WAR, PROPAGANDA, AND RUSSIAN FATALITIES IN UKRAINE*

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Abstract

This article examines how military losses shape public engagement with propaganda. We combine data on Russia's military losses in its war against Ukraine with unique data from Russian social media school groups to estimate the effect of war fatality reports on engagement with propaganda across a range of topics. Exploiting idiosyncrasies in the timing of these reports for identification, we document a sustained decline of up to 30% in likes, shares, and views for content promoting the government and the president after the first report in a municipality, while engagement with patriotic content briefly increases. Engagement with content explicitly mentioning the Russia-Ukraine war also increases, but only for commemorative posts. These effects are most pronounced in municipalities where the reports appear on social media, highlighting the role access to alternative information plays in shaping public response to propaganda. Analysis of the obituaries with a large semantic model shows that users engage most with personal stories of the KIA soldiers, and disengage when these are paired with nationalistic propaganda or references to the regime. Together, these changes in engagement patterns suggest that war fatalities can hinder the spread of propaganda and public support for the regime during conflict without promoting nationalism.

Keywords: War, propaganda, regime support, patriotism, social media
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1 Introduction

Disinformation and propaganda threaten democracy and peace (Guterres 2023). Their influence on public attitudes and political stability becomes alarmingly tangible with the advance of new information technologies, social media in particular, facilitating the spread of false information on an unprecedented scale (Tucker et al. 2018). As the world witnesses the most significant increase in both right-wing populism and armed conflict in several decades (UN 2022; PRIO 2023), understanding how the public engages and interacts with propaganda[1] is crucial to mitigate its spread and prevent future conflict.

Conflict and propaganda are inextricably connected (Miller 1939; Lasswell 1971), and the role propaganda plays in promoting conflict is well-documented. Past research has shown that propaganda and disinformation incite violence (Yanagizawa-Drott 2014), fuel nationalism (Adena et al. 2015), lead to polarization (Sunstein 2018), and help non-democratic leaders grasp power (Geddes and Zaller 1989; Guriev and Treisman 2019). War—the ultimate form of conflict—heightens the stakes of propaganda even further as governments and media institutions seek to promote national unity and justify their military endeavors (Lippmann and Curtis 2017; Jowett and O'Donnell 2012). Yet, whether and how public interaction with propaganda is shaped by the conflict itself remains unclear.

This article explores how the public interacts with propaganda during the conflict. Specifically, we examine the link between military losses and user engagement with propaganda on social media (SM) in the context of Russia and the war it is waging against Ukraine.[2] From its onset in 2014 as Russian paramilitary and false-flag operations in

[1] We use the term propaganda to emphasize that the disinformation we analyze is state-promoted. Apart from this distinction, we follow the broad definition of disinformation, which includes "fake news," rumors, factually incorrect information, and politically slanted content, as in Tucker et al. (2018).

[2] Our focus is on social media as, in recent years, online propaganda has pervaded cyberspace and has become a staple of authoritarian propaganda efforts (Deibert and Rohozinski 2010; Alyukov 2021), with Russia serving as a prime example (Fortuin 2022; Rutenberg 2022). It also provides a straightforward way to capture engagement with observed user activity, e.g., comments, shares, and reactions. In addition, regarding news and political content, likes, comments, and shares often serve as tools for active engagement and expressions of support (Ha et al. 2016; Hoelig 2016), enabling users to influence public discourse and foster civic empowerment (Manosevitch and Tenenboim 2016). Although critics often dismiss such activity

Crimea and Donbas, Russia has relied on propaganda and informational warfare to secure public support and avoid blame for the conflict. This reliance increased further when, on 24 February 2022, unexpectedly for many, president Putin publicly announced the launch of a "special military operation in Ukraine." With more than one million casualties since then, it soon became the deadliest war in Europe's history since World War II. However, Russian propaganda maintained the narrative of a limited intervention performed by the professional military, with Putin himself repeatedly claiming that there was no need for mobilization or participation of conscripts (The Current Time 2024). Moreover, in March 2022, the Parliament of Russia passed a law criminalizing the spread of military-related information not approved by the Russian Ministry of Defense (MoD), which reported close to no losses and denied any civilian casualties and war crimes (UN 2023). In this context, many Russians did not anticipate any fatalities at all, and even the first deaths reported outside official statements sparked discussion around the disconnect between the official narrative and the reality on the ground (Urman and Makhortykh 2022).

We hypothesize that in a setting like this, war fatality reports could influence engagement with state propaganda in two distinct ways. On the one hand, they may increase engagement with propaganda if it appeals to patriotic sentiment, consistent with a rally-around-the-flag dynamic reinforced by the control over the narrative on the government's part (Kizilova and Norris 2024; Boettcher and Cobb 2009) and wars fostering nationalism in general (Acemoglu et al. 2022; Juan et al. 2024). On the other hand, military losses might decrease engagement with propaganda due to the reduced credibility of official statements in view of military losses and decreased support for the ruling elite, as findings from democratic contexts suggest (Althaus, Bramlett, and Gimpel 2012; Kuijpers 2019; Karol and Miguel 2007; Hetherington and Nelson 2003).

as *slacktivism* or *clicktivism* that lacks real world impact (Christensen 2011), a growing body of research shows that online political participation complements rather than replaces traditional forms of participation, such as civic activity, protests, or party involvement (Daniel S. Lane et al. 2017; Boulianne and Theocharis 2018; Freelon, Marwick, and Kreiss 2020; Theocharis et al. 2022).

To disentangle these potentially counteracting effects, we explore the link between military losses and engagement with propaganda across a range of topics, including patriotic and pro-authorities. To achieve this, we collect unique data from VKontakte, or VK, Russia's largest SM platform, focusing on propagandistic posts on online groups of Russian schools. While these groups are not explicitly political, they are curated by the government and only post political content aligned with the state narrative alongside neutral topics like education. School groups are also present in most Russian towns and are less likely to be targeted by bots than news outlets' SM pages. Our dataset includes over 28 million posts from 36,714 school groups, with users amounting to 12% of the Russian population. We classify these posts into topics using keyword analysis and a zero-shot large language model (LLM) and perform sentiment analysis, which allows us to explore engagement with different types of content.

To isolate the exogenous effects of war fatality reports on engagement with propaganda, we exploit the idiosyncratic timing of local KIA reports. We combine our social media engagement data with the database of Russian casualties in Ukraine that contains information on more than 90 thousand war fatality reports collected from Russian sources by a team of volunteers and journalists (Mediazona and BBC 2023) and complement it with soldiers' obituaries posted by the administrators of the school groups in our sample. The precise timing of these reports across municipalities is effectively random due to bureaucratic delays in confirming a soldier's death. This setting allows us to identify the causal effect by linking the initial public announcement of a local soldier's death to shifts in user engagement immediately after, using estimators designed for staggered treatment rollout while controlling for time and municipality fixed effects.

We find that engagement with the pro-authorities propaganda declines after the first KIA report in a municipality, with an average decrease of 6–10% in like-based engagement with pro-government and pro-president content relative to neutral in the period before September

2022. In addition, the estimates aggregated by calendar month indicate that the effect size increases over time: By March 2024, among all municipalities that had experienced a KIA report by that time, engagement with pro-authorities content had decreased by more than one third. These findings suggest that information on war fatalities can render propaganda less effective and erode support for the regime as the conflict prolongs. Similar patterns hold for engagement based on user shares, views, and comments.

In contrast, after KIA reports engagement with patriotic propaganda and content related to the war against Ukraine increases by 5–6% and 51%, respectively. However, this surge is limited to the first year of the war and is primarily driven by the support users show for the families of KIA soldiers: The effect for engagement with content referring to the Russia-Ukraine war decreases in magnitude more than three-fold when we remove soldiers' obituaries from the sample of posts and becomes statistically insignificant. While the surveys show unusually consistent support for Putin's regime after the start of the invasion of Ukraine, our results indicate that the rally is, or was, indeed, around the flag and not the authorities.

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; and (iv) not driven by the users shifting their social media consumption towards more positive, entertaining content. In addition, the results indicate that on the supply side, the topical composition of content does not change after the KIA reports.

Additional analysis provides further insights into the channels behind these effects. First, we find that the effect of the KIA reports is more pronounced in municipalities where obituaries with soldiers' personal stories were shared on school group pages, highlighting the importance of direct access to information in shaping public sentiment in environments where state controls the media and underscoring the role of emotions in response to the war. Second, we explore the texts of these obituaries using a GPT-based semantic model and find that users only engage with obituaries if they focus on personal stories of the soldiers but not on nationalistic and state-promoting narratives. Finally, while there is little correlation between the total number of fatalities in a municipality and the magnitude of the effect during the first year of the war, we find that later on higher number of fatalities is associated with lower engagement in both patriotic and pro-regime propaganda.

Our study makes several contributions. First, by looking at how the KIA reports affect users' reactions to state-promoted political content, our study makes an empirical contribution to largely theoretical and experimental research on public responses to propaganda, particularly during periods of crisis (Gehlbach and Sonin 2014; Horz 2021; Little and Nasser 2018; Sirotkina and Zavadskaya 2020; Yang and Zhu 2024; Weiss and Dafoe 2019; Alyukov 2021) and the literature on the effectiveness and limits of propaganda in general (Geddes and Zaller 1989; Carter and Carter 2023; Adena et al. 2015; Yanagizawa-Drott 2014; Alyukov 2023). Second, our paper advances the understanding of the effects of military losses on public attitudes toward the conflict, the governing authorities (Althaus, Bramlett, and Gimpel 2012; Getmansky and Weiss 2023; Kuijpers 2019; Karol and Miguel 2007), and the national identity (Juan et al. 2024; Acemoglu et al. 2022; Carozzi, Pinchbeck, and Repetto 2023). Finally, we add to the literature on public attitudes in non-democracies and Russia and Russia-Ukraine war in particular (Libman 2023; Rosenfeld 2023; Reisinger, Zaloznaya, and Woo 2023; Yudin 2022; Frye et al. 2023; Enikolopov et al. 2013; McAllister and White 2017; Kizilova and Norris 2024; Kulyk 2024).

The rest of the paper is organized as follows. Section 2 describes the context of Russia and the war it is waging against Ukraine. Building on that, Section 3 relates our paper to the literature. Section 4 describes the data employed in the study. Section 5 outlines the empirical strategy, and the results are presented in Section 6. Section 7 explores the potential mechanisms behind the effect. Section 8 concludes. All supporting information is in Online Appendix.

2 Background

Russia has waged war against Ukraine since 2014, heavily relying on propaganda and information warfare from the outset to avoid blame and conceal its involvement in the Donbas war (Mejias and Vokuev 2017). However, on February 24, 2022, Russia invaded Ukraine openly as Vladimir Putin announced the start of a "special military operation." Although tensions had escalated in the lead-up to the invasion, including the "recognition" of the so-called Lugansk and Donetsk People's Republics on February 21, 2022, few in Russia anticipated that a full-scale war would follow, and even fewer expected it to last more than a few weeks.

According to many accounts, the Russian government planned the invasion as yet another "short, victorious war" (e.g., Watling and Reynolds 2022). This plan quickly unraveled due to the strength of Ukrainian resistance and the poor preparation and planning of the Russian army. Still, the government maintained the narrative of a limited intervention up until September 2022, when it announced the "partial mobilization" of reservists, triggering the largest wave of protests since the invasion began (Sherwin 2022). However, throughout the first year of the invasion, officials insisted the war was being fought solely by a professional and highly skilled army, repeatedly ruling out the possibility of mobilization (Reuters 2022). To support this claim, the government minimized public knowledge of military losses: the Ministry of Defense (MoD) either reported minimal casualties, concealed the losses, or attributed them to non-combat causes, as in the case of the Moskva battleship (TASS, n.d.).[3]

[3]For comparison, Russian Ministry of Defense has only confirmed 5,937 fatalities, while independent journalists identified more than 90 thousand KIA by name as of February 2025 (Mediazona and BBC 2023).

Nonetheless, the government could not cover the military losses completely as the reports of soldiers killed in action (KIA) circulated in local news and on social media, typically shared by relatives or municipal authorities. This discrepancy between the lack of official statements from the MoD and local reporting raised significant concerns about the transparency of the government: Comments under KIA posts became one of the few online spaces where the official narrative was openly contested (Urman and Makhortykh 2022). Although the federal government could have, in theory, banned the publication of KIA reports, too, it has largely refrained from doing so, and as of February 2025, such reports continue to appear regularly on websites and social media pages. One possible explanation is that, given the scale of the war and the reach of the internet and social media, silencing all such reports would be unfeasible regardless of government efforts, and an attempt to do so could further undermine the credibility of the regime's narrative.

Arguably, to justify the invasion, the government ramped up its propaganda, with the education system becoming a central pillar of this effort. Now, schools and universities in Russia promote state-approved narratives that justify the invasion and reinforce regime loyalty. Revised curricula framed the 2022 escalation as a defensive response to Western aggression. In 2023, a unified school history textbook expanded coverage of the 2014 annexation of Crimea and the war in Ukraine, stating explicitly that Ukraine's NATO membership "would most likely be the end of civilization … [t]hat must not be allowed to happen" (Konstantinova 2023). The state also introduced new patriotic programs, including a compulsory Russian statehood course for undergraduates and weekly "conversations on important topics" in schools, each beginning with a flag-raising ceremony and the national anthem every Monday at 8:00 (University World News, n.d.). Many schools have been renamed after soldiers killed in the war, and initiatives like the "Hero's Desk," commemorating fallen soldiers in classrooms, have become widespread (MacFarquhar and Mazaeva 2023).

Altogether, this creates a paradoxical media environment. On the one hand, the Russian state has exerted tight control over the dominant narrative, suppressing dissent, fire-hosing propaganda and dismantling independent media. In 2023 alone, authorities blocked approximately 571,000 online resources (Verstka 2025), arrested over 19,000 individuals for participating in anti-war protests and initiated more than eight thousand administrative cases against those accused of 'discrediting the Russian military forces' (OVD-Info 2023; UN 2023). On the other hand, the public still learns about the war, with the local KIA reports being one of the most easily accessible channels to do so. In this paper, we explore how these reports impact public engagement with propaganda.

3 War, Propaganda, and Public Sentiment

Previous research has extensively explored settings where propaganda was effective in promoting hate and violence. For instance, Adena et al. (2015) shows that in Germany, pro-Nazi radio propaganda caused higher votes for the Nazis in March 1933 election, as well as promoted anti-Semitism. Yanagizawa-Drott (2014) demonstrates that the propaganda broadcasts of the Radio Television Libre des Mille Collines led to more violence during the genocide in Rwanda. Instead, we focus on another scope of the problem and explore not the effects of propaganda but how the public engages with it during conflict. We look directly at how individuals interact with propaganda on social media—in the context of this study, political content promoted by the Russian government online during the Russia-Ukraine war in 2022-2024—in response to war fatality reports, bringing together the literature on conflict, propaganda, and public opinion. Below, we provide a brief review of the literature on war fatalities and public opinion and describe how engagement with propaganda might shed new light on these dynamics.

3.1 War fatalities and public sentiments

The focus is on war fatalities as they represent the human cost of conflict that has the potential to shape public opinion about the war and the leadership. Past research shows that war fatalities can erode public support for leadership, especially in the longer term (Althaus, Bramlett, and Gimpel 2012; Kuijpers 2019; Voeten and Brewer 2006; Karol and Miguel 2007; Mueller 1985). War fatalities can also shape public opinion on whether the intervention is worth continuing. On one hand, as the casualties pile up, the public might decrease its support for the leadership and the intervention, considering it too costly to continue (Sullivan 2008; Mueller 1985; Gartner 2008; Gartner and Segura 1998). On the other hand, if the intervention has not reached its goals, the military losses already incurred may be perceived as in vain or sunk cost, lending more support to continuing the war (Boettcher and Cobb 2009; Veilleux-Lepage 2013; Koch 2011). Moreover, the extent and direction of these effects are highly context-specific, depending on media coverage, framing, and narrative surrounding the intervention (Baker and Oneal 2001; Gartner 2008; Boettcher and Cobb 2009; Berinsky 2007). However, most existing studies focus on democratic settings. We test whether these dynamics hold in the vastly different institutional and informational environments of autocracies.

Fatalities in an autocracy at war may not have the same effects on public sentiment observed in democracies, among other things, because of the autocrat's control over the information (Miller 1939; Mueller 1985; Geddes and Zaller 1989; Guriev and Treisman 2019). For one, the autocrat might conceal the military losses to curtail public discontent with the war. In such a setting, having first-hand exposure to information on war fatalities might be the only way for the public to learn about how the war goes and change their attitudes towards it or the authorities, and a greater amount of such information, e.g., more KIA reports, might facilitate this change. However, our analysis indicates that while the public reacts to information on war fatalities, the impact of additional KIA reports early on in the conflict is limited.

