
Ukraine	0.0890145	0.1517093	0.0004476	0.9972161

Table 2 summarises the estimated probabilities of a post falling into our categories. In line with our keyword analysis, matters of politics, war, and patriotism appear to be frequent topics of the postings on school pages. Wordcloud figures in Appendix show the most frequent words by topic from a sub-sample of posts.

4.4 Russian war fatalities

To capture the exposure to war fatalities, we employ data from the Mediazona and BBC database of Russian military casualties (Mediazona and BBC 2023). A group of independent journalists and volunteers manages and regularly updates the database. They manually confirm each fatality using open-source data. To confirm the death of a soldier, the volunteers refer to obituaries, news articles and social media posts published by local news outlets, government officials and relatives of the Russian troops killed in action (KIA), identified by name.

Each entry in the casualties database gives details about the KIA military personnel. Most importantly, it contains an obituary publication date, i.e., when the death of a KIA was confirmed, what source was published by, and where the deceased resided. In addition, most entries include information on the deceased's military rank, military unit and its type, as well as the date and place of birth, death, and burial. Finally, the database includes information on whether the individual was affiliated with the Russian Ministry of Defense, pro-government militias such as the Wagner group, and whether he was a military professional, volunteer, or a conscript. The database does not contain information on the KIA troops of the so-called Luhansk and Donetsk People's Republics (LNR and DNR).

Importantly, the information in this database is limited to the KIA reports published by sources within Russia accessible to the Russian public. While the reports on Russian casualties provided by Ukrainian officials and independent media outside Russia have proven to be credible, people in Russia might not have access to this information or disregard it. Obituaries provided by local authorities, regional media, and relatives, on the other hand, should have more credibility even among the most ardent supporters of the regime and the *party of war*. These reports are in stark contrast to statements made by the federal government, which confirmed only 5,937 casualties by September 2022 and has not provided any updates since. In comparison, BBC and Mediazona identified by name more than 55 thousand Russian troops killed in Ukraine as of May 2024.

In our dataset, we have information on Russian fatalities until March 2024, and we geolocate 45,696 reports about Russian KIAs with municipality-level precision. In addition, we are able to identify 7,762 posts in our sample of 13 thousand school groups that directly mention the KIAs, e.g., obituaries and posts about commemoration plaques. Figure Figure A19 shows the number of KIA reports for the period from February 2022 to March 2024 by month, and Figure Figure A20 shows the distribution of the first KIA reports by municipality over time. Figure Figure A25 shows the number of total KIA reports in municipalities by March 2024.

4.5 Empirical Strategy

In this section we describe how we construct the social media engagement metrics and then elaborate on our identification strategy and underlying assumptions.

4.6 Relative Engagement Indicator

Our primary outcome of interest is social media engagement with different topics. Specifically, we examine how engagement with topics related to the war, patriotism, or the authorities changes after an obituary of a soldier from a given municipality is published by local authorities, his or her relatives, or media.[3]

[3] All the obituaries are available online. We cannot control directly who within the municipality saw the obituary.

The social media data provides various engagement metrics, including likes, views, shares, and comments. However, exploratory analysis reveals that in our sample, shares and comments are extremely rare. Consequently, we use likes as the main metric of engagement, as they are significantly more frequent and easier to interpret. Although VK allows for different types of reactions, the default is the *heart* emoji, and as of the time of data collection, VK's API did not provide information on reaction types. For simplicity, we refer to reactions of all types as likes throughout the analysis.

To account for variations in posting intensity, we adjust the number of likes by the number of posts. This adjustment ensures that fluctuations in the volume of posts—whether increasing or decreasing after the treatment—do not bias our engagement measures. As a robustness check, we also compute the number of likes per view. However, this metric is more problematic due to endogeneity between likes and views: posts with higher views tend to receive more likes, and vice versa. This issue is less relevant when normalizing likes by posts.

Another challenge is that overall engagement might decrease after the treatment, regardless of the content's topic. To address this, we calculate the difference in likes per post between politically relevant topics and neutral topics, such as those referring to school events and general education.

For keyword-based topics, the relative engagement for a topic τ in municipality i at month t is calculated as:

$$\begin{aligned}\Delta Engagement_{it,\tau}^{keywords} &= \Delta \log Likes\ per\ post_{it,\tau} \\ &= \log \frac{\sum Likes_{it,\tau}}{\sum Posts_{it,\tau}} - \log \frac{\sum Likes_{it,-\tau}}{\sum Posts_{it,-\tau}},\end{aligned} \tag{1}$$

where $-\tau$ stands for *Neutral* content.

Zero-shot topic analysis allows for higher flexibility. Specifically, for each post classified with the zero-shot model, we know the estimated quasi-probability of a post falling into a topic, allowing for multiple true classes. This approach captures the varying intensity of each topic within a single post. Given this flexibility, we adjust our relative engagement metric by weighting the sums of likes and posts by the raw zero-shot probabilities, as follows:

$$\Delta Engagement_{it,\tau}^{zero\text{-}shot} = \Delta \log \ Likes\ per\ post_{it,\tau} = \log \frac{\sum Likes_{it,\tau} \times \mathbb{P}_\tau}{\sum Posts_{it,\tau} \times \mathbb{P}_\tau} - \log \frac{\sum Likes_{it,-\tau} \times \mathbb{P}_{-\tau}}{\sum Posts_{it,-\tau} \times \mathbb{P}_{-\tau}}, \tag{2}$$

where $\mathbb{P}_\tau$ is the estimated probability of a post falling into topic τ. The inclusion of raw zero-shot probabilities in the engagement metric introduces an important feature: engagement with a single post can simultaneously contribute to both politically relevant and neutral content.

To address concerns that small variations in probabilities could disproportionately influence the engagement metrics, we also construct a complementary metric using binary zero-shot probabilities. In this alternative approach, a post is considered to belong to a topic only if its quasi-probability exceeds a predetermined threshold. This binary classification provides a robustness check against potential over-sensitivity in the weighted metric and allows for more straightforward comparison between results based on zero-shot and keywords categories.

4.7 Identification Strategy

The analysis is based on the **Callaway and Sant'Anna (2021) doubly robust (DR) Difference-in-Differences (DiD)** framework (Callaway and Sant'Anna 2021; Sant'Anna and Zhao 2020), which is well-suited for staggered treatment adoption designs. We exploit the idiosyncrasies in the precise timing of KIA reports across towns, which has a substantial random component due to variation in the time required to confirm a soldier's death. This framework accounts for treatment effect heterogeneity and avoids the limitations of traditional two-way fixed effects (TWFE) models.

The DR-DiD estimator explicitly incorporates unit and time fixed effects through its structure, while remaining more flexible than the TWFE framework. Instead of relying solely on strong linearity assumptions, the DR estimator leverages both **Inverse Probability Weighting (IPW)** and **Outcome Regression (OR)** components. The parameter of interest is the average treatment effect on the treated (ATT) for each group and time, defined as:

$$\text{ATT}_{g,t} = \mathbb{E}[Y_t(1) - Y_t(0) \mid G = g],$$

where (Y_t(1)) and (Y_t(0)) denote potential outcomes with and without treatment, respectively, for units treated in group (g) at time (t).

Given that no covariates beyond unit IDs and time periods are used in our analysis, the DR formula simplifies to effectively adjust for time and unit-specific variation without explicitly modeling covariates. The DR estimator is robust to model misspecification as long as one of the two components (IPW or OR) is correctly specified. The ATT is estimated using the following formula:

$$\widehat{\text{ATT}}_{g,t} = \mathbb{E}\left[\left(\frac{G_g}{\mathbb{E}[G_g]} - \frac{\mathbb{E}\left[\frac{p_g(X)C}{1-p_g(X)}\right]}{\mathbb{E}[G_g]} \cdot \frac{p_g(X)C}{1-p_g(X)}\right) \cdot \left(Y_t - Y_{g-\delta-1} - m^{\text{nev}}_{g,t,\delta}(X)\right)\right].$$

This approach ensures that treatment effects are estimated more flexibly and avoids the potential biases and inefficiencies associated with TWFE models, such as inappropriate weighting or homogeneous treatment effect assumptions.

To analyze the dynamic effects of treatment, we aggregate the group-time average treatment effects (GATTs) into event-study-like estimates, which allow us to examine the treatment effects relative to the timing of the first KIA report in each municipality. Specifically, we organize the GATTs by the number of periods since the initial treatment event (event time) and compute average treatment effects for each event-time period. This approach enables a detailed visualization of the temporal evolution of the treatment effects. We use simultaneous confidence intervals for these dynamic effects, following the procedure outlined in (Callaway and Sant'Anna 2021), which accounts for multiple testing across event-time periods and ensures robust inference.

Our identification strategy relies on the assumption that in the absence of news about local military losses, engagement patterns with politically charged content on social media would have followed parallel trends in treated and not treated units. The assumption is solidified given that the precise timing of KIA reports is random and not influenced by pre-war characteristics of the municipalities, which mitigates concerns about self-selection into treatment. Thus, **?@fig-days-since-death** shows substantial variation in the time elapsed between soldiers' deaths and the confirmation of those deaths among the 18950 soldiers with known dates of death (Median = 14, Mean = 26.761, SD = 41.528). Furthermore, Figure A21 illustrates that, after accounting for region fixed effects, the timing of the first KIA report in a municipality is primarily influenced by its population size, age structure, and average temperature. The latter is likely correlated with population density due to the geographical layout of many Russian regions along meridians. Finally, when Y_{it} is defined as the difference in engagement metrics between neutral and politically relevant content — our preferred specification — we assume that trends in engagement with different types of content would have evolved similarly within units. Figure A22 reports the dynamics of engagement by topic around the date of the first KIA report.

Incorporating time and unit fixed effects using the C&SA DR DiD estimator effectively addresses key concerns about estimating the causal effects of local military losses on municipal-level outcomes. This estimator accounts for differences in demographics, economic conditions, access to alternative information sources, and proximity to the war zone by leveraging covariates to satisfy conditional parallel trends. The DR DiD framework explicitly models potential heterogeneity in untreated potential outcomes over time and across municipalities, ensuring robustness to model misspecification. National trends — such as shifts in political attitudes or economic policies — are implicitly controlled through the doubly robust approach, which allows valid identification even if only the outcome or propensity score model is correctly specified. Unlike traditional fixed effects models, this approach does not assume homogeneous treatment effects or restrict outcome trends to be group-invariant, making it more flexible and suitable for capturing the complex dynamics in this context.

5 Results

5.1 Effect of KIA reports

For the main part of our analysis, the unit of analysis is municipality i observed in month t. The dependent variable is the difference in user engagement between politically relevant content and it's neutral counterpart, captured as the difference in number of likes per post (for more detail, refer to the previous section). Treatment is defined with variable *Post KIA*, equal to one for the months after the first obituary was posted on a school page and zero otherwise. We replicate the analysis separately for a set of pre-defined topics, including *War in Ukraine* and *Patriotism and Military,* — to capture changes in engagement with patriotic, nationalistic, or militarized content, — and *Authorities* — to capture engagement with content directly mentioning the president and local and federal authorities. Note that posts categorized under the *War in Ukraine* topic are excluded from all other topics to avoid contamination. To ensure that the results are not an artifact of a statistical anomaly in the data generating process behind the community administrators' posting behavior, we exclude municipality-months when no posts of a relevant topic were made, as well as schools with less than 40 members (bottom 5% of all communities). We also exclude municipalities where no school community was created before 2022, i.e. municipalities with no data available for the pre-invasion period.

For the main part of the analysis, the period in consideration is from March 2022 to September 2022, covering the first 7 months of the invasion. This allows us to focus on the effect casualty reports had prior to the "partial mobilization" of the military reservists on September 21, 2022, which was a uniform shock that might have impacted attitudes towards both the invasion and the government. Results for the full period are in Appendix.

Baseline estimates: To evaluate the average effect of KIA reports on engagement with politically relevant content, we first regress the change in engagement on *Post KIA*, effectively accounting for month and municipality as well as for the cohort fixed effects, following Callaway and Sant'Anna (2021).

Figure 1 reports our main results - the average treatment effects on the treated (ATTs) with not yet treated as the control group. The results indicate that engagement with militaristic and patriotic content, relative to neutral, increases after KIA reports across all classifiers and relevant topics. This increase reaches up to 14.2% ($p < 0.1$) for content explicitly referencing the *War in Ukraine*. Content falling into *Patriotism & Military* topic also sees a rise in engagement of 2% for zero-shot classifier and 3% for keywords classifier ($p < 0.05$).

By contrast, engagement with *Authorities* topic decreases by 5% relative to neutral content for a zero-shot based classifier and by 8.4% for a keyword-based classification ($p < 0.05$). Analysis for more detailed topics provides similar results, with a decrease in engagement being the highest for the *Government* and *Local authorities* (9-9.4% decrease, $p < 0.01$).

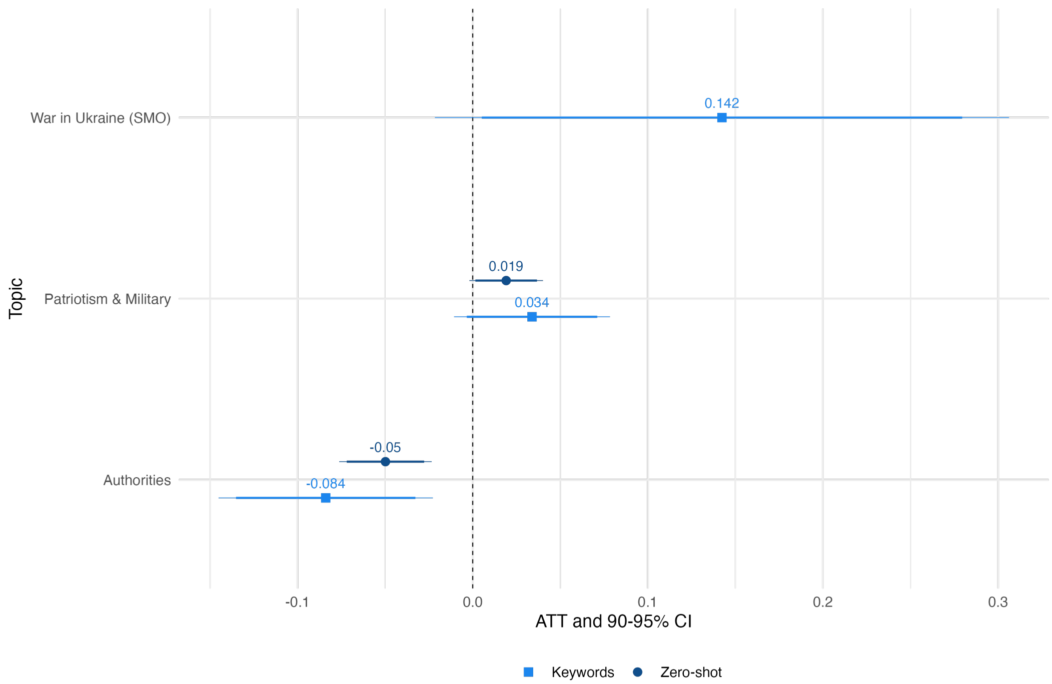


Figure 1: Change in engagement by topic relative to *Neutral* content after the first KIA report. *Note:* Dependent variable: $\Delta \log \text{Likes}$ per post. Treatment: First KIA report month in the municipality. Dots show ATT coefficients from separate Callaway and Sant'Anna (2021) estimations by topic. Topic is defined along the vertical axis. Horizontal bars represent 90% and 95% confidence intervals. Standard errors clustered at the municipality level. Squares and circles indicate classification strategy.

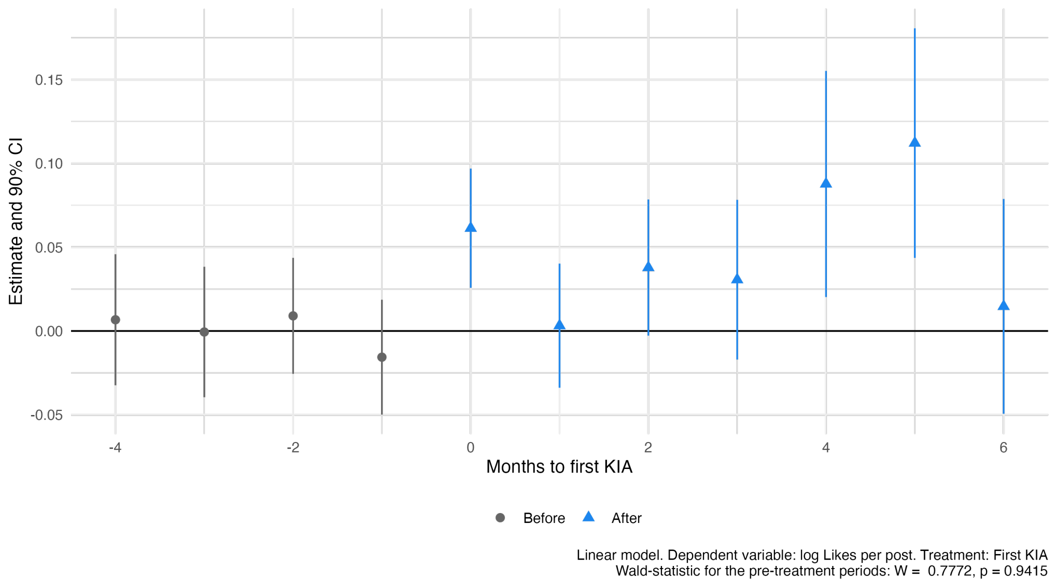
Event study estimates: The literature on the effects of war and war fatalities suggests that the attitudes towards war evolve over time: While in the first months of the intervention the government responsible for the war and the war itself often faces high public support, it starts to shrink later on when the costs of the intervention start to accumulate (Kuijpers 2019). To probe this logic further as well as to get a better understanding of whether the parallel trends assumption holds, we explore the dynamics of the effect of the KIA reports on engagement. We employ the Callaway and Sant'Anna (2021) estimator with not yet treated as the control group. Figure 2 show the dynamics of the effect by time since the first KIA report for *Patriotism & Military* and *Authorities* topics defined with keywords.[4]

[4]Resolution of the Government of the Russian Federation of 01.09.2023 N 1421 (as amended on

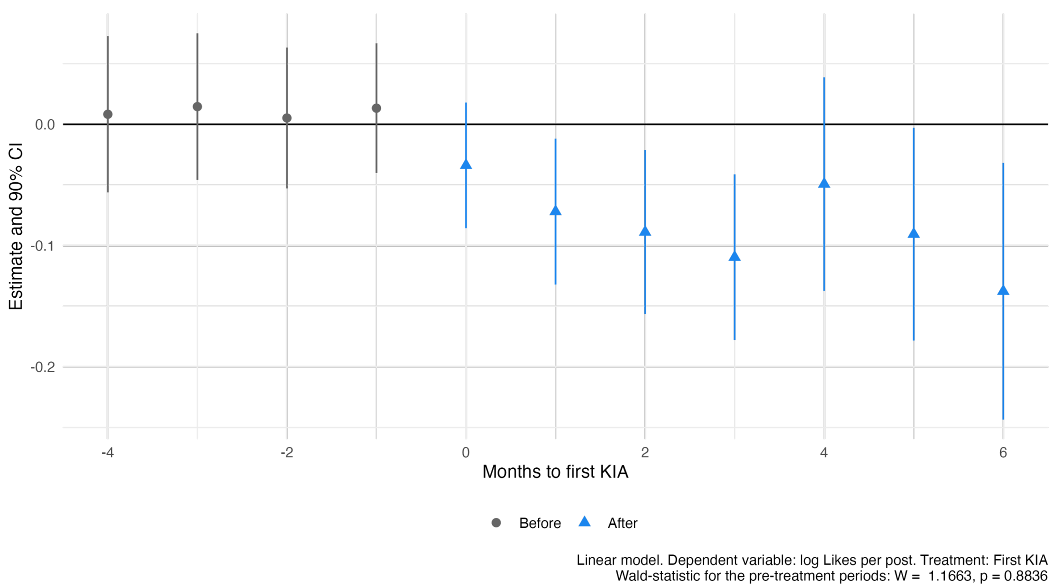
We find no evidence for a significant difference in trends in the months leading up to the publication of an obituary. The pre-treatment period coefficients are not statistically significant, both individually and jointly (Wald test of joint significance: W = 0.7772, p = 0.9415 for *Patriotism & Military*; W = 1.1663, p = 0.8836 for *Authorities*), and close to zero in magnitude for both topics. After the publication of an obituary, by contrast, we observe a sharp 6 percentage points increase in in engagement with *Patriotism & Military*. The effect, however is not limited to the immediate increase in the first month that can be attributed to the obituaries falling into the topic *Patriotism & Military*, and accumulates over several months, reaching its peak of more than 12 percentage points 5 months after the first KIA report in a municipality. Engagement with *Authorities* steadily decreases after the first KIA report, reaching magnitude of around 14% six months after the initial report.

Finally, our estimates for the keyword-based topics, applied to an extended sample covering the period until March 2024 (two years into the war), reveal a more pronounced decline in engagement with Authorities-related content ($\beta = -0.14$, p-value < 0.01). In contrast, the effect on engagement with Patriotism and Military-related content is indistinguishable from zero (see Figure A10). This suggests that the initial "rally around the flag" effect is relatively short-lived, failing to persist through the prolonged stages of the war, and reflects an increase in patriotic sentiment rather than sustained support for the political figures responsible for initiating and continuing the conflict. Results aggregated by calendar months lend further support to this reasoning: As reported in Figure A11, the increase in patriotic engagement is observed primarily in the months before the "partial mobilization", while the decline in engagement with *Authorities* continually increases in magnitude over the course of the war. Engagement with War in Ukraine remains elevated throughout the period ($\beta = 0.366$), likely driven by the continued publication of obituaries. We explore the matter of obituary publications directly on the school pages below.

05.04.2024) "On approval of the Rules … for issuing a certificate of death of a citizen, the form of a certificate on the circumstances of the disappearance of a citizen, the form of a certificate on the circumstances of the disappearance or possible death of a citizen, the form of a certificate of death of a citizen"



(a) Effect on engagement with *Patriotism & Military* topic



(b) Effect on engagement with *Authorities* topic

Figure 2: Event study graphs for the effect of the first KIA report (keywords). *Note:* Dependent variable: Δ log Likes per post. Independent variable: *Post KIA*. Estimator: Callaway and Sant'Anna (2021). Control group: Not yet treated. Dots report the point estimates. Vertical bars report the 90% confidence intervals. Standard errors clustered at municipality level.

6 Robustness

Detailed topics: To rule out the possibility that the effect we observe is driven by the idiosyncrasies in zero-shot classification or our keyword selection, we perform the above analysis on the posts classified with more detailed sets of keywords and finer zero-shot topics.

Figure A13 reports the results. We find effects similar to baseline across more detailed topics. Specifically, we observe an increase in engagement with *War*, *Patriotism*, and *World War 2* topics, and increase in *War* is the largest in magnitude and statistical significance.

Results concerning the authorities are also in line with our baseline. We document a decrease in engagement with postings mentioning the *President*, the *Government*, and the *Local authorities*. The decrease in log likes per posts relative to neutral content however is not statistically significant for president which might be due to the relative rareness of this topic as only 2% of the posts mention president.

Alternative estimator: As an alternative to the Callaway and Sant'Anna (2021) estimator, we also implement a Sun and Abraham (2021) estimation strategy. Both estimators are designed for the staggered treatment rollout scenarios, with the main difference being the control group: not yet treated in Callaway and Sant'Anna (2021) vs. last treated in Sun and Abraham (2021). The event study estimates obtained with the Sun and Abraham (2021) estimator are comparable to our baseline. Figure Figure A14 reports the results.

Repeated treatment: Another potential concern is that our findings may reflect the cumulative impact of the rising death toll in each municipality rather than the effect of individual KIA reports. To address this, we employ the estimator proposed by Chaisemartin and D'Haultfœuille (n.d.) that is robust to heterogeneous effects and limits the threat posed by contamination from other treatments. Unlike the approach in Callaway and Sant'Anna (2021), this estimator accommodates multiple treatment levels by comparing changes in outcomes across units with similar treatment histories prior to a given treatment switch. In our context, a treatment switch corresponds to an increase in the cumulative number of KIA reports within a municipality.

The results, presented in Figure A15, indicate that repeated KIA reports do not drive our findings. As in the baseline, we observe an increase in engagement with patriotic and militaristic content following KIA reports, accompanied by a decline in engagement with content that mentions the authorities.

Placebo study: As an alternative way of inference, we randomly reshuffle the month of the first confirmed KIA across the municipalities. The density plot of the baseline ATT placebo coefficients based on 500 permutations shows that the baseline estimated KIA report effect on engagement is larger than the 99th percentile of the distribution of the 500 placebo KIA report effects for *Patriotism and Military*. Similarly, the baseline ATT for *Authorities* is smaller than the bottom 1% of the placebo KIA effects. Figure A16 and Figure A17 report the results for keyword and zero-shot based topics, respectively.

7 Mechanism

7.1 Channels

7.1.1 Information channel

To better understand the channels mediating the effect of local war fatalities, we restrict the sample to municipalities where a local soldier died but no obituaries were posted on school group pages. In these cases, the death was confirmed through either a local news outlet, local authorities, or another source. This restriction helps limit the direct exposure of group users to information about military losses. Treatment is defined as before, with the variable *Post KIA* equal to one for the months following the first soldier death in a municipality and zero otherwise. All other elements of the analysis remain consistent with the baseline setup.

Figure 3 presents the results. While the baseline estimates show significant changes in social media engagement with politically relevant content following KIA reports, the effects in this restricted sample, where exposure to information about local military losses is less direct, are smaller and less statistically significant. Specifically, compared to the full sample, the restricted sample estimates indicate an 11.3 percentage point increase in engagement with *War in Ukraine* over a six-month horizon. For *War in Ukraine*, the effect size is about 3 percentage points lower than the baseline estimates (Figure 1) and is not statistically significant at conventional levels (p-value > 0.1). The effect for *Patriotism and Military* and the *Authorities* is similarly reduced. These results are statistically significant only for the zero-shot topic classifier (p-value < 0.05).

These findings suggest that direct exposure to information on war fatalities significantly amplifies the impact of military losses on engagement. The difference between the baseline and restricted sample results is unlikely to be driven by lower elasticity of engagement in school groups that do not post obituaries. On the contrary, schools posting about military losses after the start of the invasion exhibited lower engagement levels before February 2022 (Mean difference in likes per post = -2.906, t-statistic = -5.764, p-value = 0). Finally, the fact that posting decisions on school pages are made by group administrators suggests that these decisions are likely exogenous to broader municipality-level characteristics or trends. Although indirect exposure, such as through local news outlets or word-of-mouth, cannot be completely ruled out due to the consistent direction of the effects, these results point out the importance of direct access to information for the effect to fully develop.

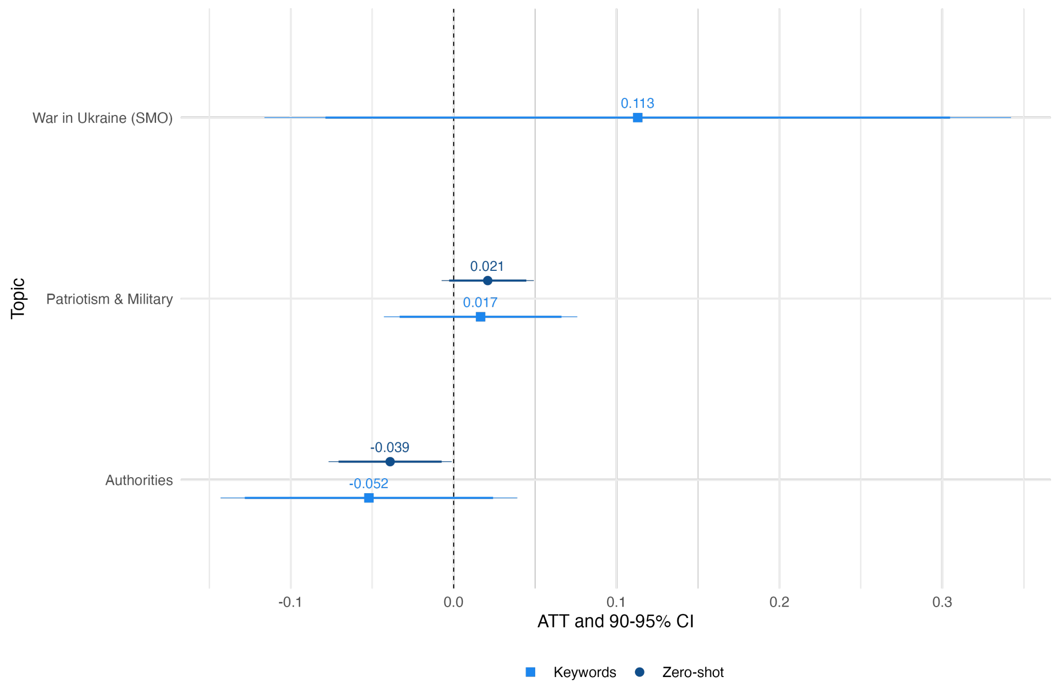


Figure 3: Change in engagement by topic relative to *Neutral* content after the first KIA report, posts with obituaries excluded. *Note:* Dependent variable: $\Delta \log \text{Likes}$ per post. Treatment: First KIA report month in the municipality. Dots show ATT coefficients from separate Callaway and Sant'Anna (2021) estimations by topic. Topic is defined along the vertical axis. Horizontal bars represent 90% and 95% confidence intervals. Standard errors clustered at the municipality level. Squares and circles indicate classification strategy.

7.1.2 Cost-benefit channel

Another mechanism frequently discussed in the literature is the cost-benefit channel. As argued by Gartner (2008a), public support for a war and the regime overseeing it is shaped by recent casualties, casualty trends, and the broader context in which these losses occur. Specifically, trends in war fatalities can influence individuals' perceptions of both the trajectory of military losses and their expected future magnitude. For instance, when fatalities increase at an accelerating rate, individuals are more likely to revise their estimates upward regarding the future costs of continuing the war. This mechanism is particularly relevant in positional warfare contexts, such as the ongoing conflict in Ukraine, where the battlefield situation remains relatively static over time.[5]

Table A1 presents the results of regressing social media engagement on the monthly changes in the cumulative number of KIA reports, controlling for municipality and month fixed effects. Compared to the baseline results, we observe no significant correlation between military loss dynamics and engagement, except for a decrease in engagement with *Authorities*.

This finding suggests that battlefield loss dynamics *do not* amplify patriotic sentiment beyond the effect of initial fatality reports and provide further evidence that the patriotic rally is limited in duration. However, regime support appears to deteriorate, as ongoing battlefield dynamics likely prompt individuals to reassess the future costs of the war, leading to further erosion of support for the authorities.

7.2 Heterogeneity

7.2.1 Content political relevance

The content of school postings often spans multiple topics simultaneously. For instance, while some posts exclusively address the authorities or the war, the majority are intertwined with themes related to school life and education. As a result, it is challenging to fully rule out the possibility that the observed effects are driven by changes in the composition of topics rather than genuine shifts in engagement. To validate our baseline results, we examine heterogeneous changes in engagement across content with varying levels of political relevance. Specifically, we compare engagement with content that has a higher or lower concentration of political topics relative to education topic.

To this end, we further investigate how the intensity of political topics in the content influences user engagement following KIA reports. *Topic relevance* is defined as a binary variable equal to 1 if the ratio of the zero-shot probability of a topic to the probability of it being neutral exceeds 0.2, and 0 otherwise. Using this definition, we estimate a TWFE model on the sample of individual posts. The outcome of

[5]Figure A24 illustrates the changes in area controlled by Russian and Ukrainian forces. Notably, the overall balance of territories controlled by both militaries has shifted minimally throughout 2023, reflecting the highly positional war of attrition.

interest is the number of likes, while the treatment variable is specified as *Post KIA* interacted with the *Topic relevance* of a post. The model includes month and school group fixed effects. Excluding schools created after January 2022, our sample contains 13346 schools and roughly 2 million posts.

It is important to note that this analysis relies on the strong form of the parallel trends assumption, which requires that trends are parallel across content with different levels of political relevance. While the inclusion of school fixed effects, rather than municipality fixed effects, alleviates this concern to some extent, as one might expect political relevance to depend on the writing style of the school administrators, our interpretation for this exercise is correlational.

Table 3 presents results that support our baseline interpretation. The changes in engagement following KIA reports are more pronounced for posts with higher political relevance. Specifically, we observe a decrease of 0.709 likes per post for content with high intensity on the *Authorities* topic (p-value < 0.01) after the first KIA report (the interaction term in the regression table). Similarly, the increase in engagement is more pronounced for content with high intensity on the *Patriotism and War* topic ($\beta = 0.578$, p-value < 0.01).

These results also provide a glimpse into how *Topic relevance* and military losses change engagement regardless of each other. We find that content mentioning the authorities gets on average 4.8 likes less — a 23 % decrease relative to the mean, — while patriotic posts get 1.78 likes more (8.5% higher than the mean). News about military losses appear to decrease likes by 0.255-0.623 (0.1-0.3%). This further highlights the ambivalent impact of war fatalities on public attitudes: while exposure to information on military casualties may erode the support for the regime, it does not appear to foster anti-war sentiment.

7.2.2 Content emotional intensity

To further explore the mechanisms behind the observed changes in engagement with different topics, we focus on the emotional tone of content. One possible explanation for our baseline findings is that the observed changes in engagement are partially driven by users avoiding uncomfortable content and shifting their consumption towards entertainment as a coping strategy. Psychological studies have

Table 3: Heterogeneity of the KIA reports effects with respect to political relevance of the content

	likes	
Topic	Authorities	Patriotism and Military
	(1)	(2)
Topic relevance	-4.81***	1.78***
	(0.106)	(0.077)
Post KIA	-0.255	-0.623***
	(0.173)	(0.178)
Topic relevance × Post KIA	-0.709***	0.578***
	(0.125)	(0.103)
Mean Likes	20.9	20.9
Mean Topic Probability	0.086	0.172
N School	13,346	13,346
N Month	13	13
Observations	2,080,875	2,080,875
R^2	0.276	0.272
School FE	✓	✓
Month FE	✓	✓

demonstrated that higher levels of stress are associated with increased social media consumption (Wolfers, Festl, and Utz 2020; Wolfers and Utz 2022), with stress often serving as a trigger for such behavior (Ingen, Utz, and Toepoel 2016; Veer, Ozanne, and Hall 2015). In addition, social media can function as a coping mechanism during stressful events such as war or pandemic. For instance, Wit, Kraan, and Theeuwes (2020) found that Twitch users utilized the platform to manage stress induced by experiencing hardship. Similarly, during the COVID-19 pandemic, individuals with higher stress levels increased their consumption of entertainment, including short videos, TV shows, and video games during lockdowns (e.g., Aghababian et al. 2021; Xu, Wang, and Ma 2023).