At the same time, inter-state conflicts forge national identities, and autocrat might exploit the losses to reinforce nationalist sentiments and blame external enemies for the bloodshed (Hutchinson, Leoussi, and Grosby 2007; see also Kulyk 2024 on the effect of the war on Ukrainian national identity). War fatalities in particular can foster ingroup favoritism and outgroup distrust, leading to stronger preferences for (Juan et al. 2024) and mobilization of nationalist movements (Acemoglu et al. 2022). While war fatalities can signal the incompetence of the leaders and the high costs of war, in the extreme case, government propaganda can be compelling enough to weaponize patriotic sentiment fatalities induce and thus offsetting potential negative effects on the support for the regime. In Russia, where the regime persecutes anti-war dissent, and the state narrative of the war dominates, we could expect the propaganda to spin information on military losses to incite nationalism and militarism.

Information on war fatalities can undermine the credibility of propaganda, especially if it goes too far in its attempts to portray the intervention as a competent and masterfully executed operation, rendering subsequent propaganda efforts less effective. From this perspective, our study relates to largely theoretical research on the effectiveness and framing of propaganda in authoritarian regimes (Horz 2021; Little and Nasser 2018). For example, Horz (2021) presents a formal model in which the extremeness of propaganda negatively correlates 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; see also Widmer 2024 on news manipulation in China), the regime in Horz's model decides whether to frame a specific event, which might convey information unfavorable to the regime, in a way that casts it in a more or less favorable light. The more extreme and rigid the dominant narrative is, the more likely citizens will become skeptical of the message. Our empirical analysis supports this formal intuition.

3.2 Public opinion and social media engagement

Understanding the dynamics of public opinion in non-democracies becomes crucial as the world faces an increase in populist and authoritarian movements (Stanley 2018). The research has shown that autocrats are more resilient in the aftermath of war, even after defeat (Mesquita and Siverson 1995), and are prone to wage longer (Bennett and Stam III 1996) and costlier (Siverson 1995) wars. To a large extent, these empirical regularities are due to fewer constraints from public opinion and domestic political pressures that these leaders face. Moreover, the 'rally-round-the-flag' effect may be stronger and more enduring in autocracies during wartime (Kizilova and Norris 2024), while international pressure often reinforces domestic support for authoritarian leaders (Hellmeier 2021), incentivizing military interventions not just to resolve international disputes but to consolidate power inside the country. While public sentiment may have a limited role in routine governance, it can become pivotal in moments of crisis, promoting regime change. 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 and the narratives they promote or, perhaps paradoxically, rally around them even more, and how it affects their views on the conflict and attitudes more generally.

Arguably, studying public opinion in autocracies is challenging, even in times of apparent stability and even more so during crises and international conflicts. A key reason for this is that, in authoritarian regimes, perceptions of widespread endorsement often shape the dynamics of public support (Buckley et al. 2024). Individuals might increase their support for a leader or a regime if they believe it to be popular, and this perception can create a feedback loop that amplifies the appearance of mass approval further. Crises intensify this dynamic, as fear and uncertainty may lead individuals to publicly express greater support for the regime, even as their private trust erodes (Jiang and Yang 2016).

Traditional surveys might struggle to capture these shifts in public sentiment due to preference falsification, further complicated by the practical difficulties of carrying research on such a sensitive topic in an autocracy during wartime (Tkachenko and Vyrskaia 2025; Libman 2023; Rosenfeld 2023; Reisinger, Zaloznaya, and Woo 2023; Yudin 2022; Frye et al. 2023). Electoral outcomes, meanwhile, are rare and unreliable due to fraud and voter demobilization (Enikolopov et al. 2013; McAllister and White 2017; The Moscow Times 2022). Other political activities, such as protests (as in Duvanova, Nikolsko-Rzhevskyy, and Zadorozhna 2023) or information sharing, are shaped by repression and persecution, discouraging broad participation and limiting involvement to a small subset of politically active individuals. Looking directly at how individuals engage with propaganda on social media via the like button provides a reasonable alternative, as engagement reflects an actual, albeit low-effort, behavior rather than self-reported attitudes or constrained formal participation.

Likes offer several advantages over other modes of engagement, such as commenting or sharing. First, clicking the like button requires minimal effort while still allowing users to express a simplified version of their sentiment or support (Sumner, Ruge-Jones, and Alcorn 2018; Lee, Hansen, and Lee 2016; Levordashka, Utz, and Ambros 2021). In addition, likes are less publicly visible since they are often aggregated, reducing the relevance of self-presentation concerns (Aldous, An, and Jansen 2019; Daniel S. Lane et al. 2019). This distinction is particularly relevant in autocratic contexts, where fear of persecution makes visible actions like comments or shares risky. For instance, according to the data collected by human rights organization OVD-Info (2023), in 2022 and 2023 more than 400 people were persecuted for their internet activity. In such environments, likes and *non-likes* allow users to express their views in a safer and more discreet way.[4]

[4]One of the potential concerns is that non-liking reflects deliberate disengagement, however, this is not always the case. For example, Ellison et al. (2020) show that the time and attention allocated does not differ between content users actively like and content they do not like. Importantly, not liking is often a conscious decision influenced by factors such as a lack of strong reaction to the content or considerations regarding the visibility of the like to their network and the platform. In line with this reasoning, Selnes (2023) find that

Liking behavior, however, is shaped not only by the topic of the content but also by its emotional tone, as studies show that surprising and emotionally charged content tends to receive more engagement (Tenenboim 2022; Feng 2024; Tenenboim and Cohen 2013; Berger and Milkman 2012), and emotional tone is one of the key features of propaganda (Miller 1939; Weston 2018; Da San Martino et al. 2019). Additionally, changes in engagement might reflect the shifts not only in public opinion but also in the patterns of online content consumption. For instance, stress can lead SM users to divert attention toward entertainment or go offline (see Wolfers and Utz 2022 for a review on stress and social media use). These dynamics can distort SM engagement metrics as indicators of public attitudes, particularly during war, when extreme mental strain may push audiences away from political content as a coping mechanism. To mitigate these concerns, it is important to account for the emotional tone of the content and interpret the dynamics of engagement with political content and propaganda against more general dynamics of content consumption.

4 Data

4.1 Social media engagement

The first set of data comes from *VK*, Russia's most popular social networking platform.[5] 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. For brevity, we refer to them as *engagement* from now on.

We primarily employ users' reactions, i.e., *likes* and derivative metrics discussed in more

users avoid liking not because of their disinterest in the content but rather due to "fear of getting similar content in their feeds and a fear to contribute to spreading potentially false news," which suggests that non-liking can be an intentional and thoughtful action rather than a simple lack of engagement.

[5]In Q1 2022, VK.com had 47.2 million daily and 73.4 million monthly active users in Russia only, and it is the 4th most popular website on the Russian segment of the internet after google.com, ya.ru, and dzen.ru.

detail in the next section, to social media posts on specific topics. This allows us to explore how individuals interact with propaganda but also provides insights into broader public sentiments: Among other things, liking reflects a straightforward response to content the user agrees with or enjoys (Alhabash et al. 2018; Sude, Pearson, and Knobloch-Westerwick 2021). Specifically, on VK, the default reaction to posts is a heart emoji labeled "I like," and most users stick to this default reaction or its absence instead of using other available emojis.[6]

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, 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.

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 Supplemental Appendix A.4.1). 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.

Second, the school communities are highly similar in terms of content and its timing. As

[6]As of the time of data collection in May 2024, the API of the VK did not allow for scraping the types of the reactions. We manually inspected posts from multiple pages and found that most posts had only the default "I like" reactions.

of 2021 Russian government requires all schools to be present online in its attempt to scale up the indoctrination and propaganda among the youth. While school group administrators have flexibility in terms of what they post, they have to do so in accordance with the guidelines provided by the government. Moreover, a large part of content 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 A.3.4 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 17,741 municipal budgetary school groups (MBOU) only 84 had more than 1 comment made by a bot (see **?@fig-bots** in 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.[7]

[7] The only exception is the city of Moscow, where official school groups do not have government verification marks and rarely post anything political. This is likely no coincidence, but the reflection of a deliberate approach the regime took to pacify the capital, which, however, is beyond the scope of the present study.

Group search criteria: We establish specific search criteria for online school groups on VK. 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 36,714 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 geolocate the pages. As shown in Figure IA, 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 A.XXIV). By March 2024, however, school groups had spread to cover all of Russia (Figure IB). 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.

Topics and emotional tone of posts: We download all the postings made by the school groups, more than 28 million in total. We exclusively consider posts created by school group administrators. We exclude reposts, i.e., posts originating from other communities shared on the school group's page, as well as posts with no text. Our main sample amounts to roughly 4 million posts made from September 2021 to September 2022, with 2 million posts being at least 100-character long. We use September 2021 as the starting date because it corresponds to the start of the academic year in Russia, while September 2022 coincided with the start of the partial mobilization of the reservists, and our full sample extends up to March 2024. 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.

We are interested in posts across three main content categories: posts that promote the authorities, express patriotism, or reference the Russia–Ukraine war—*Authorities, Patriotism*, and *War in Ukraine*, respectively. To classify posts into these topics, we use multiple approaches, starting with a keyword-based method. For each topic, we define a set of relevant keywords. For example, patriotic content includes mentions of the military, national anthem, the Russian flag, the Great Patriotic War, and holidays such as Victory Day (9 May) or Defender of the Fatherland Day. Similarly, pro-authorities content references the president or government, and posts mentioning the ongoing conflict are classified into War in Ukraine topic. Full keyword lists by topic are provided in Table A.X.

All topics except War in Ukraine are not mutually exclusive: a single post may be classified as both patriotic and pro-authorities. However, if a post mentions the war, it is assigned exclusively to War in Ukraine. This ensures comparability between pre- and post-invasion periods, since War in Ukraine posts are absent prior to February 24, 2022. Posts are assigned to a topic if they contain at least one keyword from its corresponding set. Posts that contain none of the keywords from our predefined sets are classified as neutral.

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 Russia-Ukraine war, 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 any of these topics (see Table A.VIII).

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. The model then assigns probabilities that a given post falls into one of pre-defined topics, or labels. For comparability with the keyword analysis, we set the labels to *President, Government*, *Patriotism* and *War*.[8] In addition, we select *Education* as a benchmark label, which we expect to be the most prominent topic in local online school groups. We use President and Government labels for pro-authorities content (Authorities), while Patriotism and War labels refer to patriotic content (Patriotism).

Table A.IX summarizes 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. Zero-shot analysis also validates that the keywords we selected are relevant for our topics of interest (Figure A.XIX). Figures A.XXX–A.XXXIV in Appendix show the most frequent words by topic from a sub-sample of posts.

In addition, we perform sentiment analysis on our sample of posts. Previous research in communication studies focusing on user reactions to different types of content has found that emotional tone of content might impact how users choose to react to it. In addition, emotionally charged tone is one of the key features of propaganda (Miller 1939; Weston 2018; Da San Martino et al. 2019). Thus, sentiment analysis might help us discern between nuanced and straightforward propaganda. Finally, concerning posts that mention the Russia-Ukraine, we deploy a GPT-4o mini model to identify the obituaries, and also use this model

[8]Due to the specific word markers the Russian authorities use to refer to the Russian-Ukrainian war (e.g., special military operation or SMO), in regard to this topic, we reserve to keyword analysis as zero-shot analysis provides little advantages over it. The zero-shot label War therefore refers to a broader set of content about the military or the Great Patriotic War.

to identify the presence of war glorification and personal grief narratives.

4.2 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, manually confirming each fatality using open-source data from Russian sources. 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 fatalities 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 it 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 military losses 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 simply disregard it as "enemy propaganda". 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.

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 and funerals. Figure IIA shows the number of total KIA reports in municipalities by March 2024. Figure A.XXI shows the number of KIA reports for the period from February 2022 to March 2024 by month as well as the distribution of the first KIA reports in municipalities over time.

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.

5.1 Engagement Indicators

Our primary outcome of interest is social media engagement with political content across different topics. Specifically, we look at engagement with content related to the war, patriotism, or the authorities. As the political content in question is promoted and curated by the government, we refer to it as propaganda.

Our 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 rare: In our sample, a post has on average 16.43 likes in comparison to only 0.96 shares and 0.43 comments. With this in mind, for the main part of the analysis we base our engagement indicators on likes.

To account for variations in posting intensity, we divide the number of likes by the number of posts. This ensures that fluctuations in the volume of posts, whether increasing or decreasing after the treatment, do not bias our engagement metric.[9] For keyword topics, we calculate

[9] As an alternative engagement metric, we compute the number of likes per view. However, this metric is

engagement with topic τ in municipality i at month t as

$$Engagement^{keywords}_{it,\tau} = \log Likes\ per\ post_{it,\tau} = \log \frac{\sum Likes_{pit,\tau}}{\sum Posts_{pit,\tau}},$$

where p indicates an individual post.

For zero-shot topics, we calculate engagement based on sums of likes and posts weighted by the zero-shot probability $\mathbb{P}_{p\tau}$ of post p falling into topic τ:

$$Engagement^{zero\text{-}shot}_{it,\tau} = \log\ \ Likes\ per\ post_{it,\tau} = \log \frac{\sum Likes_{pit} \times \mathbb{P}_{p,\tau}}{\sum Posts_{pit} \times \mathbb{P}_{p,\tau}}.$$

This metric however does not account for the fact that overall engagement might change 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. *This is our main outcome and we refer to it as relative engagement.* For keyword-based topics, the relative engagement indicator for a topic τ in municipality i at month t is calculated as:

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

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

more problematic because of endogeneity between likes and views: Due to the VK's recommendation system algorithms, posts with higher views tend to receive more likes, and vice versa. This issue is less relevant when normalizing likes by posts.

weighting the sums of likes and posts by the raw zero-shot probabilities, as follows:

$$\begin{aligned} \textit{Relative Engagement}^{\textit{zero-shot}}_{it,\tau} &= \Delta \log \ \textit{Likes per post}_{it,\tau} \\ &= \log \frac{\sum \textit{Likes}_{pit} \times \mathbb{P}_{p,\tau}}{\sum \textit{Posts}_{pit} \times \mathbb{P}_{p,\tau}} - \log \frac{\sum \textit{Likes}_{pit} \times \mathbb{P}_{p,-\tau}}{\sum \textit{Posts}_{pit} \times \mathbb{P}_{p,-\tau}}, \end{aligned} \tag{2}$$

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.

We also calculate the Engagement and Relative Engagement metrics based on the sentiment of the posts. Specifically, in Equation 2, we replace the zero-shot probabilities with the Positive/Negative sentiment scores and use neutral sentiment score as a benchmark, similar to *Education* for the topic analysis.

5.2 Identification Strategy

Our analysis is built around the two-way fixed-effects (TWFE) framework. For identification, we exploit the idiosyncrasies in the precise timing of KIA reports across municipalities, which has a substantial random component due to variation in the time required to confirm a soldier's death. The baseline TWFE model is:

$$Y_{it} = \beta \times \textit{Post KIA}_{it} + \gamma_i + \delta_t + \epsilon_{it}, \tag{3}$$

where Y_{it} is the outcome of interest in unit i at month t. $\textit{Post KIA}_{it}$ is a binary variable equal to one for the periods after the KIA report in unit i and zero otherwise.[10] The parameter of interest β therefore captures the effect of being exposed to local war fatalities

[10] In the baseline analysis, we assume that the treatment cannot be switched off after the initial KIA report, nor can it change after more news on military losses become available later. While this limits the analysis to the effect of the first KIA report, during the considered period most of the municipalities had only a few KIA reports, with the median number of total reports by September 2022 equal 4.

($Post\ KIA_{it} = 1$) or not ($Post\ KIA_{it} = 0$). Unit and month fixed effects are denoted with the variables γ_i and δ_t, respectively, and ϵ_{it} is the error term. To account for potential correlation in residuals across time periods within units, which is likely to occur in staggered treatment adoption designs (Abadie et al. 2022), we cluster standard errors at municipality level unless specified otherwise.

Incorporating time and unit fixed effects in the model effectively addresses key concerns about estimating the causal effects of local military losses on municipal-level outcomes. First, there is the potential issue that municipal-level differences in demographics, economic situation, access to alternative sources of information, or proximity to the war zone, might affect social media consumption patterns and, broader, political attitudes. By including municipality fixed effects, we account for any outcome differences that remain constant across municipalities. Additionally, national trends, such as shifts in political attitudes or economic and war-related policies could mistakenly be attributed to the KIA reports treatment. The month fixed effects control for variation at the national level over time.

Our study relies on a staggered difference-in-differences design, which requires additional identification assumptions for causal inference. First, we assume (group-specific) parallel trends, meaning that in the absence of KIA reports, engagement trends in municipalities treated at different times would have evolved similarly to those in not-yet-treated municipalities. This assumption allows for variation in pre-treatment trends across groups while ensuring that any observed changes in engagement following the first KIA report in a municipality can be attributed to information about war losses rather than pre-existing differences in content consumption patterns. Importantly, as the TWFE models might provide biased estimates in such settings due to effect heterogeneity and misspecified control groups, in addition to the TWFE, we use C&SA estimator (Callaway and Sant'Anna 2021). This estimator accounts for treatment effect heterogeneity and allows us to compare outcomes in municipalities that have already received the news about a local soldier's death with those that have not experienced any fatalities yet, while still accounting for municipality and time-specific variation.[11]

Second, we assume that the precise timing of observed military losses is not systematically related to pre-existing differences between the municipalities. We argue that due to bureaucratic delays, the precise date when the KIA report is published is idiosyncratic: Figure A.XX shows substantial variation in the time elapsed between soldiers' deaths and the confirmation of those deaths, even among the 18950 soldiers with known dates of death (Median = 14, Mean = 26.761, SD = 41.528). In addition, Figure A.XXII illustrates that, after accounting for region fixed effects, the timing of the first KIA report in a municipality is primarily driven by demographic factors—population size and age structure.[12] To account for these differences potentially affecting the timing of treatment, we control for log of population size, share of population older than 50 years, i.e., ineligible for the military service, and economic activity measured with the night lights intensity so that the parallel trends assumption holds only after conditioning on these covariates with the doubly robust procedure from Callaway and Sant'Anna (2021), or inverse probability weighting where the doubly robust is not feasible.

Third, we assume limited spillover effects, meaning that information about KIA soldiers impacts engagement primarily in their hometowns, rather than diffusing widely to untreated units. Although it is a possibility given that military losses from other municipalities might become known through geographically dispersed networks of friends and relatives, we expect the persuasive power of local KIA reports to be higher as these losses should bear more relevance than losses in other municipalities or highly impersonal total death toll (see Althaus,

[11] As alternatives to the Callaway and Sant'Anna (2021) estimator, we implement the estimation strategies proposed by Sun and Abraham (2021) and Chaisemartin and D'Haultfœuille (2024). The latter, in particular, is robust to heterogeneous effects and mitigates the risk of contamination from repeated treatments. Unlike Callaway and Sant'Anna (2021), this approach accommodates multiple treatment levels by comparing outcome changes across units with similar treatment histories before a given treatment switch. In our setting, a treatment switch occurs when additional KIA reports are published in municipality. We report corresponding results in Section A.1.3 and Section A.1.2.

[12] Municipalities with higher average temperatures also get the KIA reports earlier than those further North, likely due to higher population density in the European and South Siberia parts of Russia.

Bramlett, and Gimpel 2012 on the proximate casualties hypothesis). In the presence of such spillovers, our estimates would be of the additional effect of local war fatality reports.

Finally, when Y_{it} is relative engagement, i.e., the difference in engagement with politically relevant and neutral content, our model effectively transforms into a triple difference. Then, we assume that absent war fatality reports, engagement with different types of content would have followed similar trends within each municipality. This assumption ensures that shifts in engagement can be attributed to changes in political content consumption rather than general fluctuations in social media usage. Figure A.XXIII illustrates that, on average, the trends across topics evolved similarly before the first KIA report.

Unlike TWFE, which can be biased when treatment effects are heterogeneous over time or across groups, C&SA explicitly estimates group-time average treatment effects (GATTs), allowing for flexible treatment effect heterogeneity. To analyze the dynamic effects of treatment, we aggregate the 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 (months since the first KIA report) and compute average treatment effects for each event-time period. This approach enables a detailed visualization of the temporal evolution of the treatment effects, allowing us to test the parallel trends assumption as well as to estimate the effects by the individual post-treatment periods. The model in TWFE format is

$$Y_{ict} = \sum_{k=-4}^{7} \mathbb{1}(\mathit{Time\ to\ KIA}_{ict} = k) \cdot \beta_k + \gamma_i + \delta_t + \lambda_c + \epsilon_{ict}, \tag{4}$$

where *Time to KIA* is an indicator equal to 1 if the relative time to the month of first KIA report c is equal to k for municipality i at month t. β_k are the coefficients of interest. Under the parallel trends assumption, $\beta_k = 0$ should hold for $k < 0$. For $k \geq 0$, β_k would be the coefficients that capture the effect of the first KIA report in the post-treatment periods.

Importantly, the data on Russian military losses only contains information about soldiers whose deaths were confirmed from publicly accessible sources.[13] Therefore, we cannot completely rule out the possibility that the public learns about local losses in some other way, e.g., through word of mouth or closed groups and channels on social media. If so, our estimates may suffer from attenuation bias, as some treated units could be misclassified into the control group. We investigate this in more detail by repeating the analysis only on municipalities where the KIA reports were not posted on the pages of online school groups. This allows us to examine whether engagement patterns shift even in places where the KIA reports were not fully public.

6 Main Results

We explore the effect of the KIA reports on engagement with state-promoted political content across various topics, following Equation 3. The unit of analysis is municipality i observed in month t. The dependent variable is relative engagement, i.e., the difference in log likes per post between topic-relevant content and it's neutral counterpart (for more detail, refer to the previous section). Treatment is defined with variable *Post KIA*, equal to one for the months after the first KIA report in municipality and zero otherwise. For the main part of the analysis, the period in consideration is from September 2021 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.

We perform the analysis separately on a set of pre-defined topics, including Authorities—to capture engagement with content promoting the president and local and federal authorities—

[13] Reports of missing soldiers are also not a part of the database. In the presence of such reports, our estimates would be biased downward. Missing soldier reports, however, rarely become public since it is hard to establish whether a missing soldier died, deserted, or is a prisoner of war and therefore pose little threat to identification.

and War in Ukraine and Patriotism—to capture changes in engagement with patriotic, nationalistic, or militarized propaganda. 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 DGP behind the community administrators' posting behavior, we exclude municipality-months when we observe no posts on a topic of interest, as well as schools with less than 40 members (bottom 5% of all communities). We also exclude municipalities where no school community was active before 2022.

6.1 Engagement with pro-authorities content

Baseline estimates: To evaluate the average effect of KIA reports on engagement with pro-authorities propaganda, we begin by estimating a two-way fixed effects (TWFE) model regressing relative engagement for the topics of interest on Post KIA, with month and municipality fixed effects as in Equation 3. However, TWFE estimates may be biased in staggered treatment settings due to the use of already treated units as controls for later-treated ones, which can introduce negative weighting and violate the parallel trends assumption. To address this, we re-estimate the effects using the Callaway and Sant'Anna (2021) estimator, which compares each treatment cohort only to units not yet treated at a given point in time, thus avoiding contamination from post-treatment observations. In our preferred specification, we additionally control for log Population and log Night Lights.

Table I presents estimates for the Authorities topic based on zero-shot (Panel A) and keyword-based classification (Panel B). All estimates using the zero-shot metric are negative and statistically significant at 1% level, with the effect size ranging from –0.03 in the TWFE model to –0.047 in the preferred C&SA specification with controls. These results point to a consistent decline in engagement with authority-related content relative to neutral content, amounting to a 3–4.7% drop after the first KIA report in a municipality.

Keyword-based estimates in Table I, Panel B closely track the pattern observed with zero-shot classification, though they tend to be larger in magnitude. While the TWFE model yields a small and statistically insignificant estimate of 0.001, the C&SA estimator produces an effect of –0.079 without controls and –0.113 in our preferred specification, consistent with results in Panel A. These results suggest a decrease in engagement of about 8–12%, and provide further evidence of a systematic shift away from content promoting the authorities following the publication of KIA reports.

Considering on average 16.5 users like a post about authorities, a naive interpretation of these result would be that after the first KIA report, for each post, at least one user abstained from liking. Given the political nature of the posts, the effect we detect might be informative of a change in users' sentiment towards the authorities, consistent with the logic outlined in Sumner, Ruge-Jones, and Alcorn (2018).[14] Therefore, a decrease in likes for content promoting the authorities might reflect not only the diminishing engagement with propaganda on the respective topic but also a decrease in public support for the regime, specifically, the government of Russia and President Putin.

Event study estimates: To get a better understanding of whether the parallel trends assumption holds, we explore the dynamics of the effect of the KIA reports on relative engagement and estimate Equation 4 using Callaway and Sant'Anna (2021) controlling for population density and economic activity.

Figure III shows the effect dynamics for Authorities topic defined with zero-shot and keywords. We find no evidence for a significant difference in trends in the months leading up to the publication of an obituary for both metrics. The pre-treatment period coefficients are not statistically significant, both individually and jointly (Wald test of joint significance: $W = 1.115$, $p = 0.892$ for zero-shot; $W = 1.142$, $p = 0.888$ for keywords), and close to zero

[14]Alternative explanation would be that users employ the likes as a mean to show their support for a message publicly (Aldous, An, and Jansen 2019; Daniel S. Lane et al. 2019). However, since VK demonstrates user likes as an aggregate number by default, it is unlikely that the self-presentation concerns are the main driver of the result.

in magnitude for both classification approaches.

In line with our baseline estimates in Table I, we observe a decrease in relative engagement with pro-authorities content after the KIA reports. Figure IIIA shows that zero-shot relative engagement drops by around 5% one month after the first KIA report and then steadily decreases, reaching a magnitude of approximately 11% six months after the initial report. Figure IIIB demonstrates essentially the same dynamics albeit with a larger magnitude and wider confidence intervals, with the effect estimate reaching as much as -0.2. Assuming engagement with neutral content remained stable, this would imply that approximately 22.1% of users who would have liked pro-authorities posts chose not to like them after the KIA report.

This pattern may reflect the fact that, over time, more people in the municipality become aware of the fatalities and disengage from pro-authorities propaganda as their support for the regime declines. It may also reflect the effect of additional KIA reports in the months following the first one as most treated municipalities had more than one KIA report prior to the mobilization. We explore this in more detail in Section 7.

Calendar estimates: Public attitudes toward war and political authorities evolve over time as the conflict progresses, and reports of war fatalities may have different effects depending on the stage of the war. Particularly in longer conflicts, the public might further retract their support for the government (Kuijpers 2019).

To examine this possibility, in Figure VIB, we aggregate our estimates by calendar month to probe at how treatment effects change over time.[15] The results indicate that the decline in keyword-based relative engagement with pro-authorities content grows steadily in magnitude over the course of the war. By February 2024, the estimated effect reaches –0.3, corresponding to a drop of approximately 35% in engagement relative to neutral content in municipalities that had experienced a KIA report. Assuming stable engagement with neutral content and

[15] Due to computational constraints in regard of zero-shot classification, we report the full period results for keyword-based relative engagement only.

a stable user base, this implies that roughly one third of users who previously liked pro-authorities posts stopped doing so.

6.2 Engagement with patriotic content

Here, we repeat the above analysis for engagement with patriotic content, i.e. content that either promotes the national symbols or the military, with the exception of Russia-Ukraine war.

Baseline estimates: Table II presents the baseline analysis for engagement with patriotic content. All three specifications for zero-shot relative engagement in Panel A yield positive and significant estimates of magnitude from 0.026 to 0.037. Panel B provides similar estimates for keyword-based relative engagement: The TWFE estimate is 0.029 and the C&SA with controls yields an estimate of 0.068. These results suggest a modest increase in relative engagement with patriotic content of approximately 3–7%, corresponding to an increase in likes per post from 20 to 21-22.

Multiple interpretations are possible concerning the increase in engagement with patriotic and war-related content after the KIA reports. On the one hand, it may reflect the militarization of society and rising nationalist sentiment in response to military losses. On the other, it could signal the growing urgency and personal relevance of such content: As the war becomes harder to ignore, individuals may turn to patriotic narratives to make sense of local deaths, without necessarily becoming more nationalistic. To better understand these mechanisms, we next examine the dynamics of the effect.

Event study graphs: Figure IV presents the event study graphs for the effect of the KIA reports on engagement with patriotic content.

Pre-treatment coefficients are jointly and individually insignificant for both the zero-shot and keyword-based metrics even at the 10% significance level. Overall, there is little evidence for the violation of parallel pre-trends assumption.

Using zero-shot relative engagement metric, we detect an immediate 2.4 percentage points increase in in relative engagement with content promoting patriotism and military without referencing the Russia-Ukraine war. The effect accumulates over several months, reaching its peak of about 7 percentage points 4 months after the first KIA report in a municipality. However, the confidence intervals widen over time, and most post-treatment effects are insignificant. Results for keyword-based engagement metric in Figure IVA mirror this dynamic. The short-lived nature of the response suggests that the increase in engagement is unlikely to reflect a lasting rise in nationalism. Instead, it may point to a temporary emotional reaction to local losses, consistent with a brief rally-around-the-flag effect rather than a durable ideological shift. To probe this further, below, we aggregate the estimates by calendar months.

Calendar estimates: Figure VIA reports estimates aggregated by calendar month. We observe an increase in keyword-based relative engagement with patriotic content during the initial months of the invasion. However, this effect vanishes after the mobilization in September 2022 and turns negative in 2023, particularly following the PMC Wagner mutiny on June 23, 2023. This result supports the argument that the rally-around-the-flag effect had a limited duration and disappeared once the war effort required introducing an unpopular policy.

6.3 Engagement with content about Russia-Ukraine war

Baseline estimates: Table III shows the results for the effect on relative engagement for the War in Ukraine topic. In Panel A, we report the results for engagement with all posts that use the related keywords, such as Special military operation or SMO. The estimate is 0.21 for TWFE in Column 1, and it more than doubles in magnitude for C&SA with controls in Column 3 ($\beta = 0.507$), implying an increase in relative engagement with content related to the Russia-Ukraine war of up to 66% after the first KIA report in a municipality. Note that the period in consideration is shorter in comparison to Tables I and II because the posts made before February 2022 could not have mentioned the Russia-Ukraine war, and the number of municipalities where such content appears is also around 20% lower.

Table III, Panel B replicates the analysis excluding posts commemorating KIA soldiers from the sample before calculating the relative engagement metric. Specifically, the effect in Panel A may be driven by obituaries shared in school groups following KIA reports as such posts typically attract significantly more user attention than others (mean difference in likes per post = 76.29, t-statistic = 47.49, p-value = 0). Once these posts are excluded, the effect size drops by more than two-thirds and is no longer statistically significant in our preferred specification in Column 3. This drop is unlikely to be driven by selective attrition of municipalities where only commemorative posts appear in regard to the Russia-Ukraine war, as we lose only 12 municipalities in Column 3 between Panel A and Panel B. Overall, this indicates that the increase in engagement observed in Panel A is driven primarily by personal stories of dead soldiers, rather than by war propaganda per se.

Event study graphs: Figure V presents the event study graphs for the effect of the KIA reports on engagement with content about the Russia-Ukraine war.

As reported in Figure VA, in the month of the first KIA report, engagement with war-related content rises sharply, with an estimated effect of 0.48, corresponding to a 61% increase. The effect grows over time, reaching as high as 0.76 in subsequent months. Pre-treatment coefficients are individually insignificant, consistent with the parallel trends assumption. Joint significance is also low ($W = 9.2928$, $p = 0.0542$), and the magnitude of all pre-treatment estimates is roughly three times smaller than that of the first post-treatment coefficient.

Since obituaries are often posted by schools group administrators, Figure VB reports the results with commemorative posts and obituaries excluded from the relative engagement metric. As in Table III, Panel B, we find no effect of the KIA reports on engagement with content related to the War in Ukraine once such posts are excluded. only one of seven post-treatment coefficients is significant and their magnitude drops two-fold in comparison to the result reported in Figure VA.

Calendar estimates: Figure VIIA and Figure VIIB present estimates by calendar month. The results show that the rise in relative engagement following initial KIA reports was strongest during the first seven months of the invasion, prior to the announcement of mobilization. After this early period, the estimated effects decline sharply in magnitude and lose statistical significance. This pattern aligns with the end of the initial patriotic rally and suggests that mobilization may have marked a turning point in public sentiment towards the war.[16]

6.4 Robustness

Topical composition: One concern is that the detected effects may reflect shifts in topical composition rather than in engagement. After a KIA report, school administrators might increase patriotic publications due to strategic reasons or increased availability while reducing content about authorities to avoid association with war casualties. This could alter engagement simply by changing content availability. To test this, we analyze changes in number of topic-specific posts relative to neutral education posts: $\Delta Posts_{it} = \log Posts_{it,\tau} - \log Posts_{it,-\tau}$. We detect no statistically significant change in the composition of topics after the first KIA report, suggesting that the changes in engagement we observe are not likely to be driven by the changes in how often posts on certain topics appear in groups. The results are in Section A.1.1.

Alternative estimators: To validate our findings, we replicate the event study analysis using alternative estimators suited for staggered treatment settings. First, we implement the Sun and Abraham (2021) approach, which uses the last-treated units as controls, in contrast

[16] Interestingly, we observe an increase in engagement in the summer of 2023, after the PMC Wagner mutiny in late June. Considering wide support for the Wagner's leader, Evgeny Prigozhin, among the military, this might indicate an increased support for a more decisive nationalistic leader.

to the not-yet-treated controls in Callaway and Sant'Anna (2021). The event study results are in line with our main estimates (see Section A.1.2).