Building on this evidence, we hypothesize that in response to arguably traumatic news about military losses, users might shift their social media consumption toward more positive and reassuring content as a way to mitigate stress. To test this, we perform sentiment analysis on our sample of raw posts and calculate *Negativity*, *Neutrality*, and *Positivity* sentiment scores using Rogers et al. (2018) sentiment analysis model for Russian language. Each score ranges from 0 to 1. In addition, we calculate *Negativity-Positivity* score that is equal to the difference between *Positivity* and *Negativity* scores and therefore ranges from -1 to 1. We also calculate overall *Emotionality* as the maximum value of *Positivity* and *Negativity* scores for a posts, as well as *Emotional Complexity* score that is the sum of squared *Positivity* and *Negativity* scores and captures the degree of emotion heterogeneity within a post. Finally, as another measure of text complexity, we use the text length as the number of characters in a post.

Table 4 presents the results of the analysis. On average, a 10% increase in *Negativity* score decreases the number of likes per post by 1.31, respectively. Conversely, a 10% increase in *Positivity* increases engagement by 2.32 likes, equivalent to a 12% increase relative to the mean. Additionally, as shown in Table A3, a 10% increase in *Emotionality* results in 1.44 additional likes per post. Longer posts, however, tend to receive fewer likes overall.

Following the KIA reports, we observe a significant decrease in engagement with posts characterized by higher *Negativity* and *Neutrality* scores. This type of content is more likely associated with government-related topics, as shown in the correlations reported in Figure A23. The effect is most pronounced for purely neutral content,

Table 4: Heterogeneity of the KIA reports effects with respect to sentiment scores

	Likes per post		
Score	Neg	Pos	NegPos
	(1)	(2)	(3)
Post KIA	-0.344*	-1.21***	-0.370**
	(0.196)	(0.184)	(0.171)
Score	-19.9***	27.1***	21.2***
	(0.733)	(0.551)	(0.422)
Post KIA × Score	0.486	8.23***	5.21***
	(0.916)	(0.731)	(0.544)
Mean Likes	18.9	18.9	18.9
Mean Score	0.097	0.110	0.012
N School	12,971	12,971	12,971
N Month	13	13	13
Observations	2,014,787	2,014,787	2,014,787
R^2	0.273	0.284	0.284
School FE	✓	✓	✓
Month FE	✓	✓	✓

with up to a 6.67 decrease in likes per post (p-value < 0.01). While engagement with negative posts also decreases, this effect is smaller and not statistically significant.

In contrast, engagement with posts scoring higher in *Positivity* and *Emotionality* significantly increases after the KIA reports. For instance, purely positive posts receive up to 11.3 additional likes compared to what they would have received in the absence of military losses (p-value < 0.01). These findings suggest that the change in engagement, at least partly, reflects a coping mechanism, where users turn to uplifting and emotionally engaging posts following the stress-inducing news about military losses in their hometowns.

To further investigate the mechanisms at play, we interact the Negativity-Positivity sentiment score with the Topic relevance indicator, as shown in Table 3. This approach allows us to explore the heterogeneity in responses to KIA reports, accounting for both the emotional tone of posts and their topical content. In addition, we theorize that users are more likely to perceive content scoring high in both Topic relevance and Negativity-Positivity as more propagandistic due to its simplified framing and the reinforcement of polarized narratives.

As reported in Table 5, the effects of KIA reports on engagement with different topics cannot be fully explained by changes in user interactions with content of varying tones. For posts related to the authorities, engagement declines by 1.12 likes (approximately 5%), significant at the 10% level. For patriotic content, engagement increases by 0.55 likes, though this effect is not statistically significant.

Crucially, tone mediates these effects to a large extent. Consistent with Table 4, we find that engagement with more positive content increases after KIA reports, suggesting a substitution effect between negative and positive content. Strictly positive posts receive 9.64–11.4 more likes (p-value < 0.01) compared to neutral or ambiguous posts, representing a substantial increase of approximately 50%.

Interestingly, the results reveal that highly political content with a less negative tone receives fewer likes following KIA reports. Posts about the authorities that are positive in tone receive about 4 fewer likes compared to similar posts with a neutral tone. Similarly, for posts related to patriotism and military topics, those with higher Negativity-Positivity and Topic relevance also experience reduced engagement after KIA reports. These findings suggest a dampening effect on engagement with overly positive and topically intense content in the aftermath of KIA reports.

One possible explanation is that users perceive such highly positive and politically relevant posts as propaganda.[6] As pointed out in Miller (1939), Weston (2018), and Da San Martino et al. (2019) , one of the key features of propaganda is the extensive use of emotional language. If high emotional appeal combined with topic relevance signals propagandistic content, the decline in engagement could reflect a broader decrease in regime support following the reports of military losses and disillusionment with the narratives perpetrated by the regime.

[6]Since the posts in our sample are from government-curated online groups, we deem it unlikely that they will contain negative sentiment towards the government or the military. In addition, correlations show that overall emotionality is more closely aligned with higher positivity than negativity scores.

Table 5: Heterogeneity of the KIA reports effects with respect to sentiment scores and topic relevance

	Likes per post	
Topic	Authorities	Patriotism and Military
	(1)	(2)
Post KIA	-0.273	-0.469***
	(0.171)	(0.176)
Negativity-Positivity	19.5***	23.2***
	(0.429)	(0.483)
Topic relevance	-4.04***	1.55***
	(0.103)	(0.074)
Post KIA × Negativity-Positivity	6.27***	6.76***
	(0.576)	(0.666)
Post KIA × Topic relevance	-0.708***	0.327***
	(0.125)	(0.101)
Negativity-Positivity × Topic relevance	3.28***	-5.55***
	(0.637)	(0.502)
Post KIA × Negativity-Positivity × Topic relevance	-7.44***	-3.85***
	(0.868)	(0.774)
Mean Likes	18.9	18.9
Mean Topic relevance	0.213	0.370
Mean Sentiment Score	0.012	0.012
N School	12,971	12,971
N Month	13	13
Observations	2,014,787	2,014,787
R^2	0.288	0.285
School FE	✓	✓
Month FE	✓	✓

8 Discussion

This paper provides evidence that exposure to information on war fatalities impacts political attitudes in autocracy. To demonstrate this, the paper exploits idiosyncrasies in the timing of reports about Russian military personnel killed in combat during the ongoing invasion of Ukraine across Russian municipalities in 2022. Using a Doubly Robust Difference-in-Difference estimator, we show that social media engagement with authorities-related content drops significantly after local sources publicly announce the deaths of military personnel, whereas engagement with patriotic content increases. In other words, exposure to information on war fatalities may alienate citizens from the regime, but it does not necessarily foster anti-war sentiment. Therefore, as the war continues, fueling nationalism can help the regime to sustain power even if the support for individual politicians or government institutions falls.

These results bear implications for both the survival of authoritarian leaders and the potential post-regime change political dynamics in a country. When other sources of support diminish, many authoritarian leaders rely on nationalism and traditionalism to shore up their legitimacy, with Vladimir Putin in Russia serving as a notable example. In this context, military ventures and "short victorious wars" often extend this strategy, aiming, among other things, to bolster public support for the regime through the mobilization of nationalistic sentiment. However, if a military campaign goes awry, the human cost of war can offset the initial "rally-round-the-flag" effect. This creates a dual threat for the regime: as casualties mount, public disillusionment with the regime may grow, while simultaneously laying the societal foundations for a more nationalistic challenger to emerge. At the same time, it remains to be seen whether the effect documented in this article will persist and in what form. It is likely that its long-term manifestation will be contingent on the subsequent framing, commercialization, and interpretation of the war in Russian society.

Next, the sentiment analysis reveals that politically relevant posts — i.e., posts featuring either authorities or patriotic content — that are more positive in tone receive less engagement after the KIA reports. Since these posts can be viewed as more propagandistic, we interpret this effect as evidence of declining effectiveness of state propaganda. This poses a challenge for the regime. As the public becomes increasingly aware of military failures and their human cost, the regime may need to moderate its propaganda strategy to maintain credibility. However, it is during periods of conflict that the regime needs citizens' loyalty the most; therefore, it may find itself constrained in how much it can vary the spin of propaganda. Further research is needed to explore how authoritarian regimes navigate this dilemma — balancing the need to secure loyalty with the difficulties of adapting propaganda strategies in the face of rising public awareness and dissatisfaction.

This paper also contributes to the literature on the methodology behind capturing political dynamics. It offers a novel method for capturing political attitudes and public sentiment toward political events, applicable across different contexts. Alongside the recent trend of employing unstructured textual data to capture political and economic phenomena, we propose that how people engage with this unstructured data can serve as a valuable metric. Specifically, we suggest capturing public sentiment dynamics using anonymized aggregate data from social media. More precisely, we use changes in engagement with political content compared to neutral content and overall levels of engagement to proxy for changes in war and regime support. As the costs associated with traditional survey and election-based metrics for regime support escalate and social media data become more accessible and abundant, such approaches are particularly pertinent in contexts with low accessibility to conventional data, providing an alternative and insightful means of studying political dynamics.

9 References

Acemoglu, Daron, Giuseppe De Feo, Giacomo De Luca, and Gianluca Russo. 2022. "War, Socialism, and the Rise of Fascism: An Empirical Exploration*." *The Quarterly Journal of Economics* 137 (2): 1233–96. https://doi.org/10.1093/qje/qjac001.

Aghababian, Anahys H., Jennifer R. Sadler, Elena Jansen, Gita Thapaliya, Kimberly R. Smith, and Susan Carnell. 2021. "Binge Watching During COVID-19: Associations with Stress and Body Weight." *Nutrients* 13 (10): 3418. https://doi.org/10.3390/nu13103418.

Alhabash, Saleem, Nasser Almutairi, Chen Lou, and Wonkyung Kim. 2018. "Pathways to Virality: Psychophysiological Responses Preceding Likes,Shares, Comments, and Status Updates on Facebook." *Media Psychology* 22 (2): 196–216. https://doi.org/10.1080/15213269.2017.1416296.

Althaus, Scott L., Brittany H. Bramlett, and James G. Gimpel. 2012. "When War Hits Home: The Geography of Military Losses and Support for War in Time and Space." *Journal of Conflict Resolution* 56 (3): 382–412. https://doi.org/10.1177/0022002711422340.

Alyukov, Maxim. 2023. "Harnessing Distrust: News, Credibility Heuristics, and War in an Authoritarian Regime." *Political Communication* 40 (5): 527–54.

""As a Rule, They Don't Get There"." 2024. https://astra.press/russian/2024/07/26/3649/.

Baker, William D., and John R. Oneal. 2001. "Patriotism or Opinion Leadership?: The Nature and Origins of the "Rally 'Round the Flag" Effect." *Journal of Conflict Resolution* 45 (5): 661–87. https://doi.org/10.1177/0022002701045005006.

Bauer, Michal, Christopher Blattman, Julie Chytilová, Joseph Henrich, Edward Miguel, and Tamar Mitts. 2016. "Can War Foster Cooperation?" *Journal of Economic Perspectives* 30 (3): 249–74. https://doi.org/10.1257/jep.30.3.249.

Bennett, D Scott, and Allan C Stam III. 1996. "The Duration of Interstate Wars, 1816–1985." *American Political Science Review* 90 (2): 239–57.

Bennett, Scott D, and Allan C Stam III. 1998. "The Declining Advantages of Democracy: A Combined Model of War Outcomes and Duration." *Journal of Conflict Resolution* 42 (3): 344–66.

Benoit, Kenneth. 1996. "Democracies Really Are More Pacific (in General)

Reexamining Regime Type and War Involvement." *Journal of Conflict Resolution* 40 (4): 636–57.

Berinsky, Adam J. 2007. "Assuming the Costs of War: Events, Elites, and American Public Support for Military Conflict." *The Journal of Politics* 69 (4): 975–97. https://doi.org/10.1111/j.1468-2508.2007.00602.x.

Boettcher, William A., and Michael D. Cobb. 2006. "Echoes of Vietnam?: Casualty Framing and Public Perceptions of Success and Failure in Iraq." *Journal of Conflict Resolution* 50 (6): 831–54. https://doi.org/10.1177/0022002706293665.

———. 2009. ""Don't Let Them Die in Vain": Casualty Frames and Public Tolerance for Escalating Commitment in Iraq." *Journal of Conflict Resolution* 53 (5): 677–97. https://doi.org/10.1177/0022002709339047.

Bondarenko, N., T. Varlamova, L. Gokhberg, O. Zorina, V. Kuznetsova, O. Ozerova, O. Portnyagina, E. Shkaleva, and N. Shugal. 2024. *Indicators of Education in the Russian Federation: 2024 : Data Book*. Moscow: National Research University Higher School of Economics (ISSEK HSE). https://doi.org/10.17323/978-5-7598-3010-8.

Buckley, Noah, Kyle L Marquardt, Ora John Reuter, and Katerina Tertytchnaya. 2024. "Endogenous Popularity: How Perceptions of Support Affect the Popularity of Authoritarian Regimes." *American Political Science Review* 118 (2): 1046–52.

Callaway, Brantly, and Pedro H. C. Sant'Anna. 2021. "Difference-in-Differences with Multiple Time Periods." *Journal of Econometrics*, Themed issue: Treatment effect 1, 225 (2): 200–230. https://doi.org/10.1016/j.jeconom.2020.12.001.

Carozzi, Felipe, Edward Pinchbeck, and Luca Repetto. 2023. "Scars of War: The Legacy of WW1 Deaths on Civic Capital and Combat Motivation." https://econpapers.repec.org/paper/cepcepdps/dp1940.htm.

Carter, Erin Baggott, and Brett L Carter. 2023. *Propaganda in Autocracies: Institutions, Information, and the Politics of Belief.* Cambridge University Press.

Chaisemartin, Clément de, and Xavier D'Haultfœuille. n.d. "Difference-in-Differences Estimators of Intertemporal Treatment Effects." https://doi.org/10.2139/ssrn.3731856.

Da San Martino, Giovanni, Seunghak Yu, Alberto Barrón-Cedeño, Rostislav Petrov, and Preslav Nakov. 2019. "Fine-Grained Analysis of Propaganda in News Article." *Proceedings of the 2019 Conference on Empirical Methods in Natural*

Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP). https://doi.org/10.18653/v1/d19-1565.

Duvanova, Dinissa, Alex Nikolsko-Rzhevskyy, and Olha Zadorozhna. 2023. "Can Black Tulips Stop Russia Again?" *Journal of Comparative Economics*, June. https://doi.org/10.1016/j.jce.2023.06.009.

Enikolopov, Ruben, Vasily Korovkin, Maria Petrova, Konstantin Sonin, and Alexei Zakharov. 2013. "Field Experiment Estimate of Electoral Fraud in Russian Parliamentary Elections." *Proceedings of the National Academy of Sciences* 110 (2): 448–52. https://doi.org/10.1073/pnas.1206770110.

Frye, Timothy, Scott Gehlbach, Kyle L. Marquardt, and Ora John Reuter. 2023. "Is Putin's Popularity (Still) Real? A Cautionary Note on Using List Experiments to Measure Popularity in Authoritarian Regimes." *Post-Soviet Affairs* 39 (3): 213–22. https://doi.org/10.1080/1060586X.2023.2187195.

Gartner, Scott Sigmund. 2008a. "The Multiple Effects of Casualties on Public Support for War: An Experimental Approach." *American Political Science Review* 102 (1): 95–106. https://doi.org/10.1017/S0003055408080027.

———. 2008b. "Secondary Casualty Information: Casualty Uncertainty, Female Casualties, and Wartime Support." *Conflict Management and Peace Science* 25 (2): 98–111. https://doi.org/10.1080/07388940802007215.

Gartner, Scott Sigmund, and Gary M. Segura. 1998. "War, Casualties, and Public Opinion." *Journal of Conflict Resolution* 42 (3): 278–300. https://doi.org/10.1177/0022002798042003004.

Gartner, Scott Sigmund, Gary M. Segura, and Michael Wilkening. 1997. "All Politics Are Local." *Journal of Conflict Resolution* 41 (5): 669–94. https://doi.org/10.1177/0022002797041005004.

Geddes, Barbara, and John Zaller. 1989. "Sources of Popular Support for Authoritarian Regimes." *American Journal of Political Science*, 319–47.

Gehlbach, Scott, and Konstantin Sonin. 2014. "Government Control of the Media." *Journal of Public Economics* 118: 163–71.

Gelpi, Christopher. 2010. "Performing on Cue? The Formation of Public Opinion Toward War." *Journal of Conflict Resolution* 54 (1): 88–116. https://doi.org/10.1177/0022002709352845.

Gelpi, Christopher, Peter D. Feaver, and Jason Reifler. 2006. "Success Matters: Casualty Sensitivity and the War in Iraq." *International Security* 30 (3): 7–46.

https://doi.org/10.1162/isec.2005.30.3.7.

Getmansky, Anna, and Chagai M. Weiss. 2023. "Interstate Conflict Can Reduce Support for Incumbents: Evidence from the Israeli Electorate and the Yom Kippur War." *Journal of Conflict Resolution* 67 (2-3): 326–48. https://doi.org/10.1177/00220027221114086.

Guriev, Sergei, and Daniel Treisman. 2019. "Informational Autocrats." *Journal of Economic Perspectives* 33 (4): 100–127. https://doi.org/10.1257/jep.33.4.100.

Hayes, Andrew F., and Teresa A. Myers. 2009. "Testing the "Proximate Casualties Hypothesis": Local Troop Loss, Attention to News, and Support for Military Intervention." *Mass Communication and Society* 12 (4): 379–402. https://doi.org/10.1080/15205430802484956.

Hellmeier, Sebastian. 2021. "How Foreign Pressure Affects Mass Mobilization in Favor of Authoritarian Regimes." *European Journal of International Relations* 27 (2): 450–77.

Hetherington, Marc J., and Michael Nelson. 2003. "Anatomy of a Rally Effect: George W. Bush and the War on Terrorism." *PS: Political Science & Politics* 36 (1): 37–42. https://doi.org/10.1017/S1049096503001665.

Horz, Carlo M. 2021. "Propaganda and Skepticism." *American Journal of Political Science* 65 (3): 717–32.

Hutchinson, John, Athena S Leoussi, and Steven Grosby. 2007. "Warfare, Remembrance and National Identity." *Nationalism and Ethnosymbolism: History, Culture and Ethnicity in the Formation of Nations*, 42–54.

Ingen, Erik van, Sonja Utz, and Vera Toepoel. 2016. "Online Coping After Negative Life Events." *Social Science Computer Review* 34 (5): 511–29. https://doi.org/10.1177/0894439315600322.

Jiang, Junyan, and Dali L Yang. 2016. "Lying or Believing? Measuring Preference Falsification from a Political Purge in China." *Comparative Political Studies* 49 (5): 600–634.

Juan, Alexander De, Felix Haass, Carlo Koos, Sascha Riaz, and Thomas Tichelbaecker. 2024. "War and Nationalism: How WW1 Battle Deaths Fueled Civilians' Support for the Nazi Party." *American Political Science Review* 118 (1): 144–62. https://doi.org/10.1017/S000305542300014X.

Karol, David, and Edward Miguel. 2007. "The Electoral Cost of War: Iraq Casualties and the 2004 u.s. Presidential Election." *The Journal of Politics* 69 (3): 633–48. https://doi.org/10.1111/j.1468-2508.2007.00564.x.

Kizilova, Kseniya, and Pippa Norris. 2024. "'Rally Around the Flag' Effects in the Russian–Ukrainian War." *European Political Science* 23 (2): 234–50.

Koch, Michael T. 2011. "Casualties and Incumbents: Do the Casualties from Interstate Conflicts Affect Incumbent Party Vote Share?" *British Journal of Political Science* 41 (4): 795–817. https://doi.org/10.1017/S0007123411000172.

Kuijpers, Dieuwertje. 2019. "Rally Around All the Flags: The Effect of Military Casualties on Incumbent Popularity in Ten Countries 1990–2014." *Foreign Policy Analysis* 15 (3): 392–412. https://doi.org/10.1093/fpa/orz014.

Kulyk, Volodymyr. 2024. "National Identity in Time of War: Ukraine After the Russian Aggressions of 2014 and 2022." *Problems of Post-Communism* 71 (4): 296–308.

Libman, Alexander. 2023. "Credibility Revolution and the Future of Russian Studies." *Post-Soviet Affairs* 39 (1-2): 60–69. https://doi.org/10.1080/1060586X.2022.2148446.

Little, Andrew T, and Sherif Nasser. 2018. "Unbelievable Lies." *Unpublished Manuscript, University of California, Berkeley.*

McAllister, Ian, and Stephen White. 2017. "Demobilizing Voters: Election Turnout in the 2016 Russian Election." *Russian Politics* 2 (4): 411–33. https://doi.org/10.1163/2451-8921-00204002.

Mediazona, and BBC. 2023. "Russian Casualties in Ukraine. Mediazona Count, Updated." https://en.zona.media/article/2022/05/20/casualties_eng.

Meduza. 2023. "Elves Vs. Trolls Navalny's Team Says It Doesn't Have an Anti-Kremlin Social Media Army. Here's Who Does." https://meduza.io/en/feature/2023/11/18/elves-vs-trolls.

Mesquita, Bruce Bueno de, and Randolph M. Siverson. 1995. "War and the Survival of Political Leaders: A Comparative Study of Regime Types and Political Accountability." *American Political Science Review* 89 (4): 841–55. https://doi.org/10.2307/2082512.

Miller, Clyde R. 1939. "Propaganda and the European War." *The Clearing House* 14 (2): 67–73. https://www.jstor.org/stable/30192639.

"Missing in Action: How Mothers and Wives Search in Rostov for Soldiers Who Disappeared on the Front Line." 2024. https://161.ru/text/world/2024/03/11/73310255/.

Mueller, John E. 1985. *War, Presidents, and Public Opinion.* University Press of America.

North.Realities. 2022. “”Every body has a number. It’s not for the faint of heart.” How a mother searches for her conscript son who went missing in the war in Ukraine.” https://www.currenttime.tv/a/ya-pobyvala-v-adu-mat-ischet-propavshego-na-voyne-v-ukraine-syna-srochnika-/32012641.html.

OVD-Info. 2023. “Persecution of the anti-war movement report: October 2023.” https://en.ovdinfo.org/persecution-anti-war-movement-report-october-2023.

Reisinger, William M., Marina Zaloznaya, and Byung-Deuk Woo. 2023. “Fear of Punishment as a Driver of Survey Misreporting and Item Non-Response in Russia and Its Neighbors.” *Post-Soviet Affairs* 39 (1-2): 49–59. https://doi.org/10.1080/1060586X.2022.2150490.

Rogers, Anna, Alexey Romanov, Anna Rumshisky, Svitlana Volkova, Mikhail Gronas, and Alex Gribov. 2018. “COLING 2018.” In, edited by Emily M. Bender, Leon Derczynski, and Pierre Isabelle, 755763. Santa Fe, New Mexico, USA: Association for Computational Linguistics. https://aclanthology.org/C18-1064.

Rosenfeld, Bryn. 2023. “Survey Research in Russia: In the Shadow of War.” *Post-Soviet Affairs* 39 (1-2): 38–48. https://doi.org/10.1080/1060586X.2022.2151767.

Rousseau, David L, Christopher Gelpi, Dan Reiter, and Paul K Huth. 1996. “Assessing the Dyadic Nature of the Democratic Peace, 1918–88.” *American Political Science Review* 90 (3): 512–33.

Rozenas, Arturas, and Denis Stukal. 2019. “How Autocrats Manipulate Economic News: Evidence from Russia’s State-Controlled Television.” *The Journal of Politics* 81 (3): 982–96.

Sant’Anna, Pedro HC, and Jun Zhao. 2020. “Doubly Robust Difference-in-Differences Estimators.” *Journal of Econometrics* 219 (1): 101–22.

Shirikov, Anton. 2022. *How Propaganda Works: Political Biases and News Credibility in Autocracies*. The University of Wisconsin-Madison. https://www.proquest.com/openview/48d1a5c1d01fa2cfcfac6b94be156a47/1.pdf?pq-origsite=gscholar&cbl=18750&diss=y.

Sirotkina, Elena, and Margarita Zavadskaya. 2020. “When the Party’s over: Political Blame Attribution Under an Electoral Authoritarian Regime.” *Post-Soviet Affairs* 36 (1): 37–60.

Siverson, Randolph M. 1995. “Democracies and War Participation: In Defense of the Institutional Constraints Argument.” *European Journal of International Relations* 1 (4): 481–89.

Sude, Daniel J., George D. H. Pearson, and Silvia Knobloch-Westerwick. 2021. "Self-Expression Just a Click Away: Source Interactivity Impacts on Confirmation Bias and Political Attitudes." *Computers in Human Behavior* 114 (January): 106571. https://doi.org/10.1016/j.chb.2020.106571.

Sullivan, Patricia L. 2008. "Sustaining the Fight: A Cross-Sectional Time-Series Analysis of Public Support for Ongoing Military Interventions." *Conflict Management and Peace Science* 25 (2): 112–35. https://doi.org/10.1080/07388940802007223.

Sun, Liyang, and Sarah Abraham. 2021. "Estimating Dynamic Treatment Effects in Event Studies with Heterogeneous Treatment Effects." *Journal of Econometrics*, Themed issue: Treatment effect 1, 225 (2): 175–99. https://doi.org/10.1016/j.jeconom.2020.09.006.

TASS. n.d. ""Moskva" battleship sunk while being towed." https://tass.ru/armiya-i-opk/14383383.

"Telegram: Contact @Akashevarova." n.d. https://t.me/akashevarova/7643.

The Current Time. 2024. "Journalists Confirmed the Death of More Than 45 Thousand Russian Troops in the War in Ukraine." https://www.currenttime.tv/a/russian-casualities/32829273.html.

The Moscow Times. 2022. "Leaked Archive Indicates Large-Scale Election Fraud – Meduza." https://www.themoscowtimes.com/2022/08/12/leaked-archive-indicates-large-scale-election-fraud-meduza-a78558.

UN. 2023. "Russia Hits 'New Low' with Ban Against Discrediting Army: Rights Experts | UN News." https://news.un.org/en/story/2023/08/1140147.

Urman, Aleksandra. 2019. "News Consumption of Russian Vkontakte Users: Polarization and News Avoidance." *International Journal of Communication* 13: 51585182. https://boris.unibe.ch/142408/1/11161-41540-1-PB.pdf.

Veer, Ekant, Lucie K. Ozanne, and C. Michael Hall. 2015. "Sharing Cathartic Stories Online: The Internet as a Means of Expression Following a Crisis Event." *Journal of Consumer Behaviour* 15 (4): 314–24. https://doi.org/10.1002/cb.1569.

Veilleux-Lepage, Yannick. 2013. "Implications of the Sunk Cost Effect and Regional Proximity for Public Support for Canada's Mission in Kandahar." *International Journal* 68 (2): 346–58. https://www.jstor.org/stable/24709485.

Voeten, Erik, and Paul R. Brewer. 2006. "Public Opinion, the War in Iraq, and Presidential Accountability." *Journal of Conflict Resolution* 50 (6): 809–30.

https://doi.org/10.1177/0022002706291054.

Weiss, Jessica Chen, and Allan Dafoe. 2019. "Authoritarian Audiences, Rhetoric, and Propaganda in International Crises: Evidence from China." *International Studies Quarterly* 63 (4): 963–73.

Weston, Anthony. 2018. *A Rulebook for Arguments*. Hackett Publishing.

Wit, Jan de, Alicia van der Kraan, and Joep Theeuwes. 2020. "Live Streams on Twitch Help Viewers Cope with Difficult Periods in Life." *Frontiers in Psychology* 11 (November). https://doi.org/10.3389/fpsyg.2020.586975.

Wolfers, Lara N., Ruth Festl, and Sonja Utz. 2020. "Do Smartphones and Social Network Sites Become More Important When Experiencing Stress? Results from Longitudinal Data." *Computers in Human Behavior* 109 (August): 106339. https://doi.org/10.1016/j.chb.2020.106339.

Wolfers, Lara N., and Sonja Utz. 2022. "Social Media Use, Stress, and Coping." *Current Opinion in Psychology* 45 (June): 101305. https://doi.org/10.1016/j.copsyc.2022.101305.

Xu, Yi, Jiahe Wang, and Mengyuan Ma. 2023. "Adapting to Lockdown: Exploring Stress Coping Strategies on Short Video Social Media During the COVID-19 Pandemic." *Psychology Research and Behavior Management* Volume 16 (December): 5273–87. https://doi.org/10.2147/prbm.s441744.

Yang, Tony Zirui, and Hongshen Zhu. 2024. "Twisted Tongue: Limits of China's Propaganda During Crises and Policy Changes." *Available at SSRN 4589500*.

Yudin, Greg. 2022. "The War in Ukraine: Do Russians Support Putin?" *Journal of Democracy* 33 (3): 31–37. https://muse.jhu.edu/pub/1/article/860242.

A Appendix

A.1 Demographics of school group subscribers

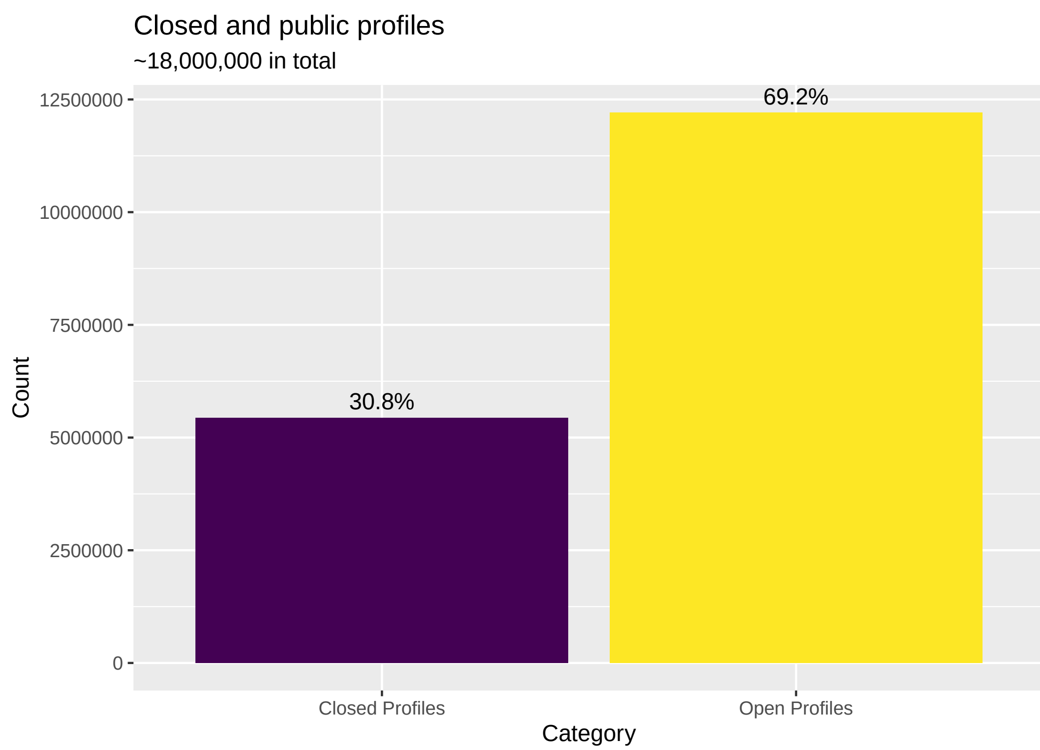


Figure A1: The distribution of closed and open profiles among school groups' subscribers