We also apply the estimator proposed by Chaisemartin and D'Haultfœuille (2024), which accounts for treatment heterogeneity and mitigates contamination from repeated treatments by comparing units with similar treatment histories. In our case, a treatment switch corresponds to an increase in the cumulative number of KIA reports. As reported in Section A.1.3, the results remain consistent: Engagement with patriotic content rises following KIA reports, while engagement with pro-authority content declines, suggesting a short-term rally effect rather than a cumulative response to rising death tolls.

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 DR DiD 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. Similarly, the baseline ATT for Authorities is smaller than the bottom 1% of the placebo KIA effects. The results are in Section A.1.4.

Restricted sample: We perform the analysis restricting the sample in several ways. First we restrict our sample of municipalities to those that had at least one active school group as early as September 2021 instead of January 2022 in our baseline specification to ensure that the effect is not driven by the municipalities where school groups were created right on the eve of the invasion. Respective estimation results reported in Section A.1.5 closely track our baseline estimates. Second, we perform a leave-one-out estimation excluding regions one-by-one. The results show that estimates are not driven by the effect in one particular region.

Sentiment composition: Another concern is that the observed effect may be attributed to changing engagement patterns conditional on content's sentiment. For example, one might expect positive or entertaining content to attract more engagement following KIA reports.[17] To test this, we replicate the analysis for the number of positive and negative posts, as well as likes per post, relative to neutral content. As reported in Section A.1.6, we find no significant change in the supply of posts by sentiment or in engagement with positive or negative content, suggesting that the effect is driven by the topics of posts rather than their sentiment.

Sentiment score adjustment: To ensure that the observed effects are driven by topical content rather than differences in emotional tone across topics (e.g., education posts might be more positive than political), we repeat the analysis using a sentiment-adjusted sample. Specifically, we recalculate the zero-shot relative engagement metric from posts with comparable sentiment scores—those above the median within each sentiment category (Neutral, Negative, and Positive). As shown in Table A.VI and Table A.VII, the results remain similar in both magnitude and significance.

Region leave-one-out: To ensure the results are not driven by single region outliers, we repeat the baseline analysis iteratively, removing one region from the sample at each iteration. Results in Section A.1.8 show that it is unlikely that the effect we observe is due to one particular region.

Alternative engagement metrics: In Section A.1.9, we additionally report the results for alternative engagement metrics based on shares, comments, and views per post. We find similar patterns across all engagement metrics. Specifically, we find a drop in the number of shares and views per post for pro-authorities propaganda and a similar increase for patriotic propaganda after the first KIA report. However, the effect for these other metrics fades

[17] Studies in psychology have 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). Social media can also 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).

faster than that for our likes-based metric and is only detectable on a horizon of one to three months, so we report it at a 3-month horizon.

7 Mechanism and Heterogeneity

7.1 Heterogeneity

Heterogeneity by topic: To assess whether the effect of war fatalities varies across narrative strands, we repeat the analysis using disaggregated topics related to patriotism and authorities. For patriotic content, we distinguish between mentions of the Great Patriotic War (WW2), other wars, and national symbols. For pro-authorities content, we consider posts about the president, the federal government, and local government.

Figure A.XVI shows estimates from Equation 3 for relative engagement by topic. The largest decline in engagement following the first KIA report occurs for content promoting federal and local government (–0.12 to –0.16 for keyword-based engagement; –0.06 for zero-shot). Engagement with posts about the president also declines, but the effect is not statistically significant. For patriotic content that does not mention war in Ukraine, we find the strongest positive effect for posts referencing the military in general ($\beta = 0.057$). While effects for other patriotic topics are positive, they are not statistically significant. Finally, engagement increases for posts that mention the war in Ukraine, but the effect disappears once commemorative posts are excluded, as in the baseline. This suggests that people respond to KIA reports by engaging with personal stories of the deceased—likely as acts of mourning or solidarity—rather than by showing their support for the conflict in general.

Heterogeneity by municipality characteristics: To better understand under what conditions the effect develops, in Section A.2 we conduct heterogeneity analyses by splitting the sample at the median based on education, population, age, gender, and urban-rural composition, as these characteristics likely reflect underlying differences in media consumption, social network structures, and proximity to war. For instance, the probability of being drafted is higher for younger males without higher education, which may shape how war fatalities influence propaganda engagement. We find that the negative effect of local war fatalities on engagement with pro-authorities content is more pronounced in younger, more educated, urban, and more populated municipalities. The effect on engagement with patriotic content, while generally weaker and less consistently significant, is also somewhat stronger in these contexts. However, we observe no systematic differences based on gender composition.

These patterns point to several possible mechanisms. First, a larger magnitude of the effect on engagement with pro-authorities propaganda in younger and more educated municipalities may reflect an increased sensitivity to contradictions between propaganda and reality among groups with greater information access. Second, the greater size of the effects in more populated municipalities may arise from a higher likelihood of individuals learning about local war fatalities, e.g., through denser social networks. The effect may also be more significant in these areas due to a higher absolute number of fatalities: the correlation between population size and cumulative KIA reports by September 2022 in our sample is 0.58. Below, we probe these channels in more detail.

7.2 Channels

Cost-benefit channel: Public support for war and the politicians waging it is shaped not only by recent casualties but also by trends and the broader wartime context (e.g., Gartner 2008). In particular, trends in fatalities and the overall death toll can shift perceptions about the likely trajectory and future costs of the conflict. When losses accumulate at an accelerating pace, individuals may revise their expectations of continued costs upward. This mechanism is especially relevant in positional wars like the conflict in Ukraine, where frontlines shift little over time.[18] When losses are already high, the public might either consider the cost prohibitive or, on the contrary, embrace the "don't let them die in vain" mentality (Boettcher and Cobb 2009).

To probe this logic, in Table VII we show additional TWFE regressions of keyword-based relative engagement on monthly changes in cumulative KIA reports, controlling for municipality and month fixed effects. We exclude pre-February 2022 observations and municipalities with no reported KIAs. We find an increase in engagement with war-related content (column 1), but it disappears when we exclude obituaries from the sample of war-related posts (column 2). The effect on other patriotic engagement is positive and significant (column 4), while pro-authorities content remains unaffected (column 3). These results suggest that the effect we detect in our baseline analysis is driven primarily by the initial shock of the first war fatality in the municipality, while additional fatalities had little effect. It may also reflect that, prior to mobilization, most municipality-months with a KIA report recorded only a single fatality. Extending the analysis through March 2024 in Table VIII, however, we find a negative association between cumulative KIA reports and engagement with both patriotic and pro-authority content (columns 3 and 4), and the magnitude of the effect decreases for the war-related content (columns 1 and 2). In line with the findings reported in Figure VI, these patterns suggest that cumulative battlefield losses do not strengthen patriotic sentiment beyond the initial rally and may erode regime support over time.

Information channel: To better understand the role of information access in mediating the effect of local war fatalities, we restrict the sample to municipalities where a local soldier died but schools did not engage in commemoration on their VK pages. In these cases, the KIA report appeared in a local news outlet, local authorities, or another source. This restriction helps limit the direct exposure of group users to information about military losses.

[18] Figure A.XXIX 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.

Treatment, as before, is 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.

Tables IV and V present 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 mostly statistically insignificant, with zero-shot relative engagement for pro-authorities content being a notable exception. Similarly, in Table VI we find no effect on engagement with war-related content and, since we excluded schools with obituaries, the coefficients are identical across panels with and without commemoration.

These findings suggest that direct exposure to information on war fatalities significantly amplifies the impact of military losses on engagement, especially for patriotic content. 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 = -5.761, p-value = 0). Finally, the fact that group administrators make the posting decisions 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 effect to fully develop. To understand the mechanism behind this channel better, below, we explore how the public engages with the obituaries based on the narratives they present.

7.3 Obituaries

To better understand why war fatality reports lead to disengagement with content that promotes the authorities while promoting engagement with patriotic content we examine the texts of the obituaries posted directly by schools. As we show above, the effects of war fatality reports are most pronounced in the municipalities where the obituaries appear on school pages, and this allows us to probe which narrative elements actually drive engagement. Specifically, we classify all obituary texts, 19,517 in total, based on the prominence of two distinct narrative frames: (1) personal tragedy and (2) nationalistic propaganda, using a GPT-based semantic model. The prompt provided to the model is in Section A.3.3.

We then estimate the following regression model at the level of individual obituary posts:

$$\begin{aligned} Engagement_{pst} = \beta_1 Grief_{pst} &+ \beta_2 Propaganda_{pst} \\ &+ \beta_3 Grief_{pst} \times Propaganda_{pst} \\ &+ X'_{pst}\Gamma + \epsilon_{pst}, \end{aligned} \tag{5}$$

where p denotes individual obituary posts, s is the school, and t is the month. $Propaganda_{pst}$ and $Grief_{pst}$ are the propaganda and the personal tragedy scores. Specifically, $Propaganda_{pst}$ is defined from 0 to 4 where lower values correspond to lower intensity of propaganda, and vice versa. $Grief_{pst}$ is a binary variable equal to one if the Grief score assigned by the model is greater than 3 out of 5. The vector X_{pst} includes keyword-based dummies and school and month fixed effects. The interaction term allows us to test whether grief-based narratives are more or less effective when embedded in nationalistic rhetoric. In addition, to test whether linking these narratives to the authorities undermines engagement, we complement the model with an additional interaction term based on whether the obituary mentions the authorities:

$$Engagement_{pst} = \beta\, Grief_{pst} \times Propaganda_{pst} \times Authorities_{pst} \\ + X'_{pst}\Gamma + \epsilon_{pst}, \tag{6}$$

where $Authorities_{pst}$ is a dummy equal to one if the obituary mentions the federal or local government or the president, and $Grief_{pst} \times Propaganda_{pst} \times Authorities_{pst}$ is the full interaction between three variables.

Figure VIII presents the results. We show that engagement with obituaries is primarily driven by narratives of personal tragedy. Across all outcomes—likes, shares, views, and comments—obituaries expressing high levels of grief consistently attract more engagement than those with low grief. In contrast, propaganda plays a minimal or even negative role: Engagement remains constant across propaganda scores, and higher levels of propaganda reduce the gap between high- and low-grief posts.

Further analysis of interactions between propaganda, grief, and the Authorities dummy reveals that references to the state substantially reduce engagement. For example, when authorities are mentioned, high-grief, low-propaganda obituaries receive 20% fewer likes and shares, 1.5 times fewer views, and the number of comments drops two-fold. This suggests that while audiences typically engage with grieving content to express condolences or solidarity with the bereaved, they are far less willing to do so when such engagement could be interpreted as support for the regime.

These findings help explain the shift in engagement patterns we observe following reports of local war fatalities. While overall engagement with pro-authority content declines and patriotic content receives more engagement, this appears to not be driven by increased support for the state- and war-promoting narratives. Instead, the public appears to selectively engage with posts that emphasize personal tragedy and grief, while distancing themselves from content that propagates nationalism or promotes the authorities. Our results suggest that propaganda dampens the positive association between grief and engagement, and that any association with authorities undermines it further. This suggests that the rise in patriotic engagement reflects a collective mourning process rather than renewed support for the state or rise in nationalism.

8 Concluding Remarks

This paper provides evidence that exposure to information on war fatalities impacts how the public engages with propaganda on social media. Exploiting variation in the timing of reports about Russian military personnel killed in combat across their hometown municipalities during the 2022-–2024 invasion of Ukraine, we show that social media engagement with pro-authorities content drops significantly following local fatality announcements, and the effect intensifies over time. At the same time, the KIA reports promote engagement with patriotic and war-related content, although this effect is confined to the early months of the war.

We also explore the mechanisms behind the effect. Our results indicate that the effects are strongest in younger, more populated, and more educated municipalities where users have direct access to information on war fatalities, and further analysis of the narratives in the KIA obituaries shows that personal stories of fallen soldiers are what drives the effects. Obituaries that combine high grief and high glorification receive less engagement than those focused solely on personal tragedy, suggesting that while narratives of grief consistently increase engagement, glorification of the war does not. Moreover, when such narratives blend with references to state authorities, the grief premium disappears altogether. This finding points out that users might be reluctant to engage with content that appears to exploit personal stories of the deceased soldiers for political purposes.

While social media engagement may reflect strategic behavior, such as signaling or training the algorithm, likes and similar metrics are, at their face value, designed to express approval. In this sense, our findings may reflect a drop in support for the authorities and, to some extent, a rise in patriotic sentiment. These dynamics echo patterns found in democratic settings, where war fatalities can reduce support for the government (Althaus, Bramlett, and Gimpel 2012; Kuijpers 2019). However, in our case, the surge in patriotic engagement appears to be rooted in emotional responses to personal stories of the fallen soldiers but not in changing support for the regime or the war.

Our findings also have practical implications. If content promoting the authorities receives less engagement, it becomes less likely to appear in algorithm-driven social media feeds. In the context of our study, this implies that fatality reports may suppress the online visibility of content that promotes President Putin and the Russian government.

These results contribute to the literature on the limits of propaganda. While previous research has shown that propaganda can incite violence and nationalism (Adena et al. 2015; Yanagizawa-Drott 2014), our study suggests that propaganda may lose effectiveness when confronted with the human cost of conflict (Alyukov 2021). For autocratic regimes, this creates a strategic dilemma. As the public becomes increasingly aware of military failures and the death toll, the regime may need to moderate its propaganda strategy to maintain credibility. However, during periods of conflict, 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 research also speaks to broader debates on authoritarian survival and the rise of right-wing movements (Algan et al. 2017; Stanley 2018). Many autocrats, including Putin, rely on nationalism and militarism to consolidate legitimacy. 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, creating 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 trustworthy challenger to emerge. In this regard, our findings echo recent work on how war fatalities reshape patriotism and elite competition (Acemoglu et al. 2022; Juan et al. 2024). At the same time, it remains to be seen whether the effect documented in this article will persist and in what form. Its long-term manifestation will likely be contingent on the subsequent framing, commemoration, and interpretation of the war in Russian society.

Finally, this paper contributes methodologically by showing how social media engagement with unstructured text can serve as a proxy for political sentiment. In line with recent work leveraging textual data to study political and economic behavior (e.g., Ash, Gauthier, and Widmer 2021; Widmer 2024), we propose using aggregate engagement patterns—not just text content—as a discreet measure of regime support and public sentiment, which might be especially valuable in low-data or repressive contexts, where surveys and elections offer limited insight.

While this study establishes a link between war fatalities and individual interaction with propaganda, the analysis presented here has limitations. Most importantly, a decline in engagement with (war) propaganda we document in the aftermath of war fatality reports, although indicative of shifts in public sentiment, may not necessarily translate into individual action to actively resist the regime or its war effort. Investigating this is a promising avenue for future research.

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9 References

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Table I. Effect of the KIA reports on relative engagement with pro-authorities content

Specification	TWFE (1)	C&SA (2)	C&SA + Controls (3)
Panel A:		Authorities (zero-shot)	
ATT	-0.032***	-0.045***	-0.056***
	(0.009)	(0.014)	(0.021)
Outcome Mean	-0.44	-0.441	-0.468
Outcome SD	0.46	0.46	0.465
Observations	24259	24259	18576
Municipalities	1987	1987	1520
Months	13	13	13
Panel B:		Authorities (keywords)	
ATT	-0.006	-0.086***	-0.089*
	(0.02)	(0.033)	(0.051)
Outcome Mean	-0.116	-0.116	-0.139
Outcome SD	0.907	0.907	0.929
Observations	21370	21370	16439
Municipalities	1978	1978	1513
Months	13	13	13

Note: Results from estimating Equation 3 for Authorities topic Dependent variable: Δ log Likes per post. Classification strategy in the panel header. Treatment: first KIA report in a municipality. Controls: log average Night Lights intensity, log Population, % Population age 50 or older. Standard errors in parentheses are clustered at the municipality level. Estimation strategy is indicated in the column header. Single, double, and triple asterisks report significance at 10%, 5%, and 1%, respectively.

Table II. Effect of the KIA reports on relative engagement with patriotic content

Specification	TWFE (1)	C&SA (2)	C&SA + Controls (3)
Panel A:		Patriotism (zero-shot)	
ATT	0.022***	0.031***	0.041**
	(0.007)	(0.011)	(0.017)
Outcome Mean	0.018	0.02	0.024
Outcome SD	0.328	0.328	0.333
Observations	24259	24259	18576
Municipalities	1987	1987	1520
Months	13	13	13
Panel B:		Patriotism (keywords)	
ATT	0.032**	0.033	0.069**
	(0.013)	(0.02)	(0.032)
Outcome Mean	0.337	0.337	0.346
Outcome SD	0.608	0.609	0.624
Observations	23736	23736	18200
Municipalities	1984	1984	1519
Months	13	13	13

Note: Results from estimating Equation 3 for Patriotism topic. Dependent variable: Δ log Likes per post. Classification strategy in the panel header. Treatment: first KIA report in a municipality. Controls: log average Night Lights intensity, log Population, % Population age 50 or older. Standard errors in parentheses are clustered at the municipality level. Estimation strategy is indicated in the column header. Single, double, and triple asterisks report significance at 10%, 5%, and 1%, respectively.