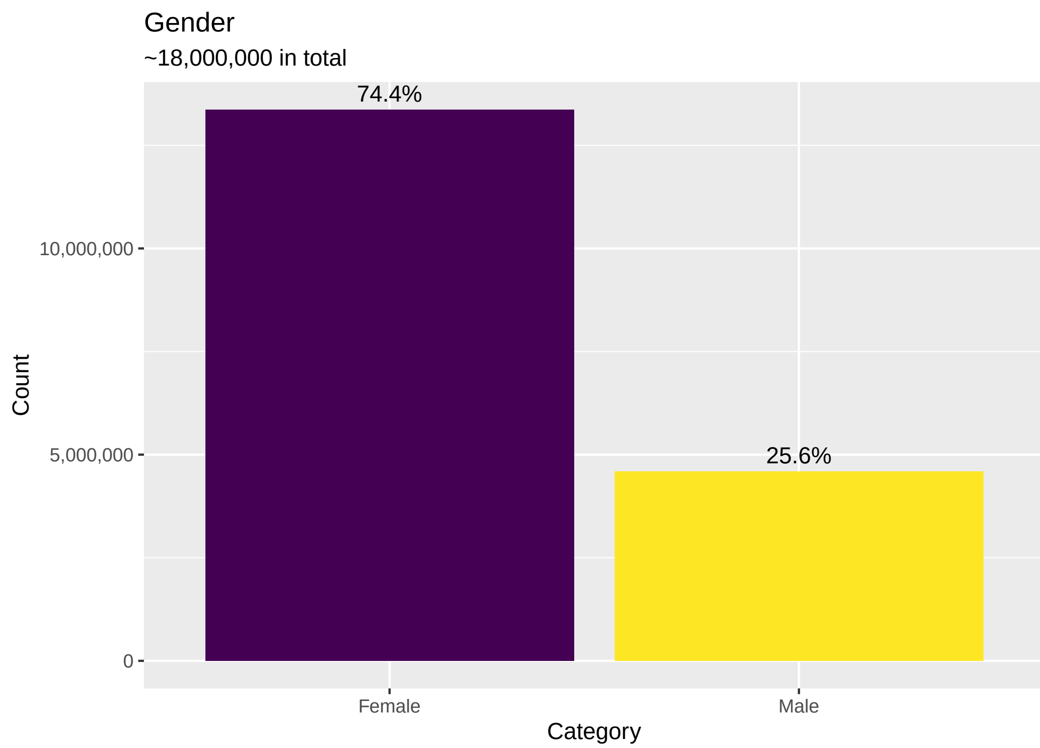


Figure A2: Gender distribution among school groups' subscribers

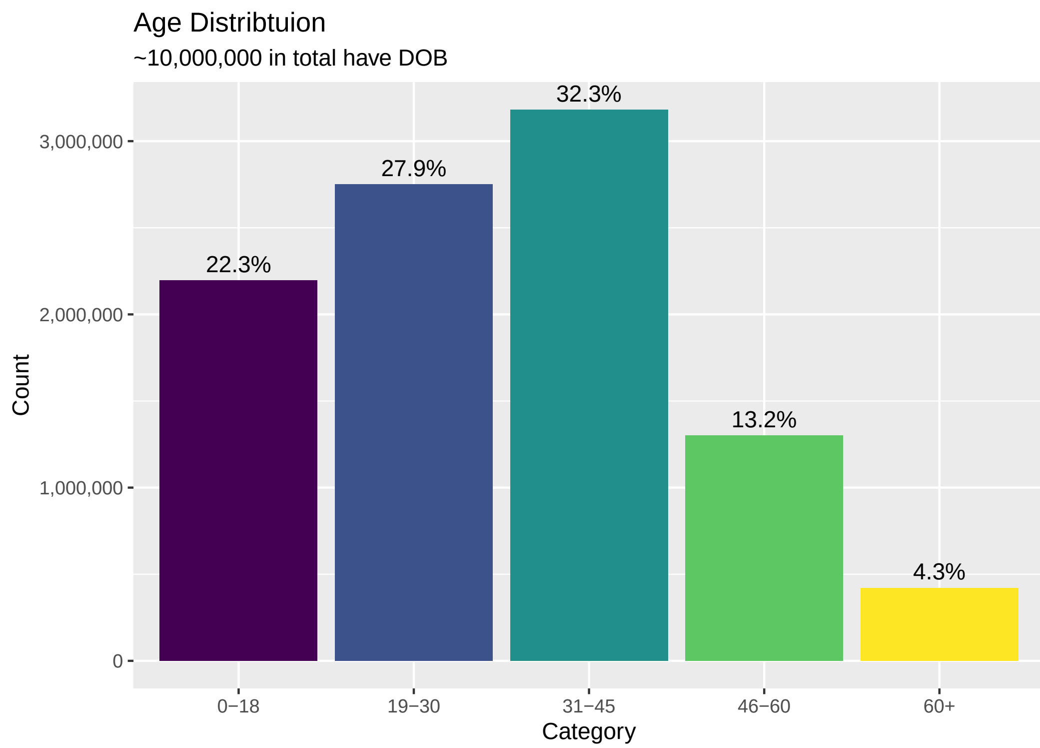


Figure A3: Age distribution among school groups' subscribers

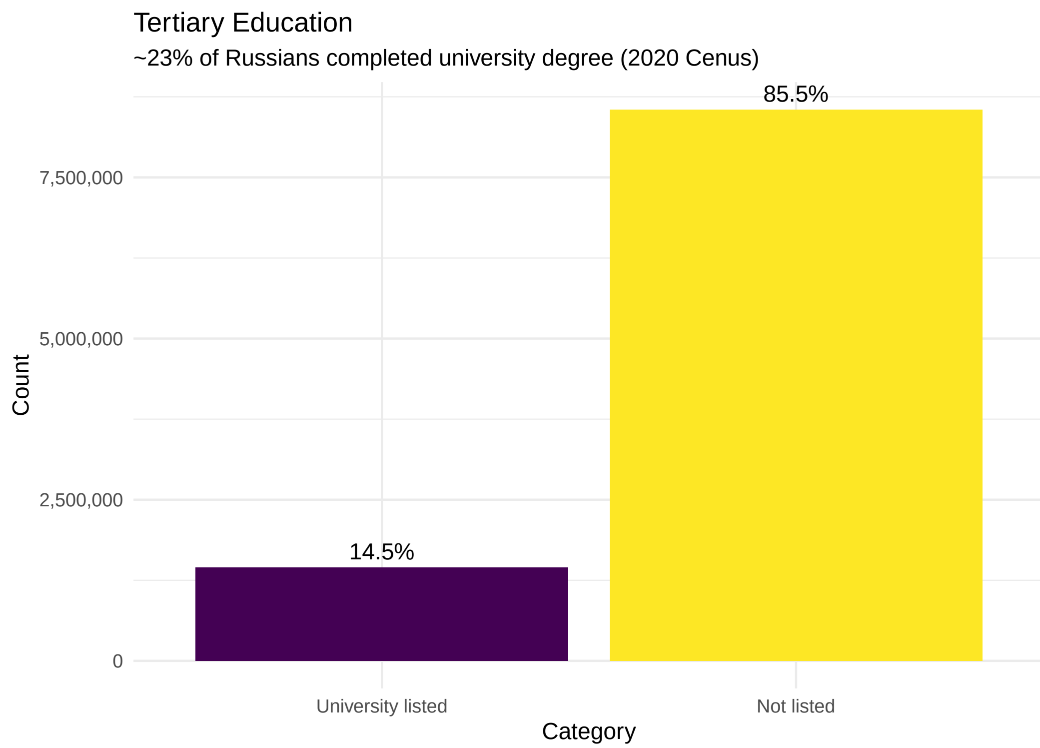


Figure A4: Percentage of subscribers with listed tertiary education

A.2 Example posts in schools groups

Figure A5: Neutral Post

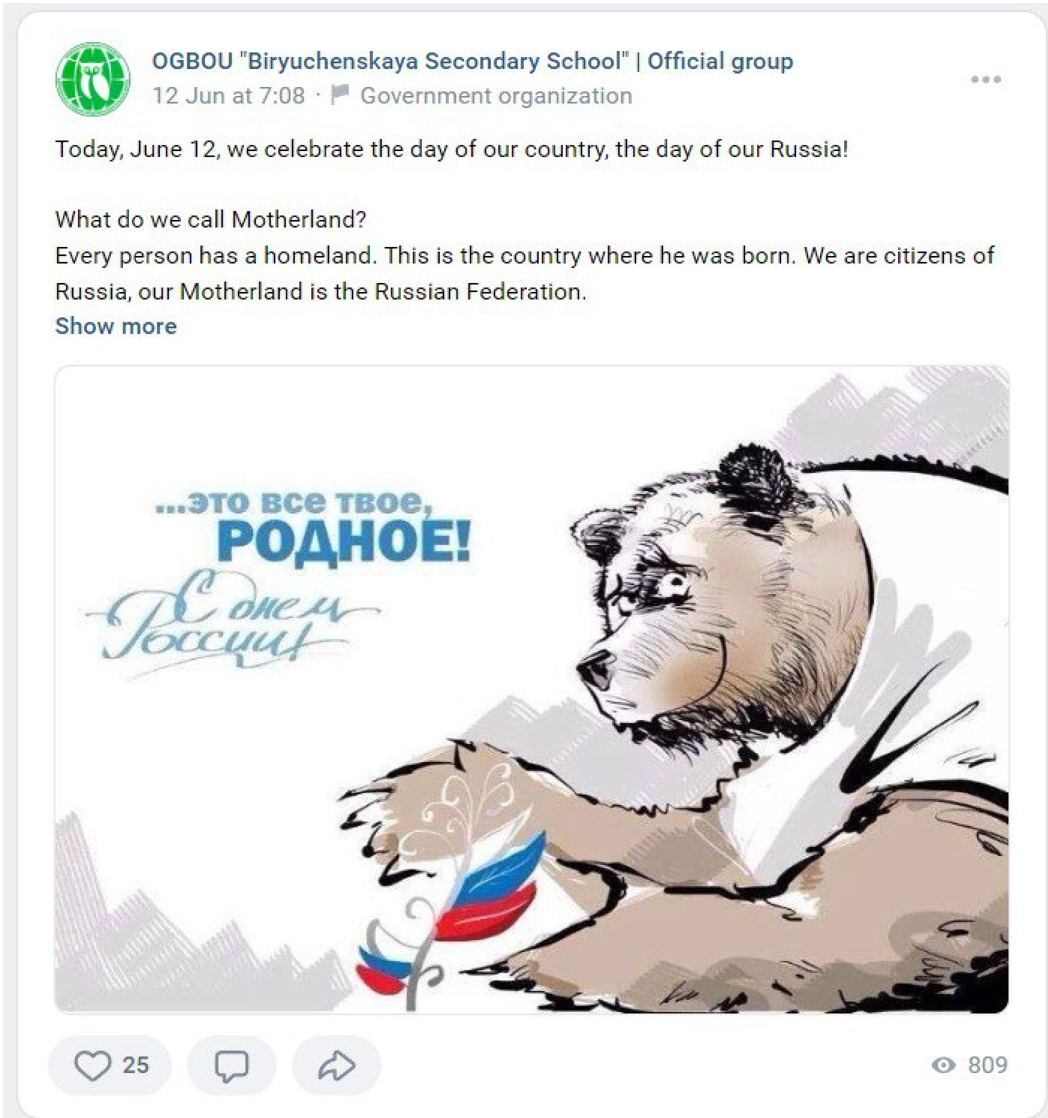
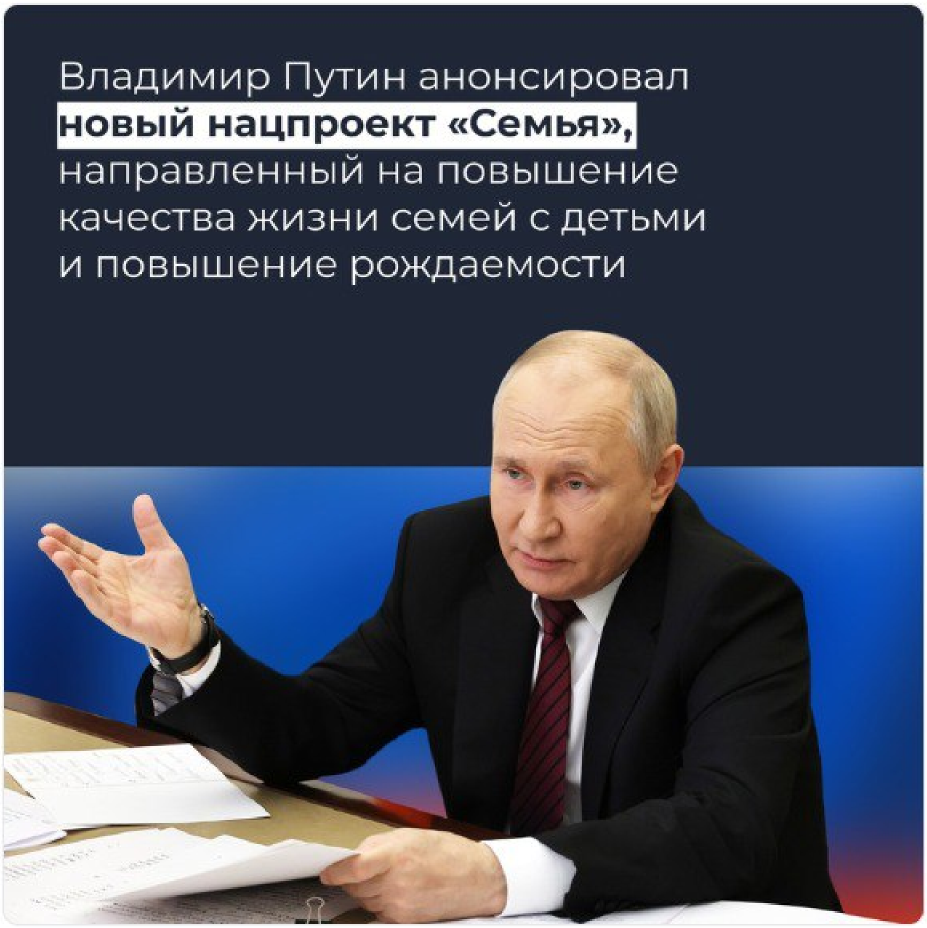


Figure A6: Patriotic Post

The President of the Russian Federation announced the launch of a new national project "Family". He announced this while delivering a message to the Federal Assembly.

The national program will provide financial support to regions with low birth rates.

#OGBOUBiryuchenskayaSOSOofficial group



14 1K

Figure A7: President Post

Figure A8: Special Military Operation Post

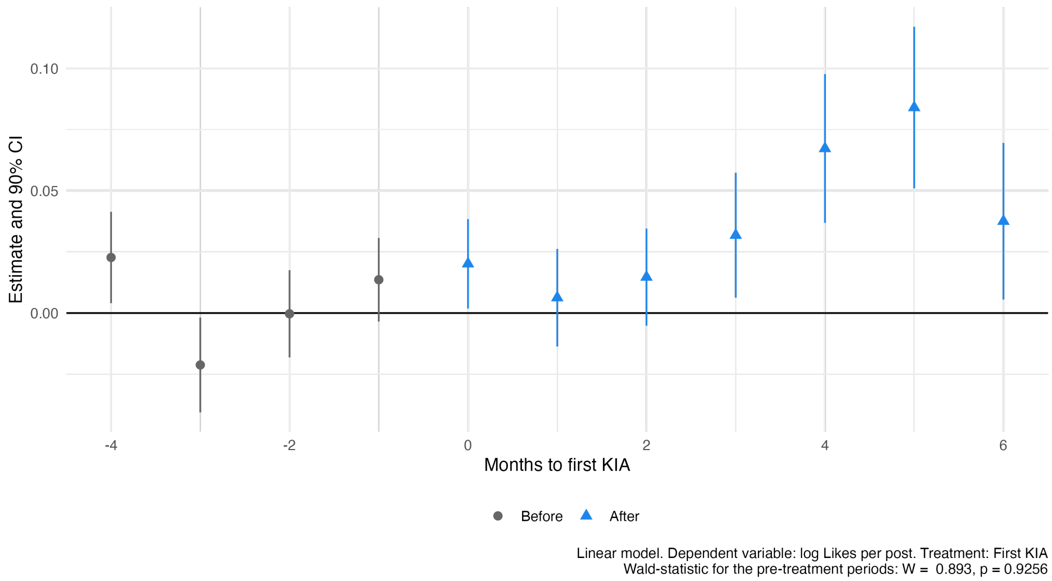
Table A1: The effect of cumulative KIA reports on engagement.

	Δ log Likes per post				
Topic	War in Ukraine	Authorities	Patriotism	Authorities	Patriotism
	(1)	(2)	(3)	(4)	(5)
Cumulative KIA	0.006	-0.002	0.0009	-0.002**	0.0008
	(0.005)	(0.002)	(0.0007)	(0.0009)	(0.0007)
Classifier	Keywords	Keywords	Keywords	Zero-shot	Zero-shot
N Municipality	1,687	2,030	2,035	2,038	2,038
N Month	13	13	13	13	13
Observations	5,345	21,990	23,853	24,886	24,886
R^2	0.435	0.282	0.205	0.340	0.275
Municipality FE	✓	✓	✓	✓	✓
Month FE	✓	✓	✓	✓	✓

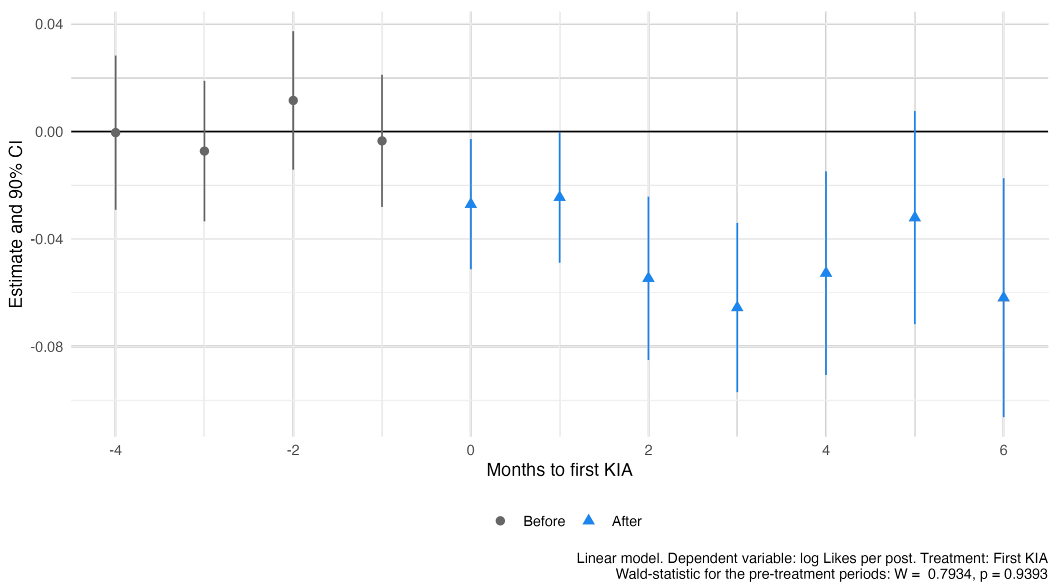
A.3 Additional results

A.3.1 Cumulative KIA reports

A.3.2 Event-study graphs for zero-shot topics



(a) Effect on engagement with *Patriotism & Military* topic



(b) Effect on engagement with *Authorities* topic

Figure A9: Event study graphs for the effect of the first KIA report (zero-shot topics). *Note:* Dependent variable: Δ log Likes per post. Independent variable: *Post KIA*. Estimator: Callaway and Sant'Anna (2021). Control group: Not yet treated. Dots report the point estimates. Vertical bars report the 90% confidence intervals. Standard errors clustered at municipality level.