Table III. Effect of the KIA reports on relative engagement with content related to the War in Ukraine

Specification	TWFE (1)	C&SA (2)	C&SA + Controls (3)
Panel A:	War in Ukraine (keywords)		
ATT	0.208***	0.472***	0.51***
	(0.058)	(0.088)	(0.105)
Outcome Mean	0.066	0.017	0.04
Outcome SD	0.985	0.976	0.98
Observations	4730	2834	2406
Municipalities	1633	1072	872
Months	7	7	7
Panel B:	War in Ukraine without commemoration (keywords + GPT)		
ATT	0.019	0.135	0.077
	(0.052)	(0.094)	(0.107)
Outcome Mean	-0.098	-0.122	-0.109
Outcome SD	0.85	0.844	0.84
Observations	4408	2678	2266
Municipalities	1601	1053	856
Months	7	7	7

Note: Results from estimating Equation 3 for Authorities topic on a subsample of municipalities where schools did not commemorate the soldiers. Dependent variable: Δ log Likes per post. Classification strategy in the panel header. Treatment: first KIA report in a municipality. Controls: log average Night Lights intensity, log Population, % Population age 50 or older. Standard errors in parentheses are clustered at the municipality level. Estimation strategy is indicated in the column header. Single, double, and triple asterisks report significance at 10%, 5%, and 1%, respectively.

Table IV. Effect of the KIA reports on relative engagement with pro-authorities content in municipalities without commemoration

Specification	TWFE (1)	C&SA (2)	C&SA + Controls (3)
Panel A:		Authorities (zero-shot)	
ATT	-0.024**	-0.053**	-0.053**
	(0.011)	(0.023)	(0.024)
Outcome Mean	-0.452	-0.491	-0.491
Outcome SD	0.474	0.483	0.483
Observations	17978	13081	13081
Municipalities	1488	1084	1084
Months	13	13	13
Panel B:		Authorities (keywords)	
ATT	-0.013	-0.086	-0.086
	(0.024)	(0.057)	(0.054)
Outcome Mean	-0.153	-0.194	-0.194
Outcome SD	0.932	0.965	0.965
Observations	15515	11301	11301
Municipalities	1479	1077	1077
Months	13	13	13

Table V. Effect of the KIA reports on relative engagement with patriotic content in municipalities without commemoration

Specification	TWFE (1)	C&SA (2)	C&SA + Controls (3)
Panel A:		Patriotism (zero-shot)	
ATT	0.016**	0.011	0.011
	(0.008)	(0.018)	(0.018)
Outcome Mean	0.012	0.019	0.019
Outcome SD	0.341	0.351	0.351
Observations	17978	13081	13081
Municipalities	1488	1084	1084
Months	13	13	13
Panel B:		Patriotism (keywords)	
ATT	0.03**	0.045	0.045
	(0.015)	(0.033)	(0.034)
Outcome Mean	0.322	0.328	0.328
Outcome SD	0.628	0.654	0.654
Observations	17512	12745	12745
Municipalities	1485	1083	1083
Months	13	13	13

Note: Results from estimating Equation 3 for Patriotism topic on a subsample of municipalities where schools did not commemorate the soldiers. Dependent variable: Δ log Likes per post. Classification strategy in the panel header. Treatment: first KIA report in a municipality. Controls: log average Night Lights intensity, log Population, % Population age 50 or older. Standard errors in parentheses are clustered at the municipality level. Estimation strategy is indicated in the column header. Single, double, and triple asterisks report significance at 10%, 5%, and 1%, respectively.

Table VI. Effect of the KIA reports on relative engagement with patriotic content in municipalities without commemoration

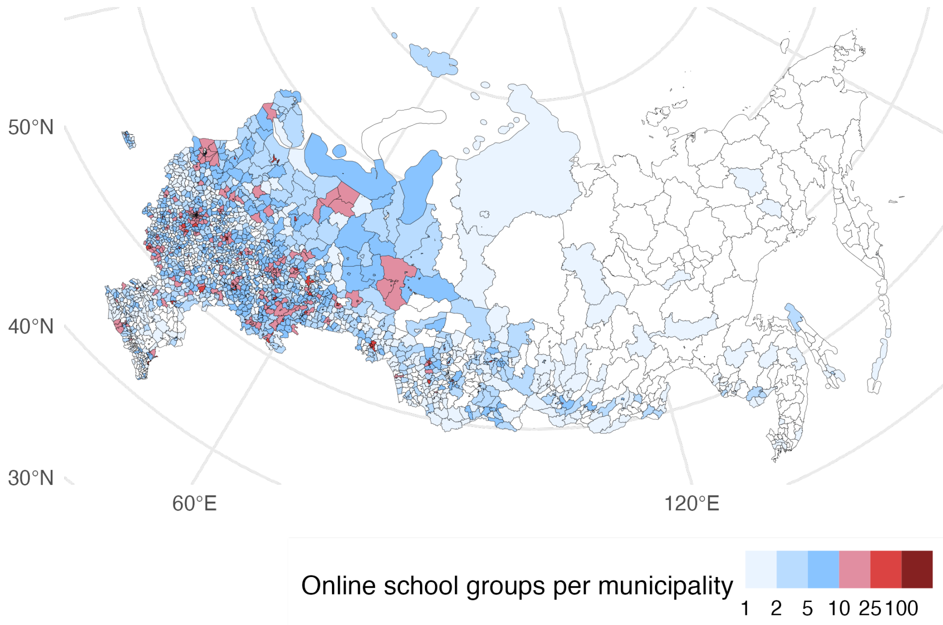
Specification	TWFE (1)	C&SA (2)	C&SA + Controls (3)
Panel A:	War in Ukraine (keywords)		
ATT	-0.021	0.057	0.057
	(0.066)	(0.124)	(0.116)
Outcome Mean	-0.143	-0.133	-0.133
Outcome SD	0.839	0.833	0.833
Observations	2777	1625	1625
Municipalities	1135	661	661
Months	7	7	7
Panel B:	War in Ukraine without commemoration (keywords + GPT)		
ATT	-0.021	0.057	0.057
	(0.066)	(0.12)	(0.116)
Outcome Mean	-0.143	-0.133	-0.133
Outcome SD	0.839	0.833	0.833
Observations	2777	1625	1625
Municipalities	1135	661	661
Months	7	7	7

Note: Results from estimating Equation 3 for War in Ukraine topic on a subsample of municipalities where schools did not commemorate the soldiers. Dependent variable: Δ log Likes per post. Classification strategy in the panel header. Treatment: first KIA report in a municipality. Controls: log average Night Lights intensity, log Population, % Population age 50 or older. Standard errors in parentheses are clustered at the municipality level. Estimation strategy is indicated in the column header. Single, double, and triple asterisks report significance at 10%, 5%, and 1%, respectively.

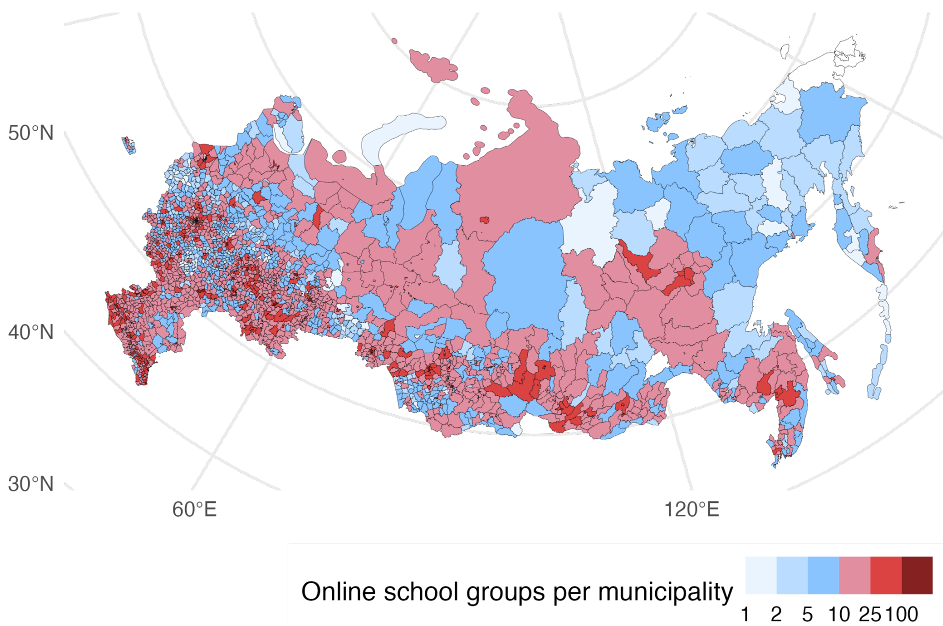
Figure I.

Spatial distribution of online school groups across Russian municipalities

(A) Active online school groups in January 2022



(B) Active online school groups in March 2024

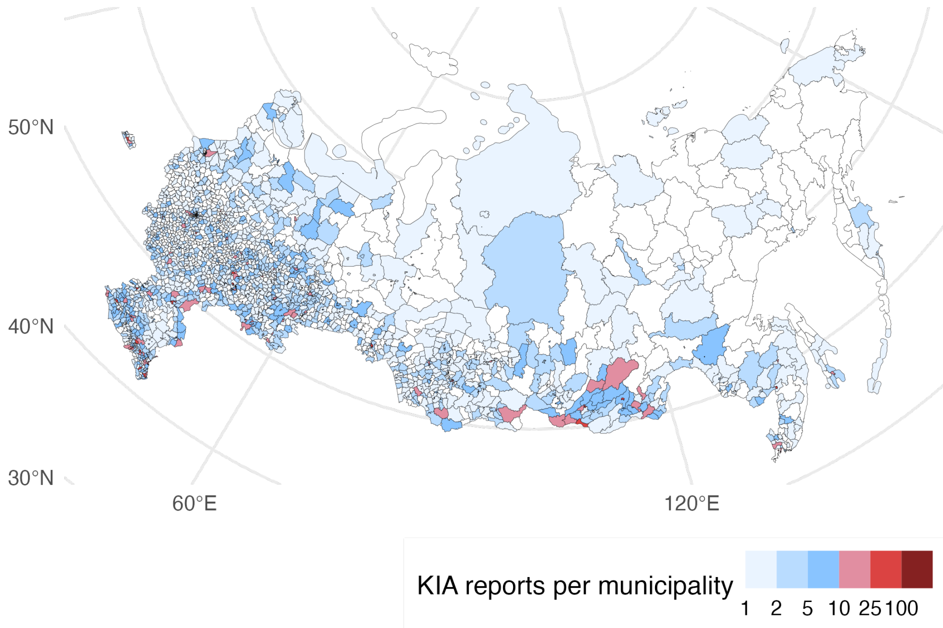


The maps illustrate the increase in coverage from 2,040 municipalities with at least one active school group in January 2022 (top) to 2,522 municipalities in March 2024 (bottom). Light-gray areas are municipalities with no active school groups.

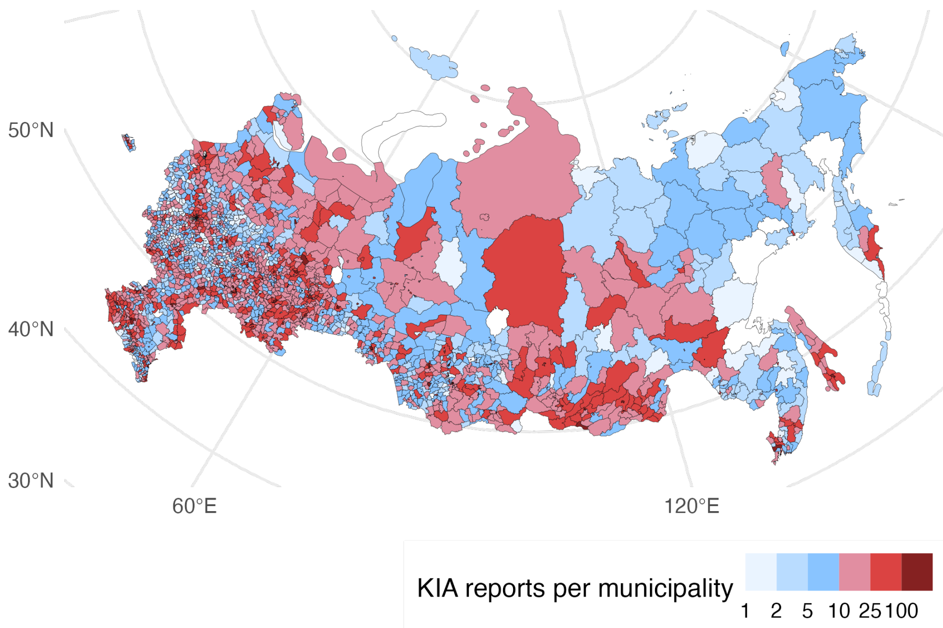
Figure II.

Spatial distribution of KIA reports across Russian municipalities

(A) September 2022



(B) March 2024

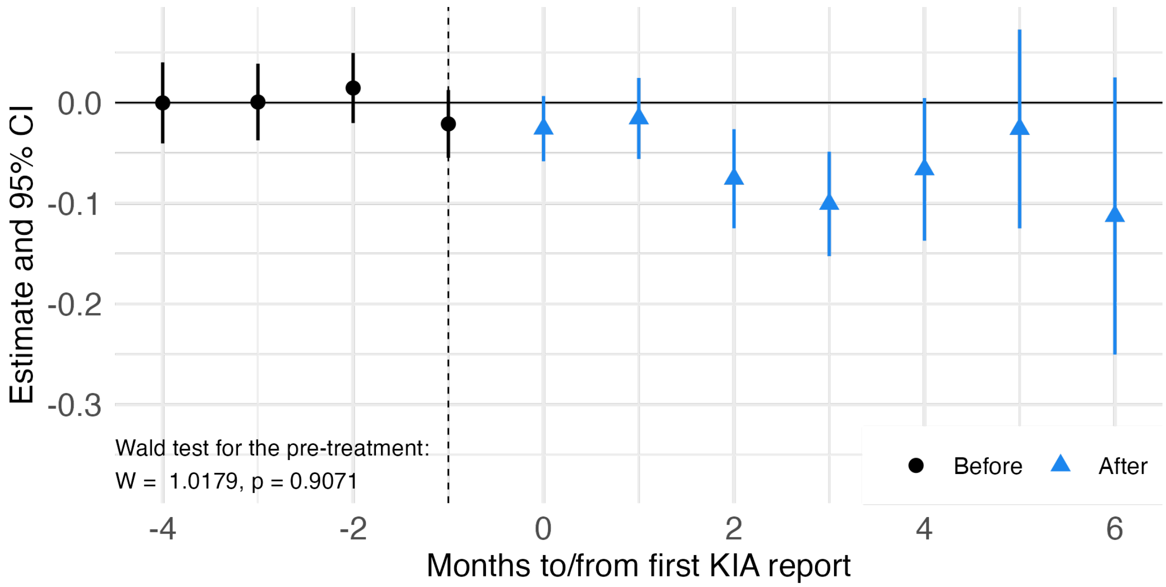


The maps illustrate the total number of KIA reports in a municipality in September 2022 (top) and March 2024 (bottom). By the partial mobilization announcement on September 21, 2022, about one-third of municipalities had no KIA reports, while most of the rest had only a single confirmed fatality. In contrast, by March 2024 the majority of Russian municipalities had multiple reported KIAs. Light-gray areas are municipalities with no KIA reports.

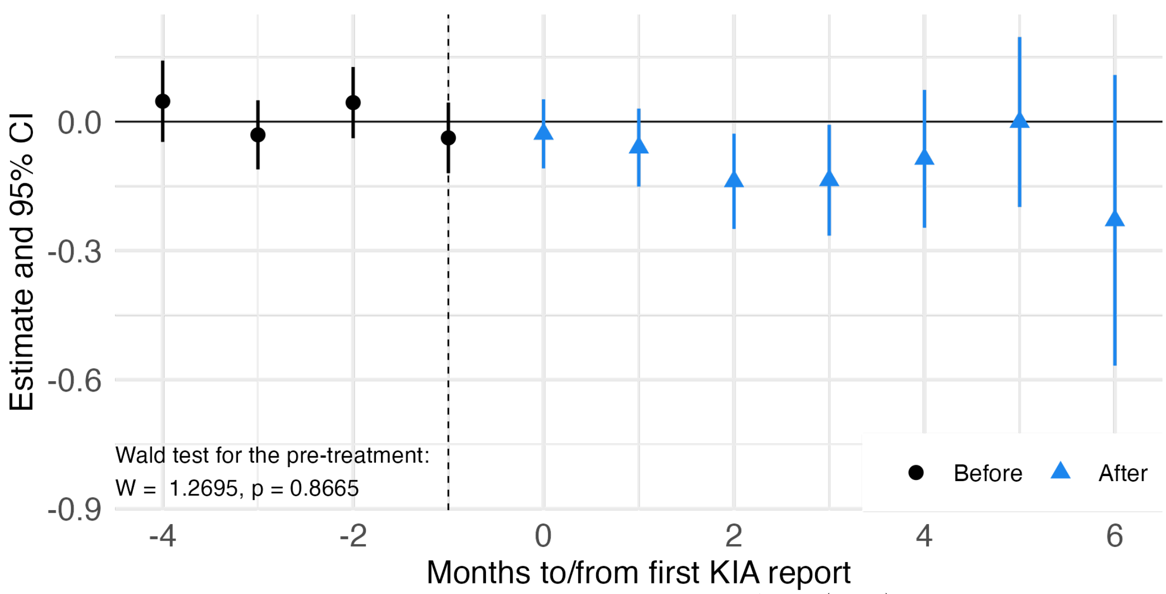
Figure III.