A.3.3 Extended sample estimates

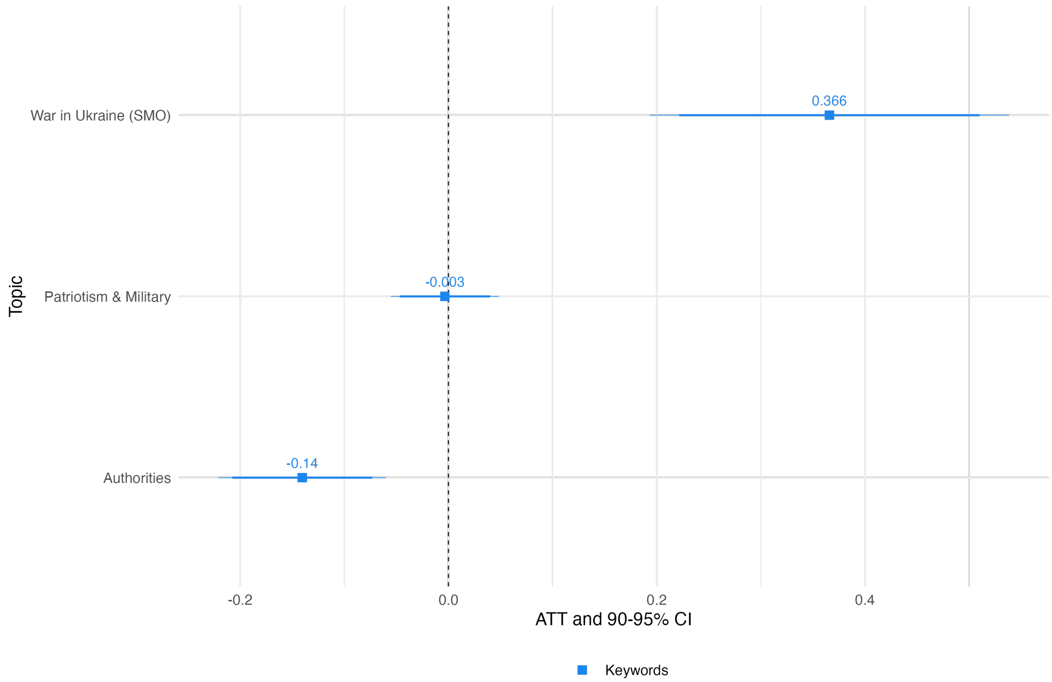
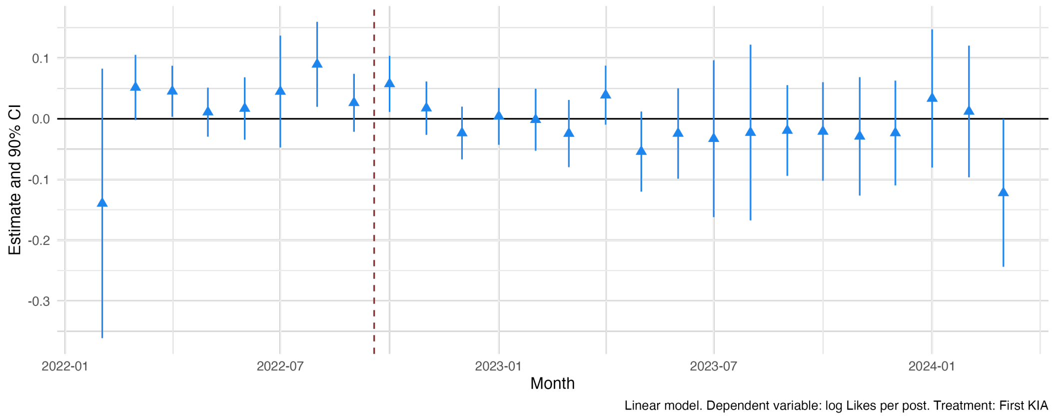
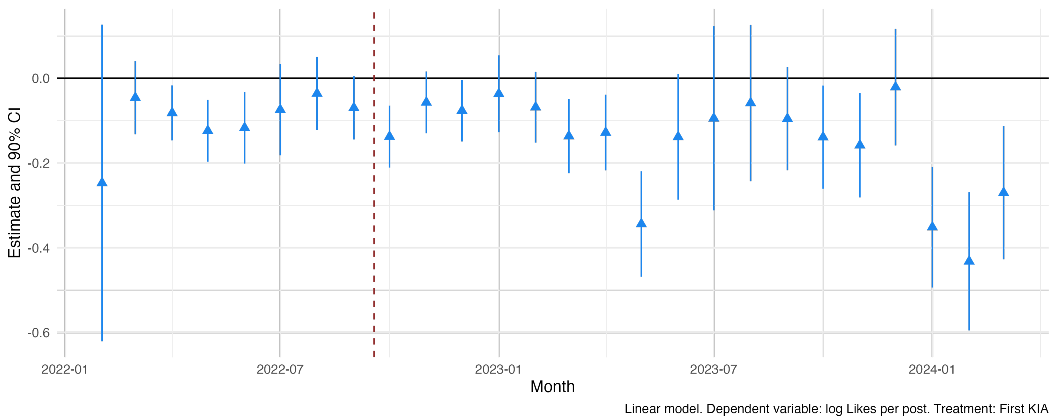


Figure A10: Change in engagement by topic relative to *Neutral* content after the first KIA report. *Note:* Dependent variable: $\Delta \log \text{Likes per post}$. Treatment: First KIA report month in the municipality. Dots show ATT coefficients from separate Callaway and Sant'Anna (2021) estimations by topic. Topic is defined along the vertical axis. Horizontal bars represent 90% and 95% confidence intervals. Standard errors clustered at the municipality level. Squares and circles indicate classification strategy.

A.3.4 Estimates aggregated by calendar months



(a) Effect on engagement with Patriotism & Military topic



(b) Effect on engagement with *Authorities* topic

Figure A11: Graphs for the effect of the first KIA report aggregated by calendar months (keywords). *Note:* Dependent variable: Δ log Likes per post. Independent variable: *Post KIA*. Estimator: Callaway and Sant'Anna (2021). Control group: Not yet treated. Dots report the point estimates. Vertical bars report the 90% confidence intervals. Standard errors clustered at municipality level. Dashed vertical line indicated the start of the "partial mobilization" in late September 2022.

A.4 Robustness

A.4.1 Results with obituaries excluded

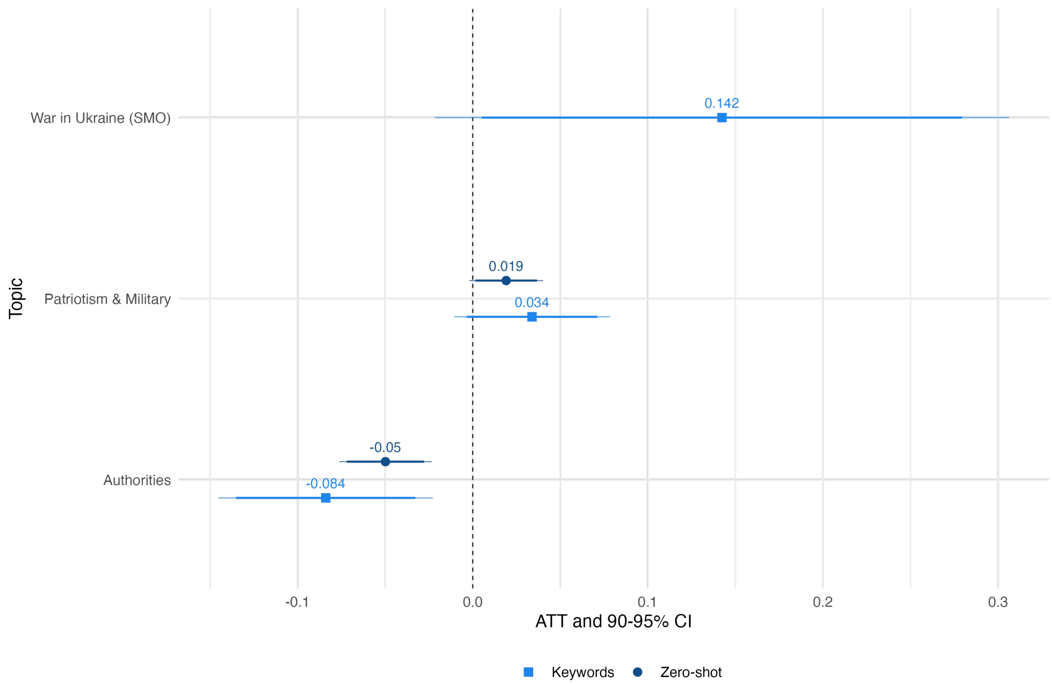


Figure A12: Change in engagement by topic relative to *Neutral* content after the first KIA report (no obituary posts). *Note:* Obituaries removed from the sample of the posts. Dependent variable: $\Delta \log \text{Likes}$ per post. Treatment: First KIA report month in the municipality. Dots show ATT coefficients from separate Callaway and Sant'Anna (2021) estimations by topic. Topic is defined along the vertical axis. Horizontal bars represent 90% and 95% confidence intervals. Standard errors clustered at the municipality level. Squares and circles indicate classification strategy.

A.4.2 Detailed topics

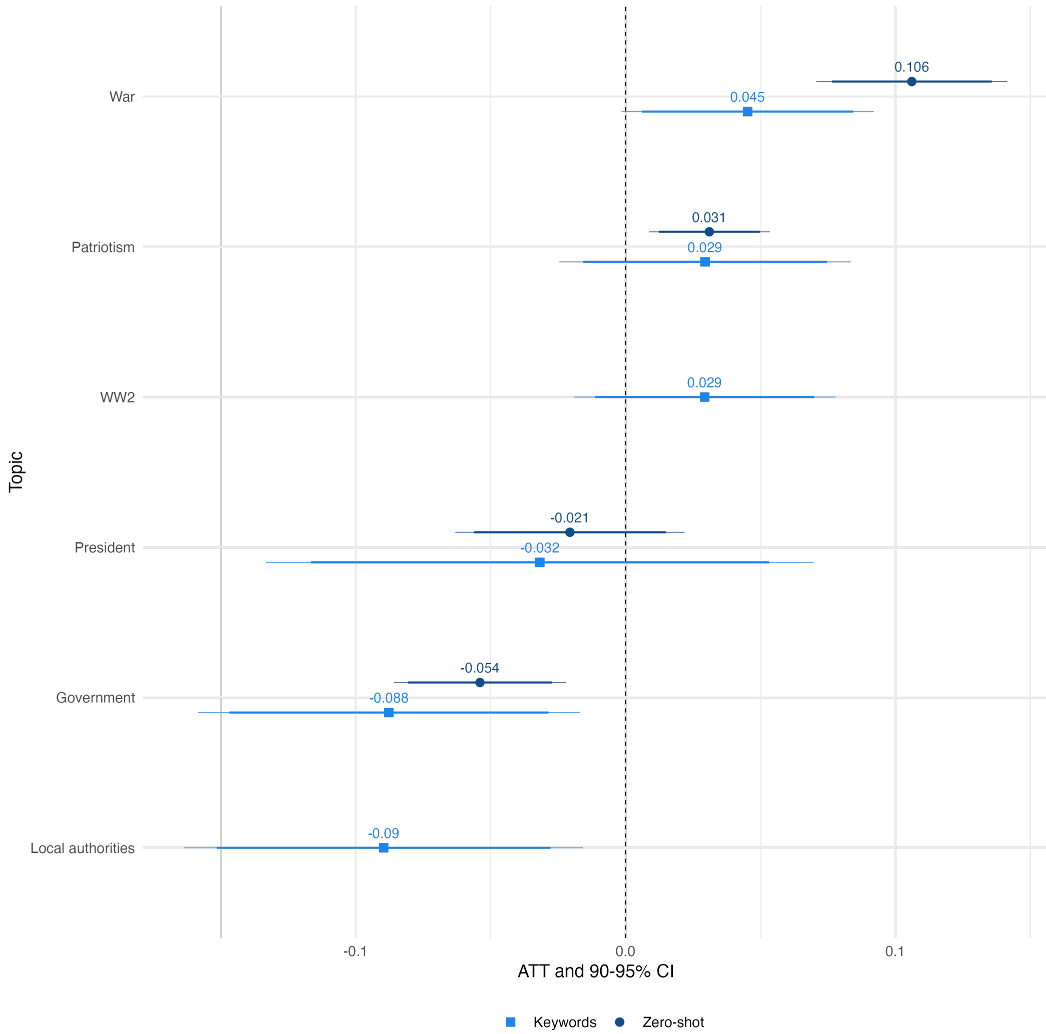
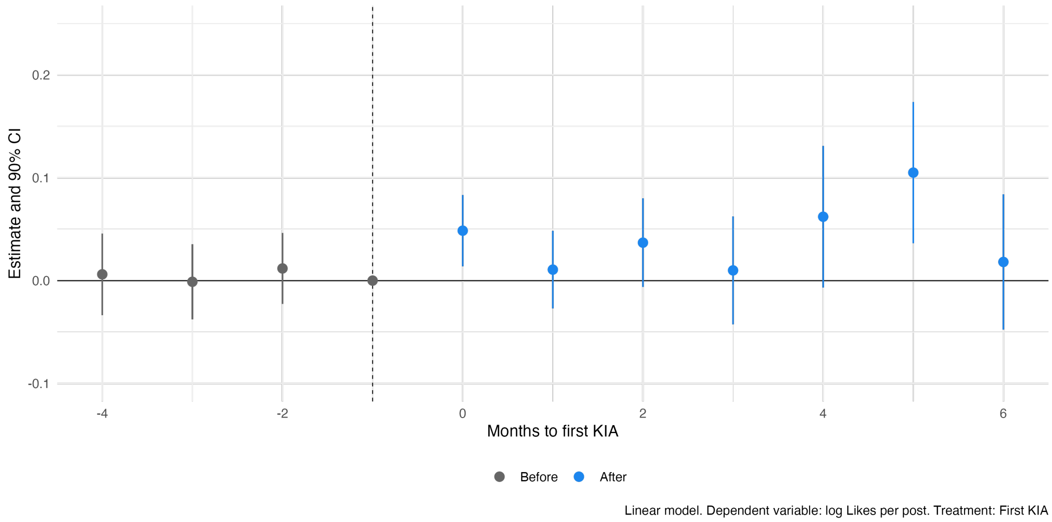
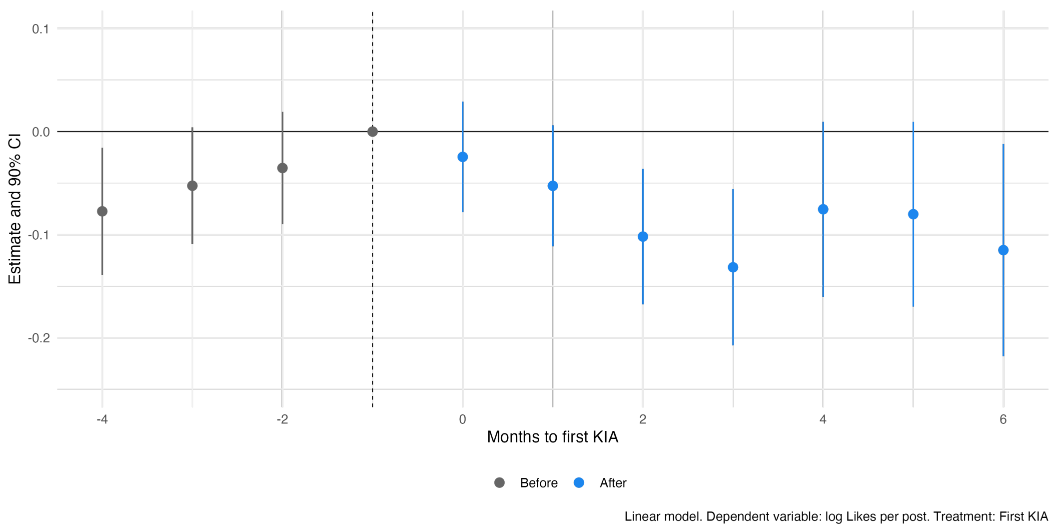


Figure A13: Change in engagement by topic relative to *Neutral* content after the first KIA report. *Note:* Dependent variable: $\Delta \log \text{Likes per post}$. Treatment: First KIA report month in the municipality. Dots show ATT coefficients from separate Callaway and Sant'Anna (2021) estimations by topic. Topic is defined along the vertical axis. Horizontal bars represent 90% and 95% confidence intervals. Standard errors clustered at the municipality level. Squares and circles indicate classification strategy.

A.4.3 Alternative Estimator



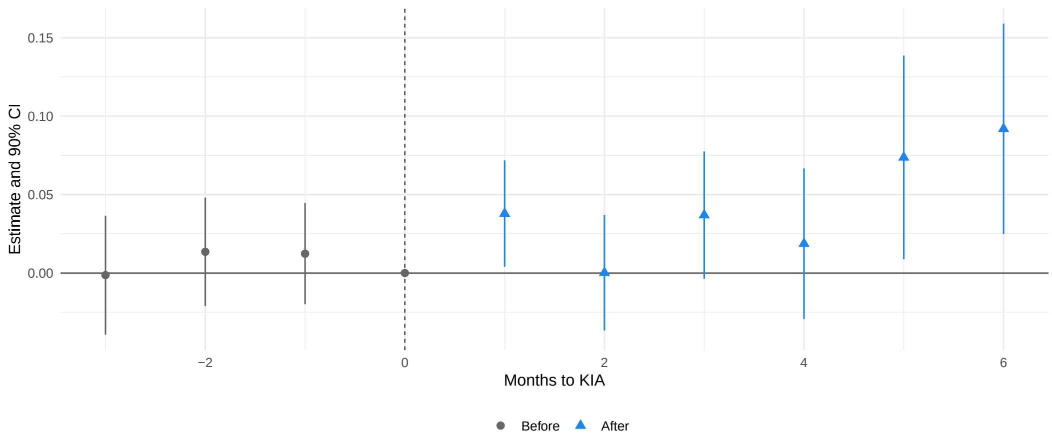
(a) Effect on engagement with *Patriotism & Military* topic



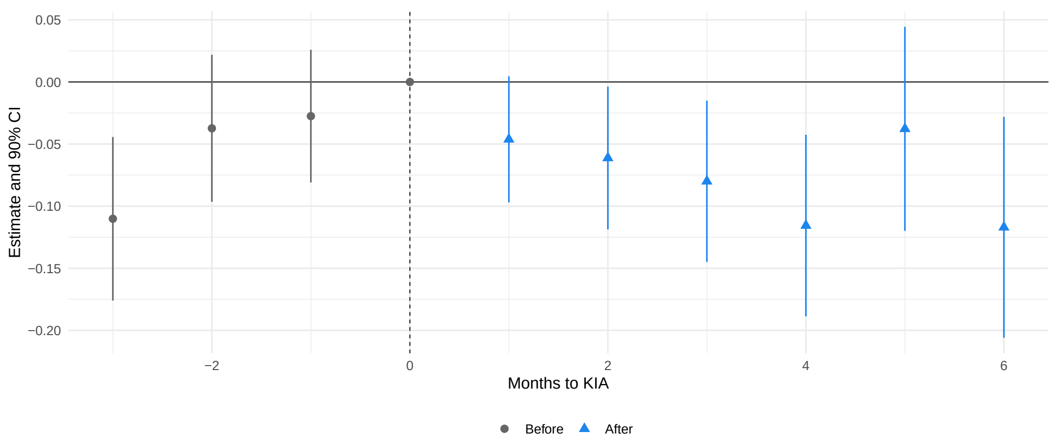
(b) Effect on engagement with *Authorities* topic

Figure A14: Event study graphs for the effect of the first KIA report (keywords). *Note:* Dependent variable: Δ log Likes per post. Independent variable: *Post KIA*. Estimator: Sun and Abraham (2021). Control group: Not treated by the end of the considered period (January 2022 – September 2022). Dots report the point estimates. Vertical bars report the 90% confidence intervals. Standard errors clustered at municipality level.

A.4.4 Repeated Treatment



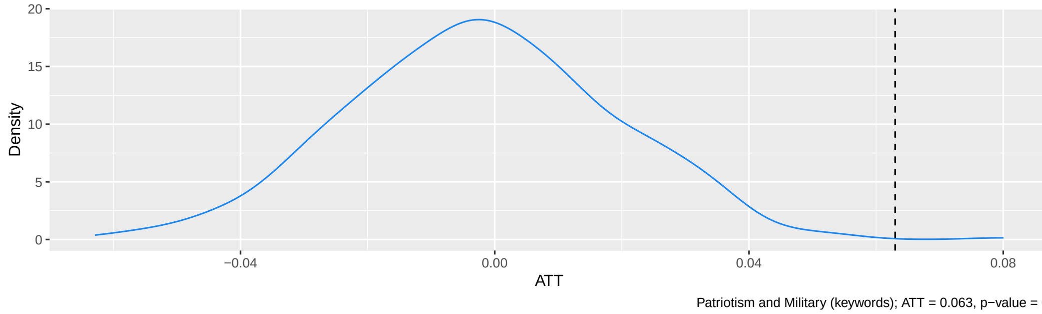
(a) Effect on engagement with *Patriotism & Military* topic



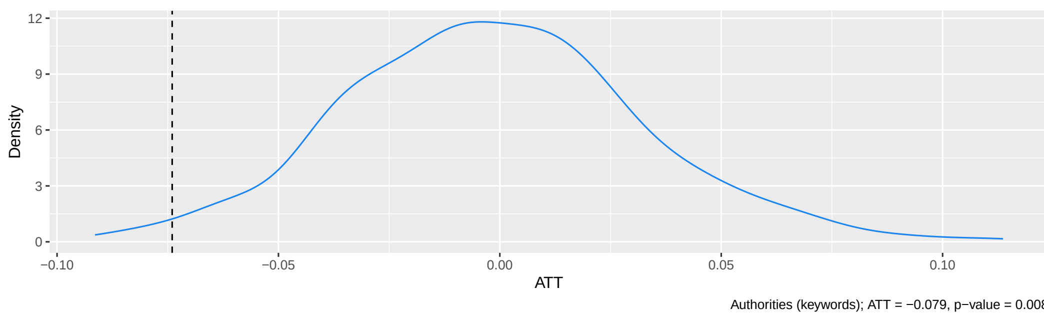
(b) Effect on engagement with *Authorities* topic

Figure A15: Event study graphs for the effect of a KIA report (keywords). *Note:* Dependent variable: Δ log Likes per post. Independent variable: *Post KIA*. Estimator: Chaisemartin and D'Haultfœuille (n.d.), allowing for treatment switching on and off. Control group: Not treated at a given month with a similar treatment history. Dots report the point estimates. Vertical bars report the 90% confidence intervals. Standard errors clustered at municipality level.

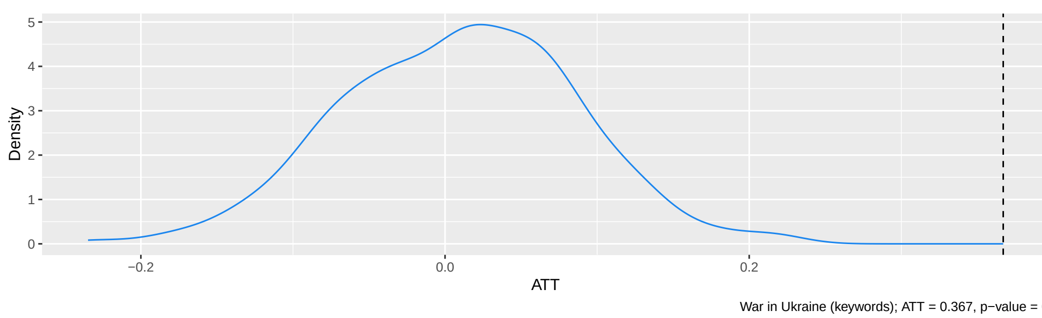
A.4.5 Placebo studies



(a) Effect on engagement with *Patriotism & Military* topic

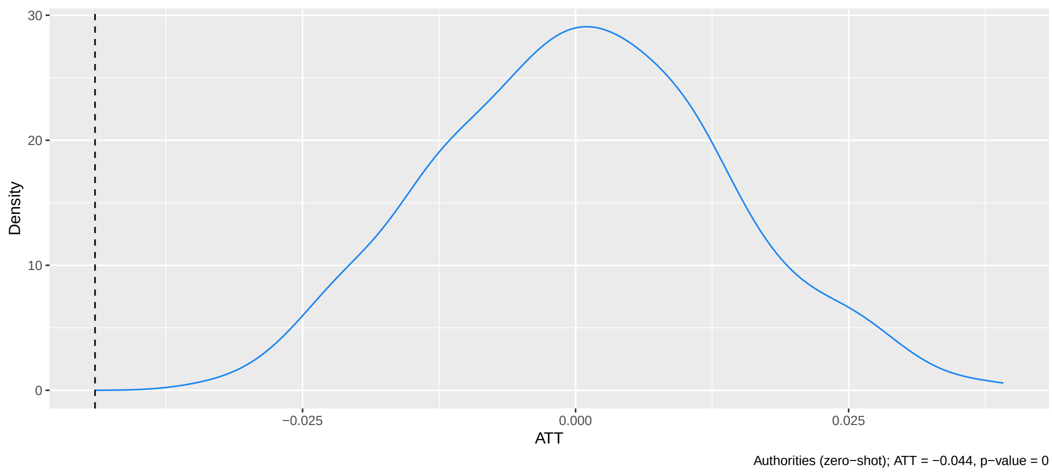


(b) Effect on engagement with *Authorities* topic

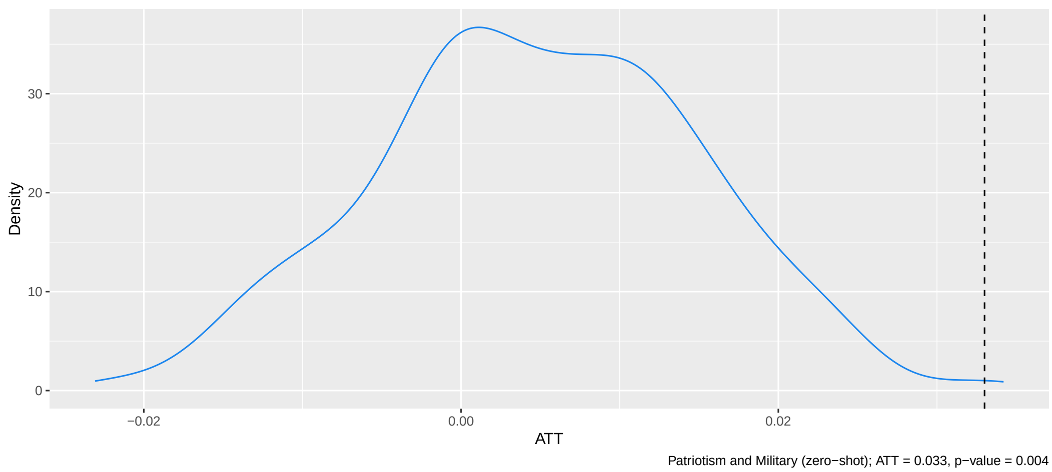


(c) Effect on engagement with *War in Ukraine* topic

Figure A16: Monte-Carlo simulation for the effect of the first KIA report (keywords). *Note:* Dependent variable: Δ log Likes per post. Independent variable: *Post KIA*. Estimator: Callaway and Sant'Anna (2021). Control group: Not yet treated. Dashed vertical line reports the ATT estimate on the original sample. Standard errors clustered at municipality level.



(a) Effect on engagement with *Patriotism & Military* topic



(b) Effect on engagement with *Authorities* topic

Figure A17: Monte-Carlo simulation for the effect of the first KIA report (zero-shot). *Note:* Dependent variable: Δ log Likes per post. Independent variable: *Post KIA*. Estimator: Callaway and Sant'Anna (2021). Control group: Not yet treated. Dashed vertical line reports the ATT estimate on the original sample. Standard errors clustered at municipality level.

Table A2: Keywords and Topics. *Note:* Russian translation in *italics*. Keywords allow for flexible patterns at the end of strings to account for various grammatical forms. * *Conversations* or *conversations on important topics* is a term used by the Russian Ministry of Education to refer to patriotic upbringing lessons.

Topic	Keywords
War in Ukraine	
Special military operation	SMO, special military operation, letter to a soldier, a hero's desk
Ukraine	Crimea, Sevastopol, Ukraine, Donbass, Luhansk, Kherson, Zaporizhzhia, Mariupol, Donetsk, Kyiv
Authorities	
President	president, Putin
Government	deputy, parliament, state duma, minister, ministry
Local authorities	head of region, governor
Patriotism and Military	
War	soldier, military, warrior, mobilization, special operation, protection, defender, hero, serviceman, frontline, valor, veteran, motherland, fighter, fighting
WW2	Great patriotic war, great victory, World War II, 1940s, victory
Patriotism	flag, national anthem, conversations*, lesson of bravery, heroism, duty

A.5 Descriptives

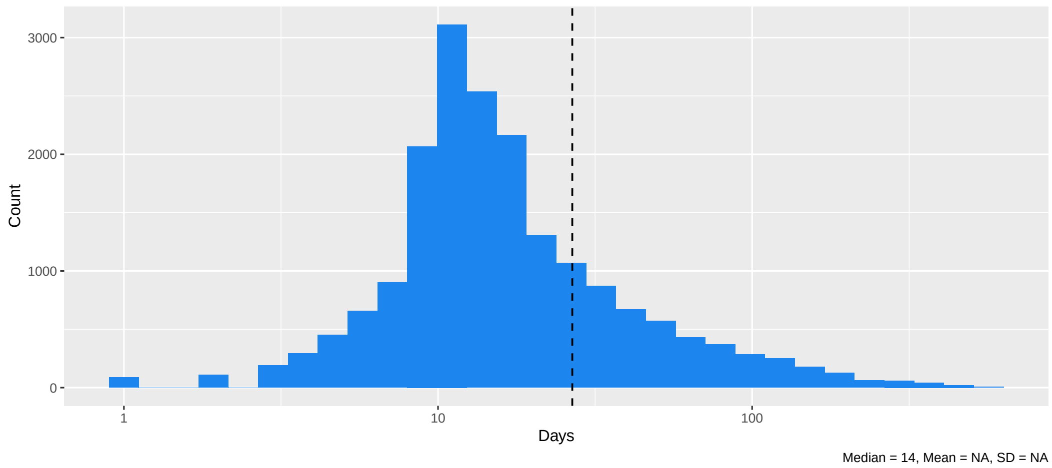


Figure A18: Days between a soldier's death and a death act

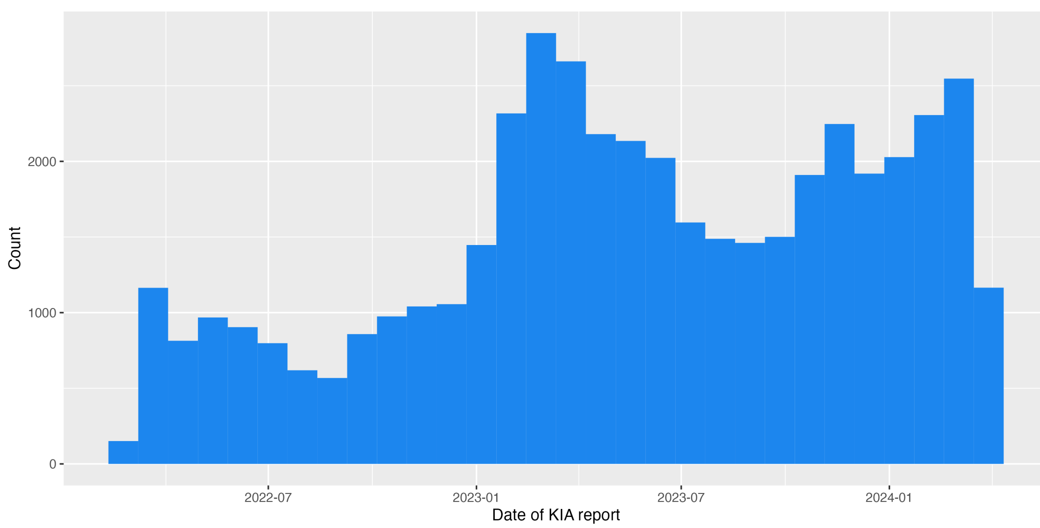


Figure A19: Dynamics of monthly KIA reports

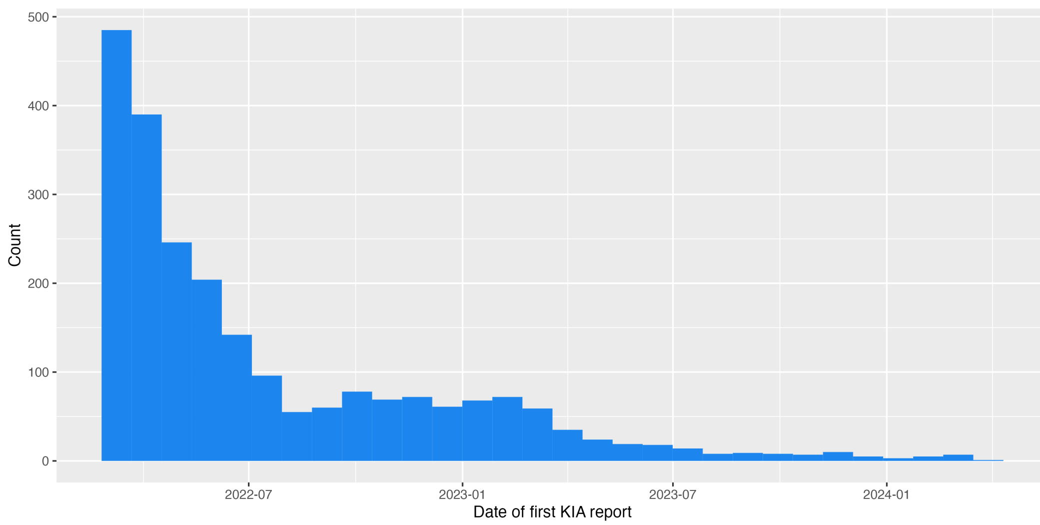


Figure A20: Date of first KIA reports

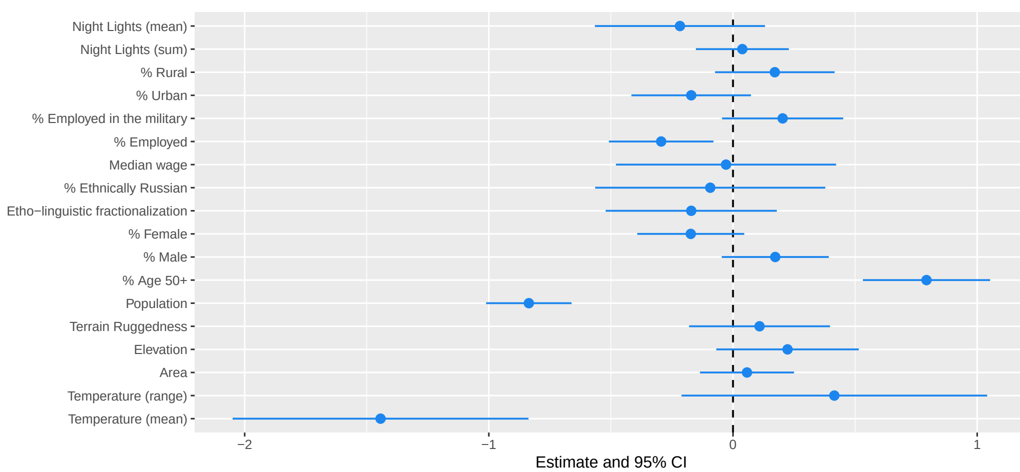
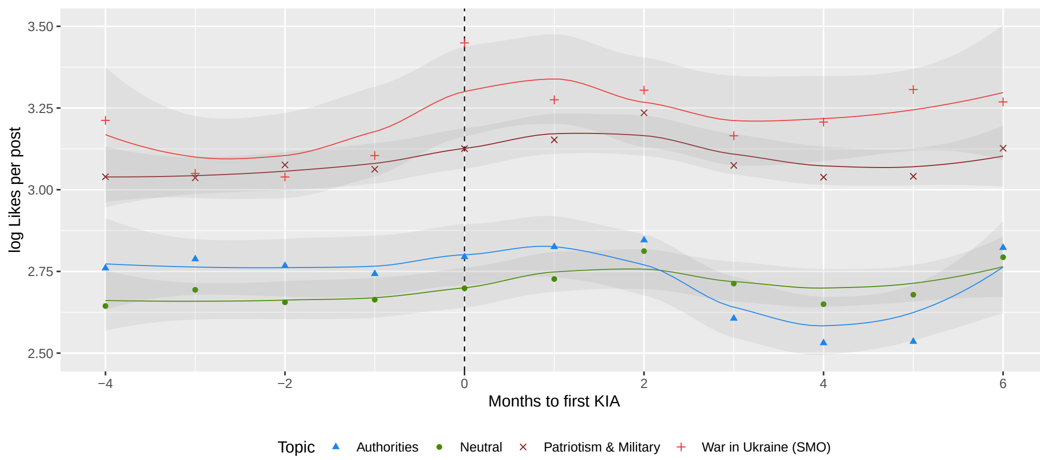
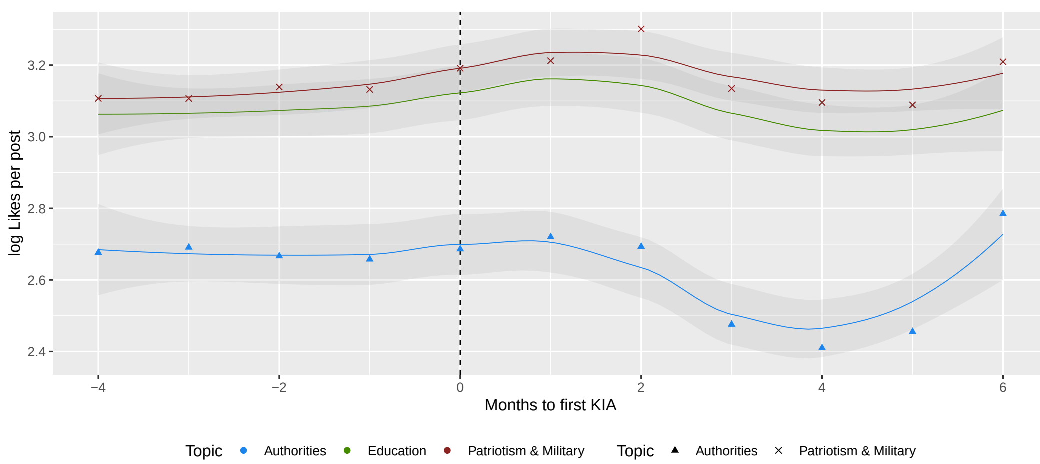


Figure A21: Correlates of the KIA report treatment with covariates. *Note:* Dependent variable: Month of the first KIA report. Independent variables: Covariates defined along the vertical axis and region fixed effect. Dots show the standardized coefficient from a separate regression. Negative coefficients correspond to earlier treatment time. Standard errors clustered at the region level. Data sources: Federal State Statistics Service of Russia (Rosstat); NASA VIIRS.