Dynamic effect of the KIA reports on relative engagement with pro-authorities content

(A) Authorities (zero-shot)



(B) Authorities (keywords)

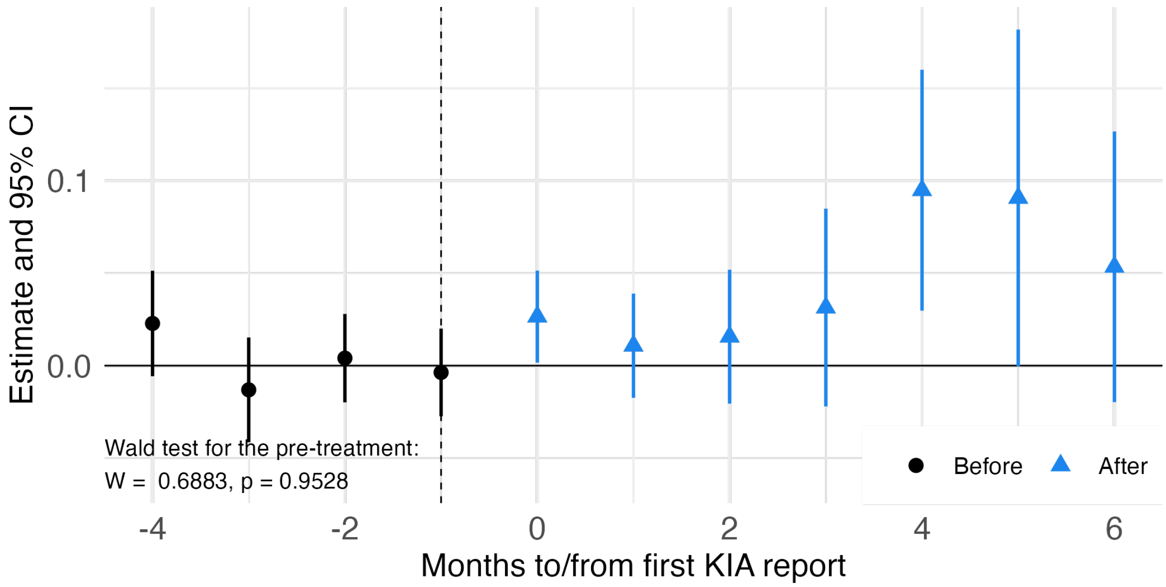


Note: Results from estimating Equation 4 with Callaway and Sant'Anna (2021) estimator. Dots report the point estimates and vertical bars report the 90% confidence intervals. Dependent variable: Δ log Likes per post for Authorities topic defined with zero-shot (top) and keywords (bottom). Treatment: first KIA report in a municipality. Controls: log average Night Lights intensity, log Population, % Population age 50 or older. Standard errors clustered at municipality.

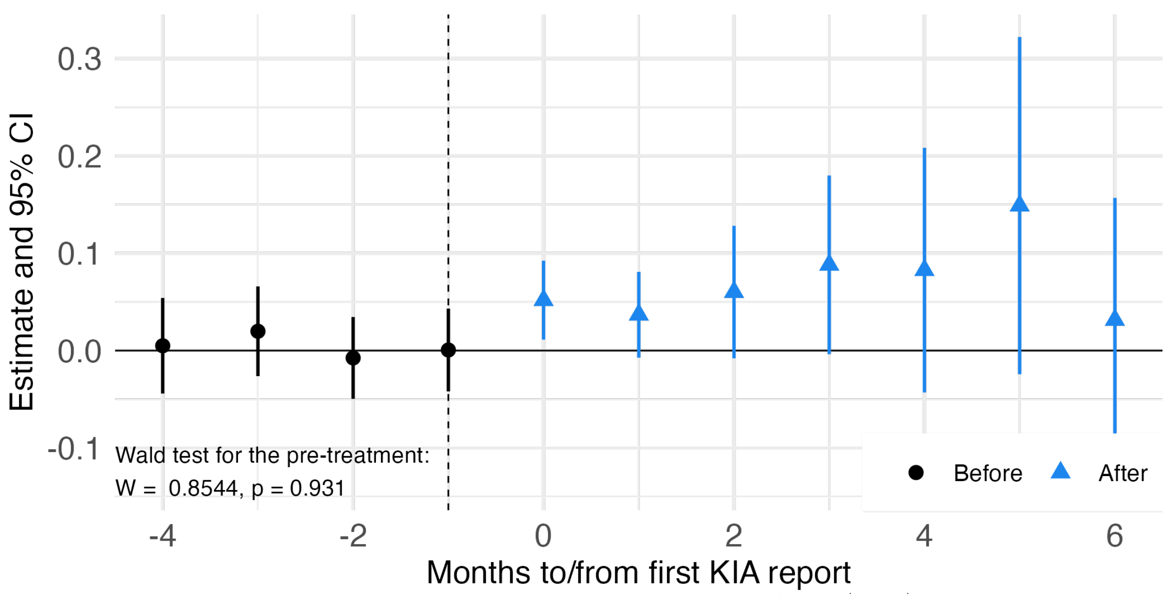
Figure IV.

Dynamic effect of the KIA reports on relative engagement with patriotic content

(A) Patriotism (zero-shot)



(B) Patriotism (keywords)

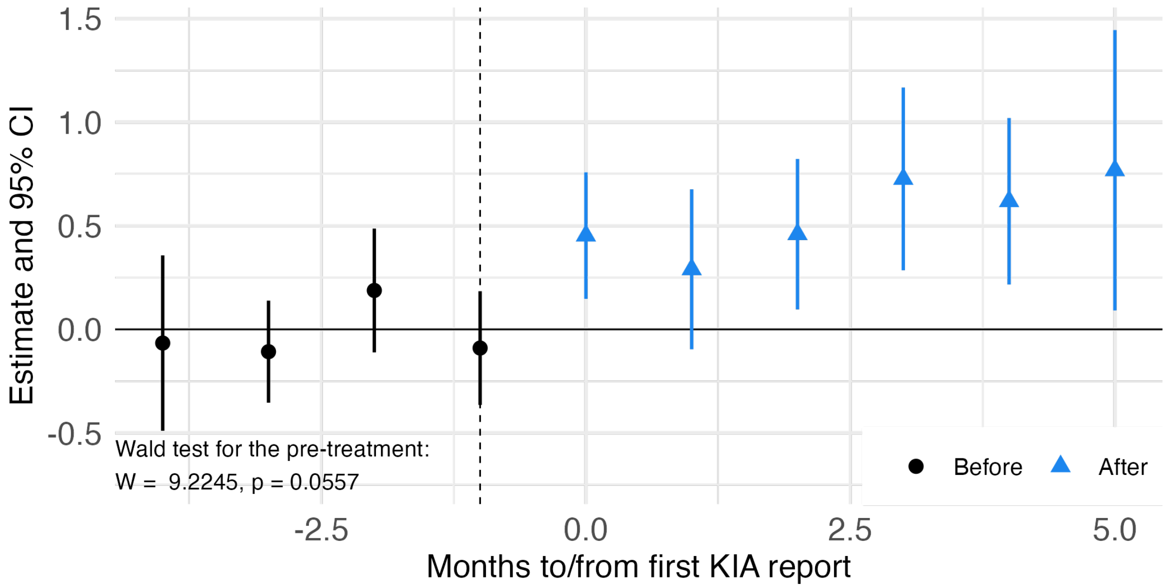


Note: Results from estimating Equation 4 with Callaway and Sant'Anna (2021) estimator for Patriotism topic. Dots report the point estimates and vertical bars report the 90% confidence intervals. Dependent variable: Δ log Likes per post for Patriotism topic defined with zero-shot (top) and keywords (bottom). Treatment: first KIA report in a municipality. Controls: log average Night Lights intensity, log Population, % Population age 50 or older. Standard errors clustered at municipality.

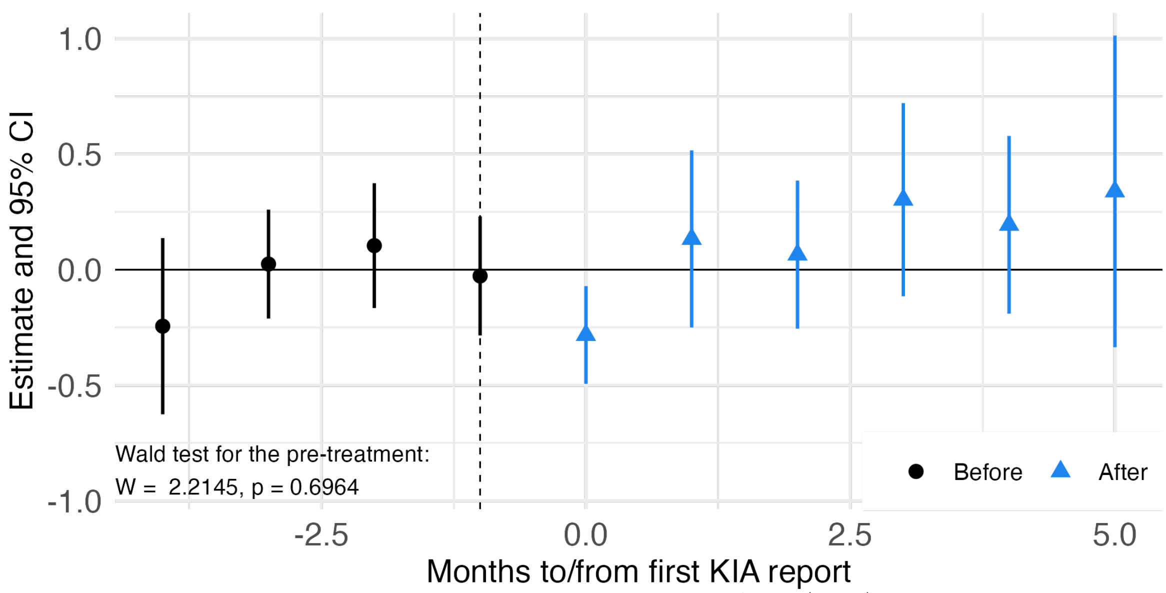
Figure V.

Dynamic effect of the KIA reports on relative engagement with content related to the War in Ukraine

(A) War in Ukraine (keywords)



(B) War in Ukraine without commemoration (keywords + GPT)



Note: Results from estimating Equation 4 with Callaway and Sant'Anna (2021) estimator for War in Ukraine topic. Dots report the point estimates and vertical bars report the 90% confidence intervals. Dependent variable: Δ log Likes per post for War in Ukraine topic defined with keywords with (top) and without commemorative posts (bottom). Treatment: first KIA report in a municipality. Controls: log average Night Lights intensity, log Population, % Population age 50 or older. Standard errors clustered at municipality.

Table VII. Effect of cumulative KIA reports on engagement by topic (pre-mobilization).

	Δ log Likes per post			
Topic	War in Ukraine	w/o commemoration	Authorities	Patriotism
	(1)	(2)	(3)	(4)
log Cumulative KIA	0.127***	0.013	0.002	0.020**
	(0.028)	(0.025)	(0.013)	(0.009)
Mean KIA	5.07	5.07	5.07	5.07
Municipalities	1,292	1,270	1,494	1,501
Months	7	7	7	7
Observations	3,961	3,705	9,687	10,275
R^2	0.592	0.632	0.725	0.813
Municipality FE	✓	✓	✓	✓
Month FE	✓	✓	✓	✓

Note: Results from regressing relative engagement on log of cumulative KIA reports in municipality by given month. Dependent variable: Δ log Likes per post. Classification strategy: Keywords. Independent variable: log Cumulative KIA reports in municipality by given month. Period in consideration: February 2022 — September 2022. All regressions include month and municipality fixed effects. Standard errors in parentheses are clustered at municipality. Estimation strategy is indicated in the column header. Single, double, and triple asterisks report significance at 10%, 5%, and 1%, respectively.

Table VIII. Effect of cumulative KIA reports on engagement by topic (full period).

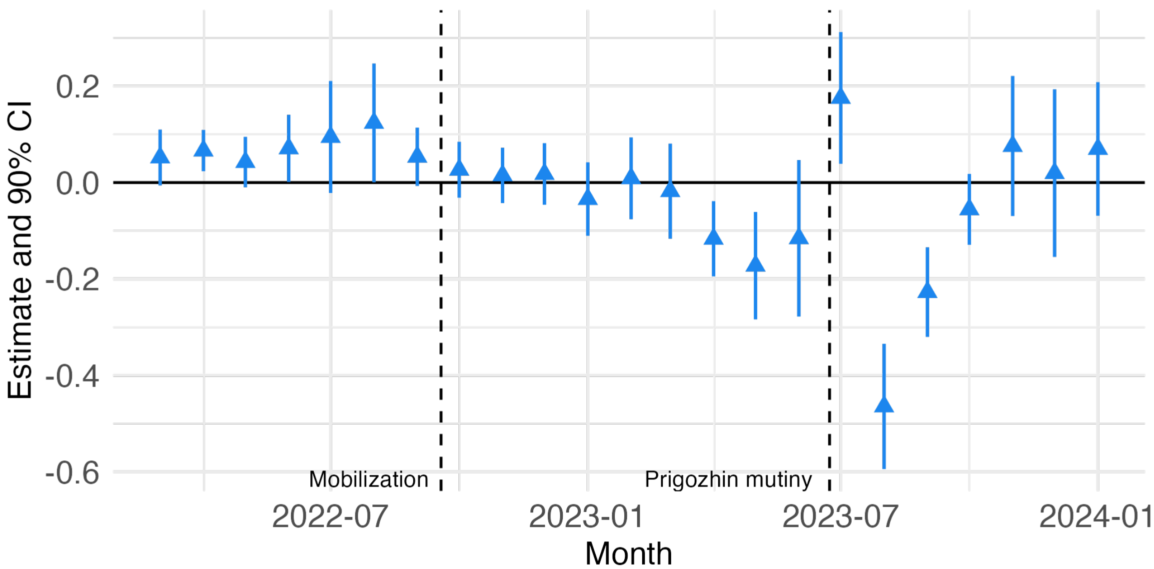
	Δ log Likes per post			
Topic	War in Ukraine	w/o commemoration	Authorities	Patriotism
	(1)	(2)	(3)	(4)
log Cumulative KIA	0.029***	0.012***	-0.020***	-0.008***
	(0.004)	(0.004)	(0.004)	(0.003)
Mean KIA	16.8	16.8	16.8	16.8
Municipalities	1,987	1,987	1,989	1,989
Months	25	25	25	25
Observations	34,763	34,252	48,196	49,339
R^2	0.465	0.487	0.604	0.698
Period	Pre-mobilization	Pre-mobilization	Full	Full
Municipality FE	✓	✓	✓	✓
Month FE	✓	✓	✓	✓

Note: Results from regressing relative engagement on log of cumulative KIA reports in municipality by given month. Dependent variable: Δ log Likes per post. Classification strategy: Keywords. Independent variable: log Cumulative KIA reports in municipality by given month. Period in consideration indicated at the bottom of the column. All regressions include month and municipality fixed effects. Standard errors in parentheses are clustered at municipality. Estimation strategy is indicated in the column header. Single, double, and triple asterisks report significance at 10%, 5%, and 1%, respectively.