(a) Keyword topics



(b) Zero-shot topics

Figure A22: SM engagement around the date of the first KIA report

A.6 Supplemental Appendix

A.6.1 Topic and sentiment score correlations

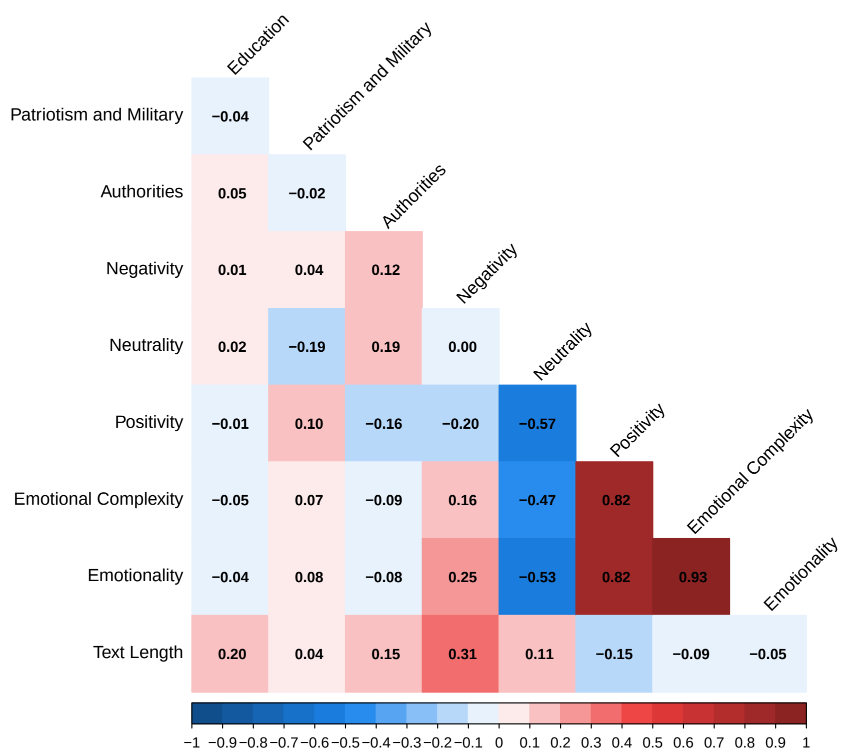


Figure A23: Correlation matrix of Zero-shot topic probabilities and sentiment scores

Table A3: Heterogeneity of the KIA reports effects with respect to alternative sentiment scores

	Likes per post			
Score	Neutrality	Emotinality	Complexity	log Length
	(1)	(2)	(3)	(4)
Post KIA	2.98***	-1.52***	-0.754***	0.424
	(0.288)	(0.198)	(0.177)	(0.657)
Topic relevance	-23.1***	18.6***	28.6***	-1.36***
	(0.367)	(0.497)	(0.881)	(0.079)
Post KIA × Topic relevance	-5.55***	7.92***	11.7***	-0.120
	(0.396)	(0.701)	(1.29)	(0.107)
Mean Likes	18.9	18.9	18.9	18.9
Mean Score	0.577	0.153	0.038	6.09
N School	12,971	12,971	12,971	12,971
N Month	13	13	13	13
Observations	2,014,787	2,014,787	2,014,787	2,014,787
R^2	0.319	0.276	0.275	0.272
School FE	✓	✓	✓	✓
Month FE	✓	✓	✓	✓

A.6.2 Emotional intensity and text length

A.6.3 Battlefield dynamics

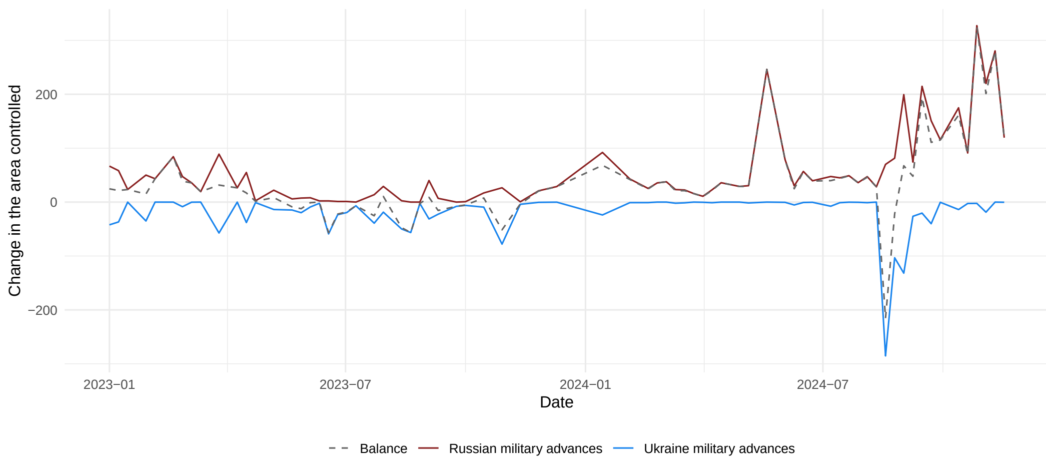


Figure A24: War in Ukraine battlefiled dynamics in 2023-2024. *Note:* Red and blue lines shows the changes in the area controlled by Russian and Ukrainian military in squared kilometers, respectively. Dashed line indicates the changes in the overall balance in terms of controlled territory. Note that the overall balance was very stable in 2023. Source: Meduza

A.6.4 Maps

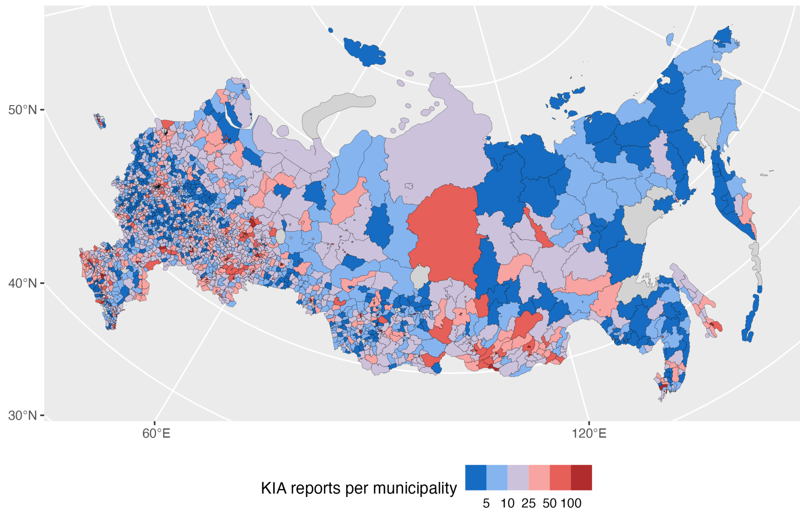


Figure A25: Map of confirmed military losses in Russian municipalities by March 2024

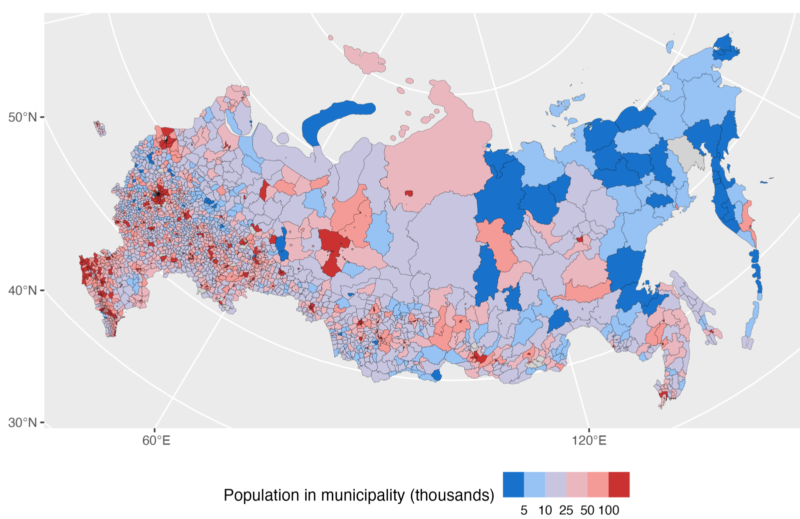


Figure A26: Map of population in Russian municipalities

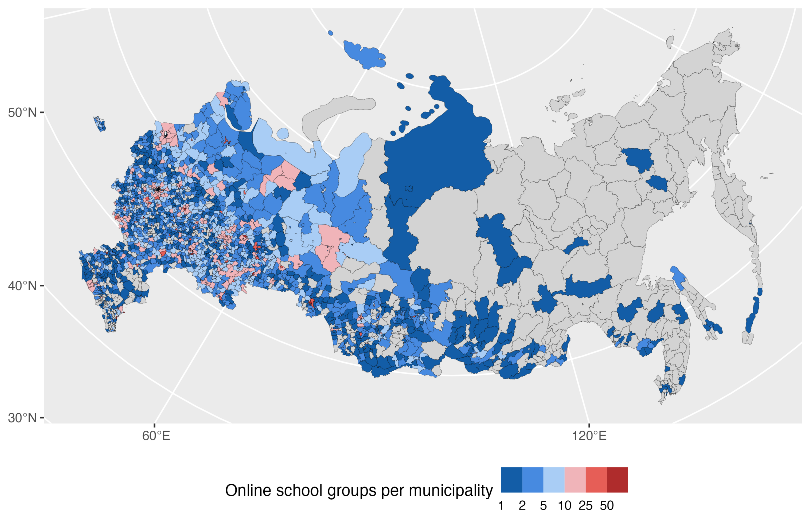


Figure A27: Map of online school groups in Russian municipalities in January 2022

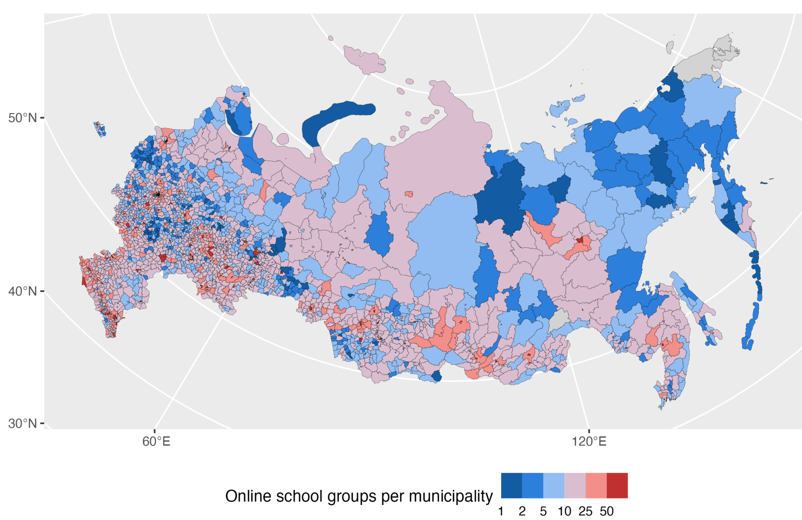


Figure A28: Map of online school groups in Russian municipalities in March 2024

A.6.5 Wordclouds

Figure A29: Wordcloud for *Education* topic from a random subsample of posts (zero-shot probability > 0.8)

Figure A30: Wordcloud for *War* topic from a random subsample of posts (zero-shot probability > 0.8)

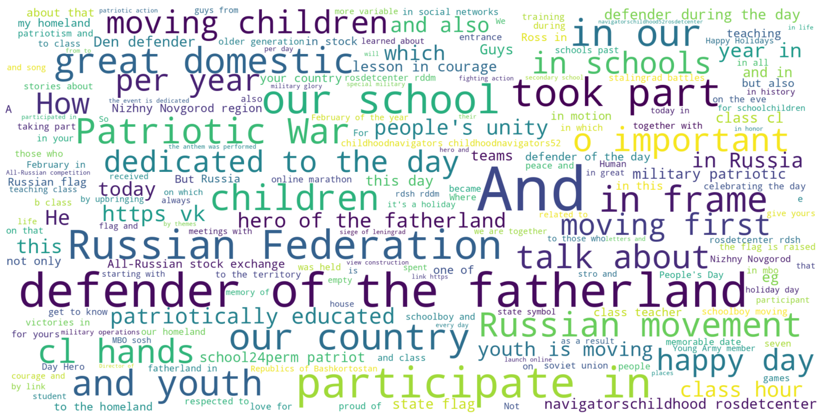


Figure A31: Wordcloud for *Patriotism* topic from a random subsample of posts (zero-shot probability > 0.8)

Figure A32: Wordcloud for *President* topic from a random subsample of posts (zero-shot probability > 0.8)

Figure A33: Wordcloud for *Government* topic from a random subsample of posts (zero-shot probability > 0.8)

A.6.6 Procedure for declaring a serviceman dead

Until 2023, in accordance with Russian law, a person could be declared dead either by a death certificate issued by a medical professional or through a court decision based on prolonged absence.[7] In the context of the Russo-Ukrainian war, it meant that many servicemen killed on the front lines could not be declared dead until their bodies were retrieved from the battlefield and examined by a medical professional. In cases, where a deceased had no identification documents, the body had to be identified by the relatives, introducing significant delays in declaring a person dead due to logistics, informational friction, and mandatory DNA testing.[8]

The procedure has been significantly simplified since. As of September 2023, a death certificate for a servicemember killed in action can be issued instead of the medical death certificate in cases where medical confirmation is not possible.[9] The

[7] Federal Law of 15.11.1997 N 143-FZ (as amended on 08.08.2024) "On Acts of Civil Status" (as amended and supplemented, entered into force on 19.08.2024)

[8] North.Realities (2022); "Missing in Action: How Mothers and Wives Search in Rostov for Soldiers Who Disappeared on the Front Line" (2024); "Telegram: Contact @Akashevarova" (n.d.)

[9] Resolution of the Government of the Russian Federation of 01.09.2023 N 1421 (as amended on 05.04.2024) "On approval of the Rules ... for issuing a certificate of death of a citizen, the form of a certificate on the circumstances of the disappearance of a citizen, the form of a certificate on the circumstances of the disappearance or possible death of a citizen, the form of a certificate

commander of the military unit prepares an official report confirming the death within 30 days of the presumed date of death. This step is necessary if the body cannot be returned but eyewitness accounts confirm the death. The signed report is then sent to the military commissariat at the servicemember's place of registration, which has to issue the death certificate to the family no later than 10 days after receiving the report. Therefore, a serviceman should be declared dead within 40 days since the supposed date of death. However, journalistic accounts suggest that the commanders of the military units have incentives to cover soldiers' deaths as the unit's KPI is calculated as a function of the number of people killed in action but not those missing.[10]

If no death certificate is available from a medical professional or the military, Russian civil law allows a court to declare a citizen dead. This requires five years of absence without information about the person's whereabouts. However, in cases where the individual went missing under life-threatening circumstances, this period can be reduced to six months. Before September 2023, servicemembers could only be declared dead no sooner than two years after the end of military operations. Following legal changes in September 2022, this waiting period was further reduced to a maximum of three months for those missing in the "Special Military Operation zone."[11]

of death of a citizen"

[10]For instance, some military units have been reported for declaring soldiers who have not yet entered the battle missing "in advance" to appropriate their salary bank cards and increase the KPI of the unit (see ""As a Rule, They Don't Get There"" 2024).

[11]Federal Law of 30.11.1994 N 52-FZ (as amended on 25.12.2023) "On the entry into force of Part One of the Civil Code of the Russian Federation" (as amended and supplemented, entered into force on 01.05.2024)