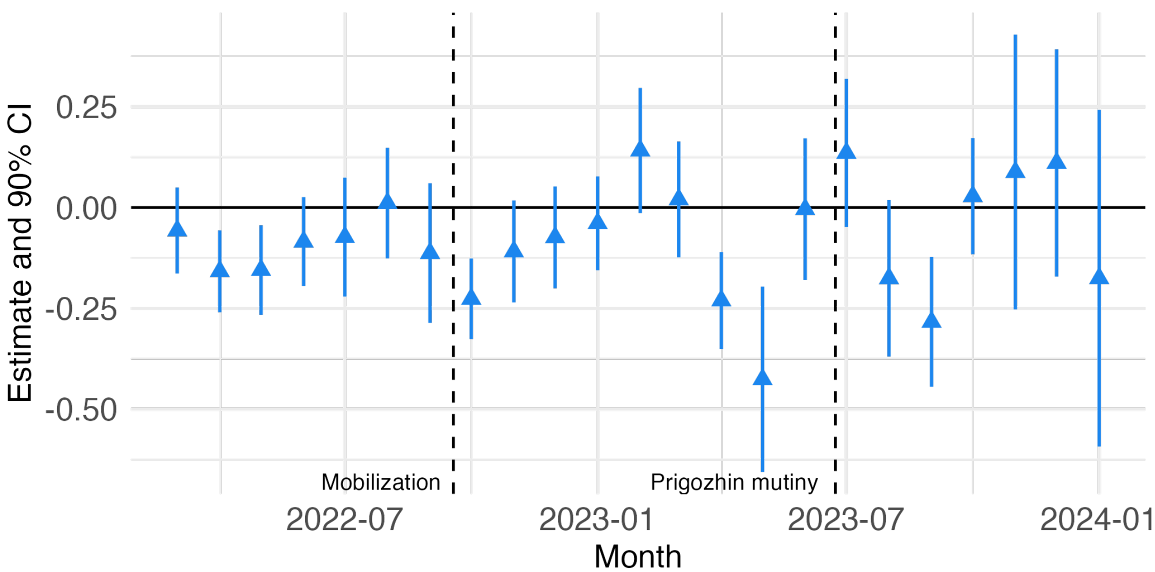
Figure VI.

Effect of the KIA reports on relative engagement aggregated by calendar months

(A) Patriotism



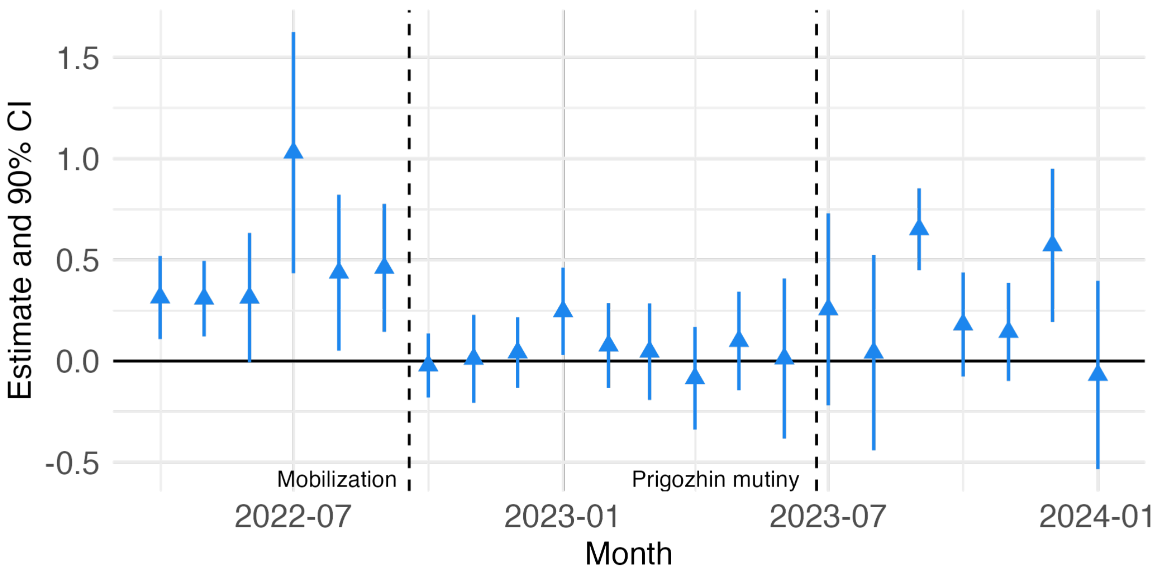
(B) Authorities



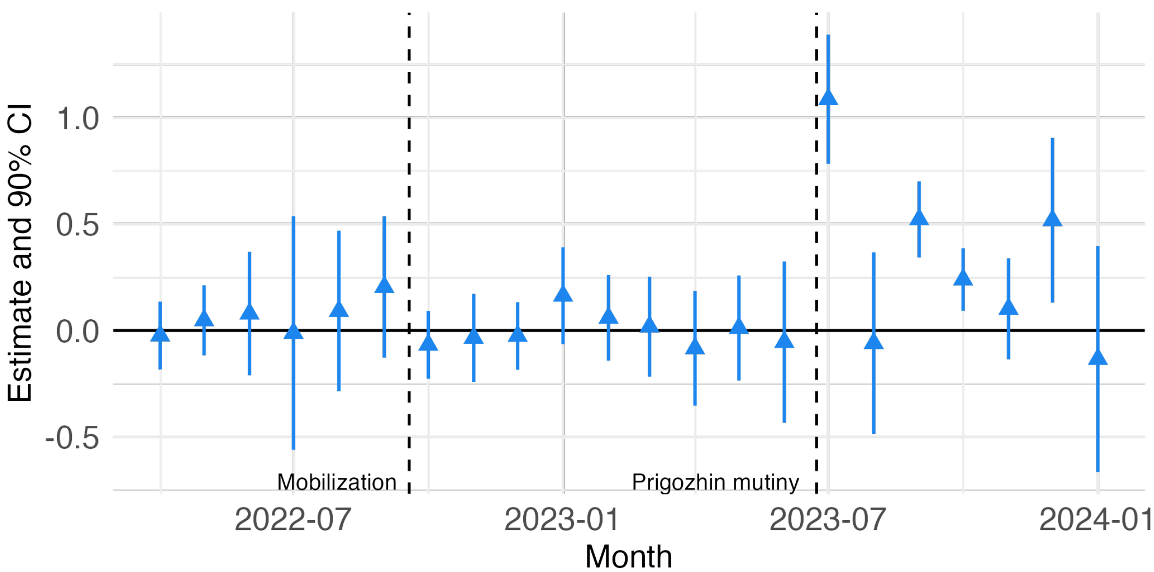
Note: Results from estimating Equation 3 by calendar month. Dependent variable: Δ log Likes per post for a given keywords-based topic. Treatment: first KIA report in a municipality. Estimation strategy: Callaway and Sant'Anna (2021) with controls. Controls: log average Night Lights intensity, log Population, % Population age 50 or older. Standard errors clustered at municipality. Dashed vertical lines indicate the start of the "partial mobilization" on 17 September, 2022, and the PMC Wagner mutiny on June 23, 2023.

Figure VII.
Effect of the KIA reports on relative engagement aggregated by calendar months

(A) War in Ukraine (keywords)



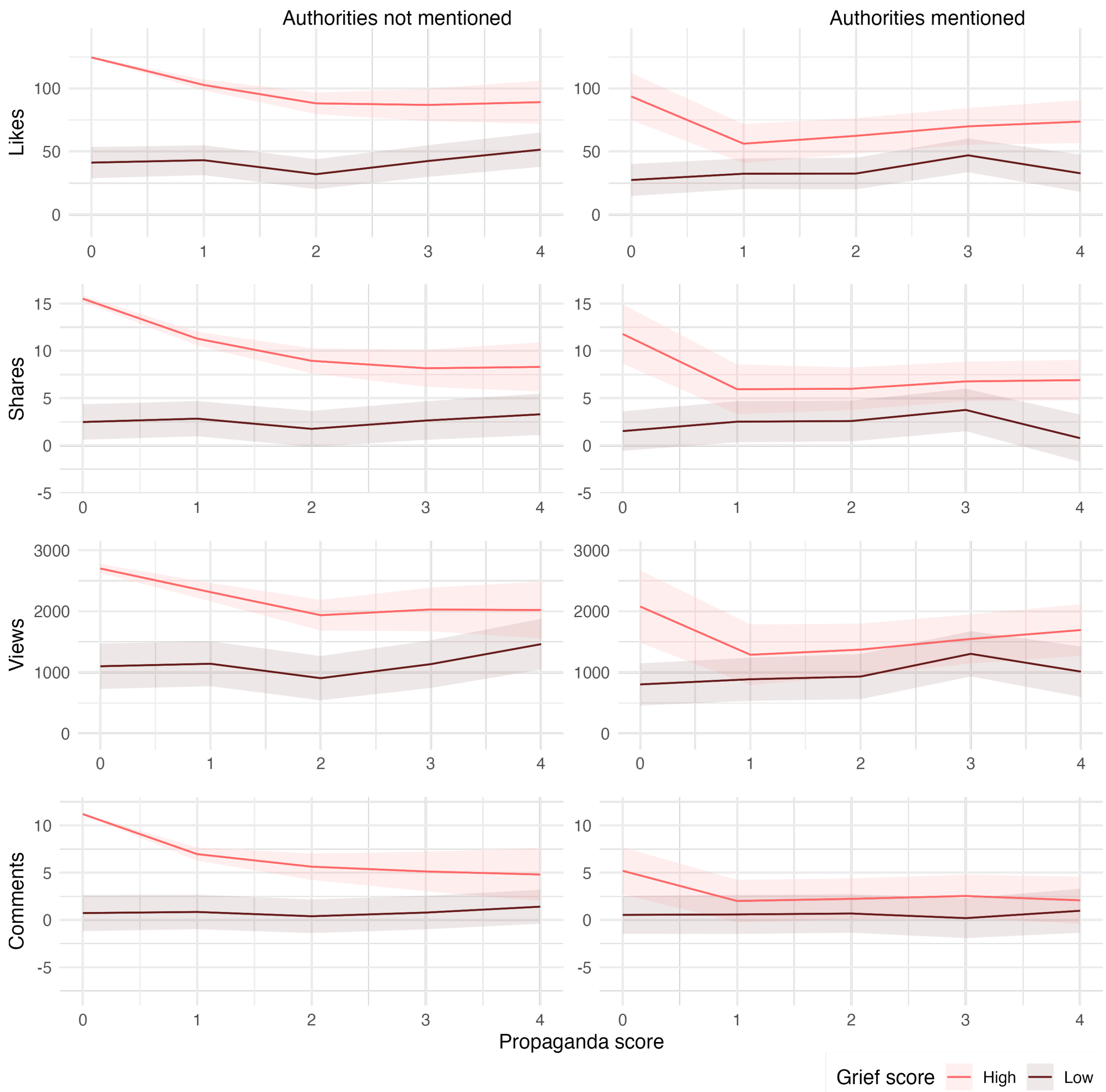
(B) War in Ukraine without commemoration (keywords + GPT)



Note: Results from estimating Equation 3 by calendar month. Dependent variable: Δ log Likes per post for a given keywords-based topic. Treatment: first KIA report in a municipality. Estimation strategy: Callaway and Sant'Anna (2021) with controls. Controls: log average Night Lights intensity, log Population, % Population age 50 or older. Standard errors clustered at municipality. Dashed vertical lines indicate the start of the "partial mobilization" on 17 September, 2022, and the PMC Wagner mutiny on June 23, 2023.

Figure VIII.

Effect of grief and glorification narratives on engagement with obituaries



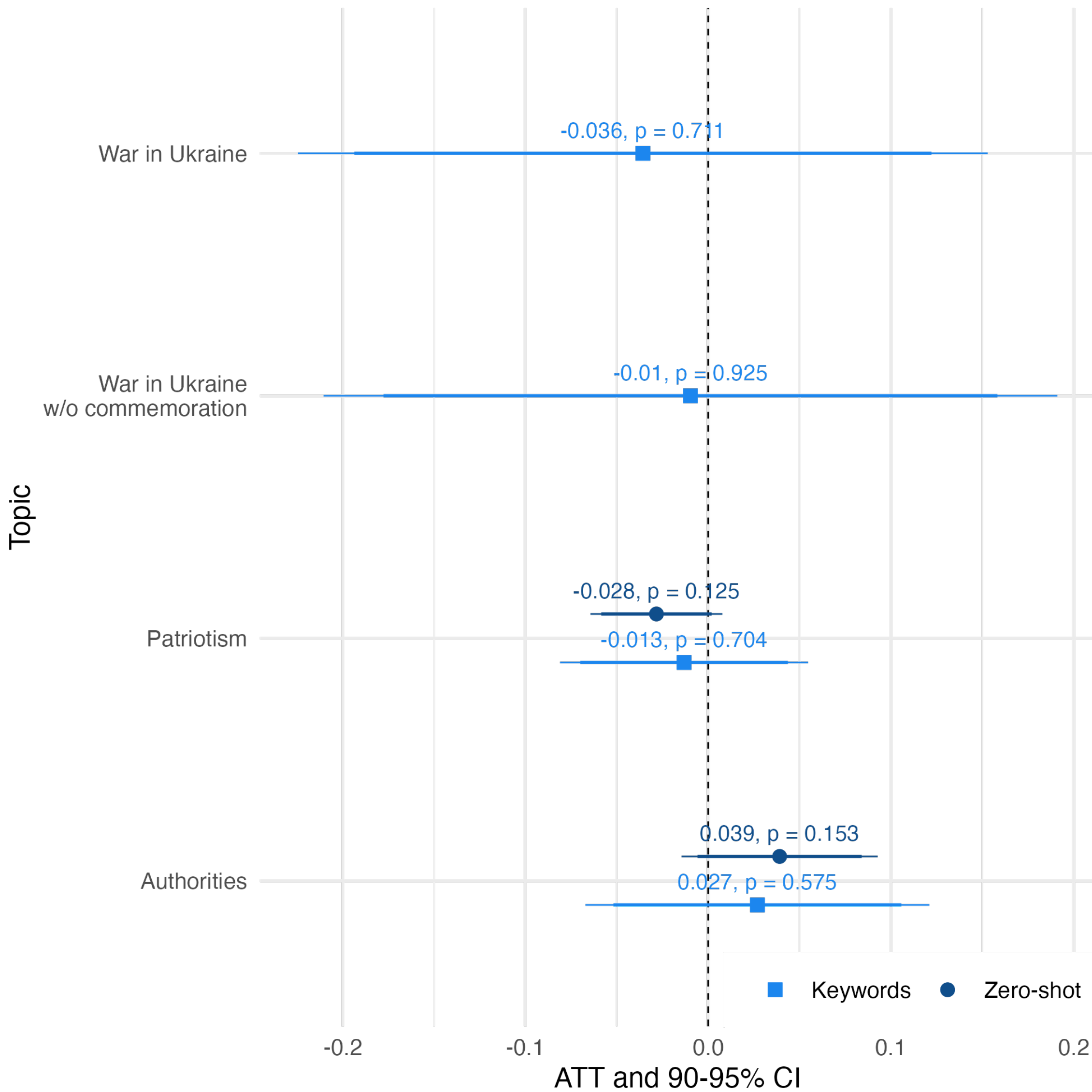
Note: Results from estimating Equation 6. Dependent variable denoted on the vertical axis. Glorification score is defined on 0-4 scale. Grief score is a binary indicator where high and low values are defined as above and below the median GPT grief score. Lines show predicted engagement by glorification level, separately for low and high grief obituaries. Shaded areas represent 95% confidence intervals. Results for posts (not) mentioning the authorities in the (left) right column. Controls: keyword-based dummies, school and month fixed effects. Standard errors clustered at school level.

A Online Appendix

A.1 Robustness

A.1.1 Results for topical composition

Figure A.I.
Effect of the KIA reports on topical composition

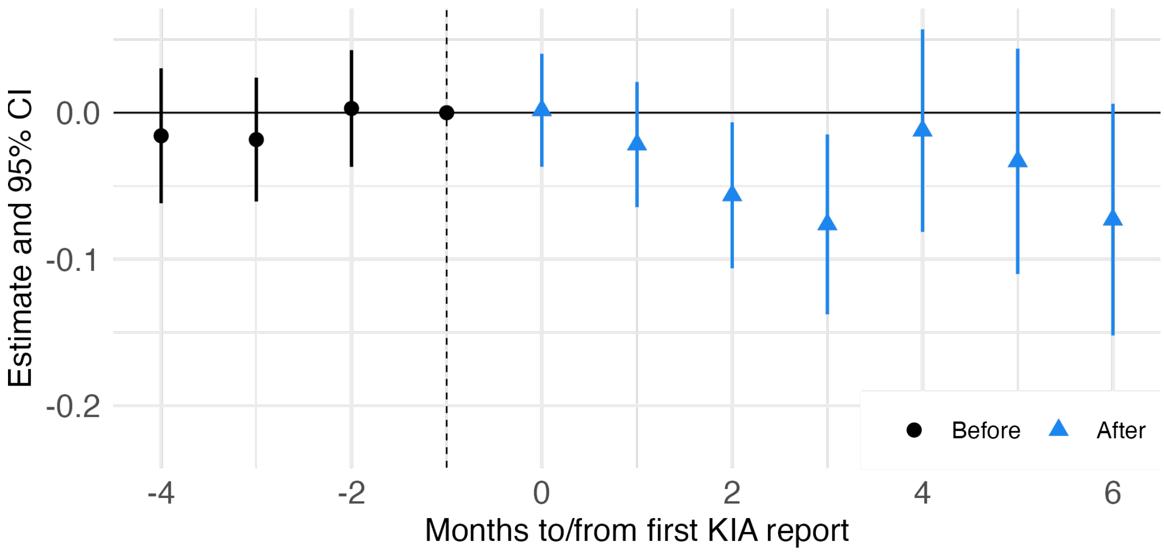


Note: Results from estimating Equation 3 for topical composition. Topic outlined on the vertical axis. Dependent variable: Δ log Post. Classification strategy: keywords (squares) or zero-shot (circles). Estimation strategy: Callaway and Sant'Anna (2021) with controls. Treatment: first KIA report in a municipality. Controls: log average Night Lights intensity, log Population, % Population age 50 or older. Standard errors clustered at municipality.

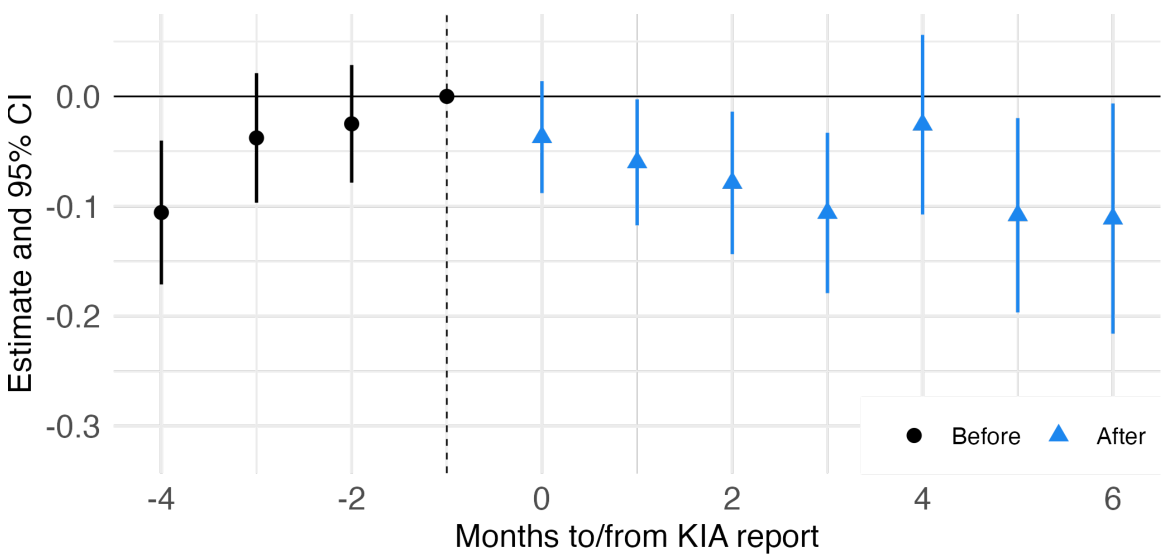
A.1.2 Sun and Abraham (2021) Estimator

Figure A.II.
Dynamic effect of the KIA reports on relative engagement with pro-authorities content (Sun and Abraham 2021 estimator)

(A) Authorities (zero-shot)



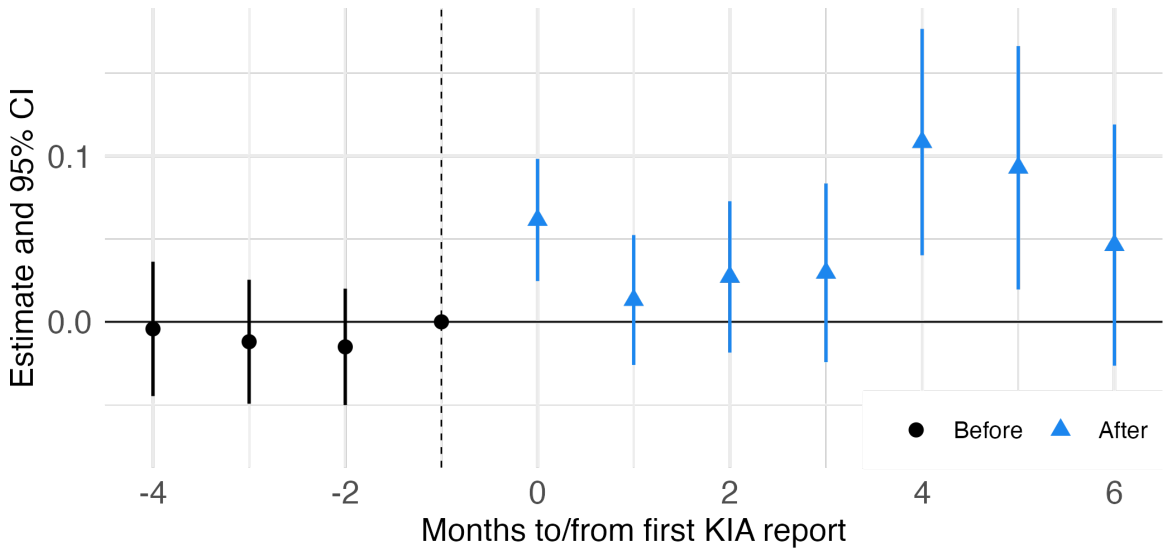
(B) Authorities (keywords)



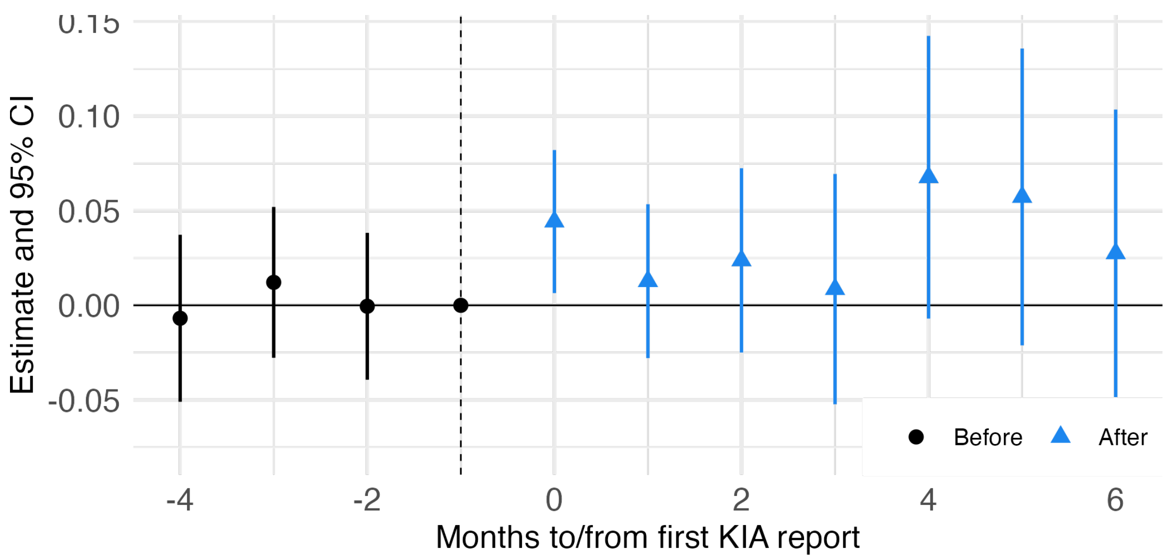
Note: Results from estimating Equation 4 with Sun and Abraham (2021) estimator for pro-authorities content. Dots report the point estimates and vertical bars report the 90% confidence intervals. Dependent variable: Δ log Likes per post for Authorities topic defined with zero-shot (top) and keywords (bottom). Treatment: the first KIA report in a municipality. Standard errors clustered at municipality.

Figure A.III.
Dynamic effect of the KIA reports on relative engagement with patriotic content (Sun and Abraham 2021 estimator)

(A) Patriotism (zero-shot)



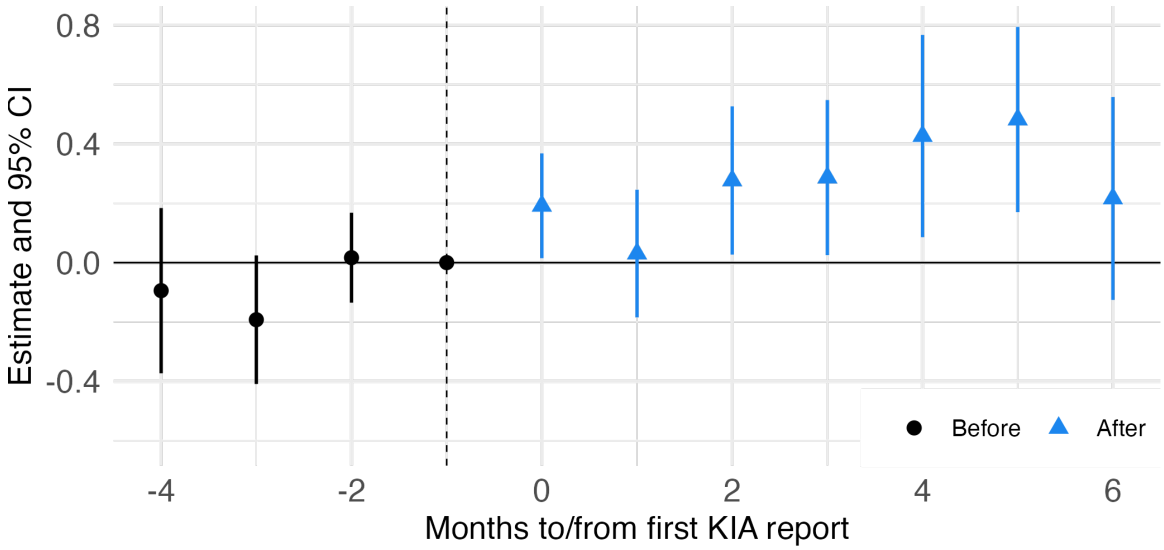
(B) Patriotism (keywords)



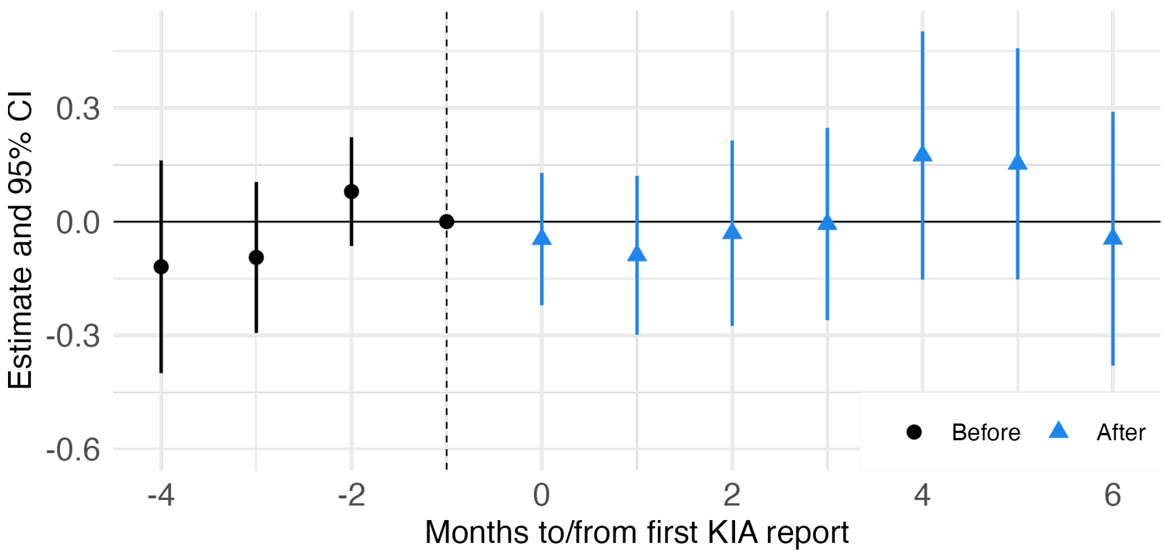
Note: Results from estimating Equation 4 with Sun and Abraham (2021) estimator for patriotic content. Dots report the point estimates and vertical bars report the 90% confidence intervals. Dependent variable: Δ log Likes per post for Patriotism topic defined with zero-shot (top) and keywords (bottom). Treatment: the first KIA report in a municipality. Standard errors clustered at municipality.

Figure A.IV.
Dynamic effect of the KIA reports on relative engagement with content related to the War in Ukraine (Sun and Abraham 2021 estimator)

(A) War in Ukraine (keywords)



(B) War in Ukraine without commemoration (keywords + GPT)



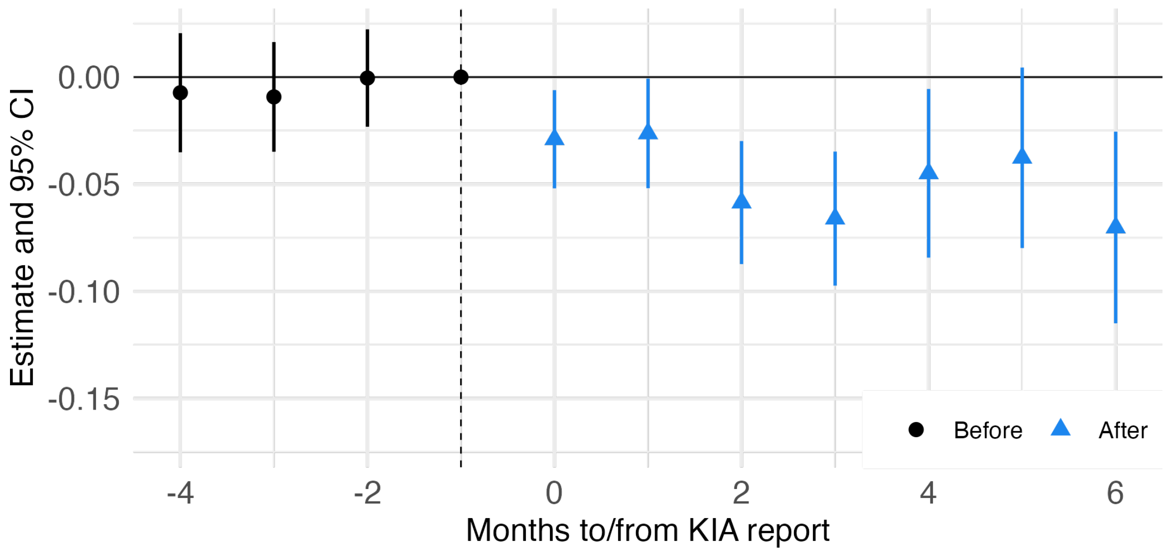
Note: Results from estimating Equation 4 with Sun and Abraham (2021) estimator for patriotic content. Dots report the point estimates and vertical bars report the 90% confidence intervals. Dependent variable: Δ log Likes per post for Patriotism topic defined with zero-shot (top) and keywords (bottom). Treatment: the first KIA report in a municipality. Standard errors clustered at municipality.

A.1.3 de Chaisemartin and d'Haultfoeuille (2024) Estimator

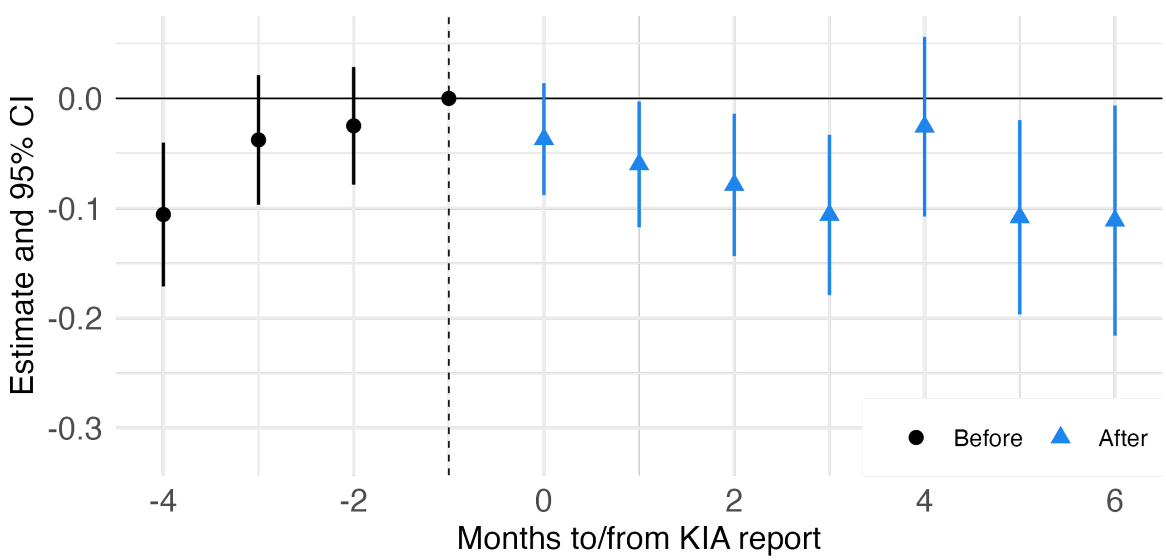
Figure A.V.

Dynamic effect of the KIA reports on relative engagement with pro-authorities content (Chaisemartin and D'Haultfœuille 2024 estimator)

(A) Authorities (zero-shot)



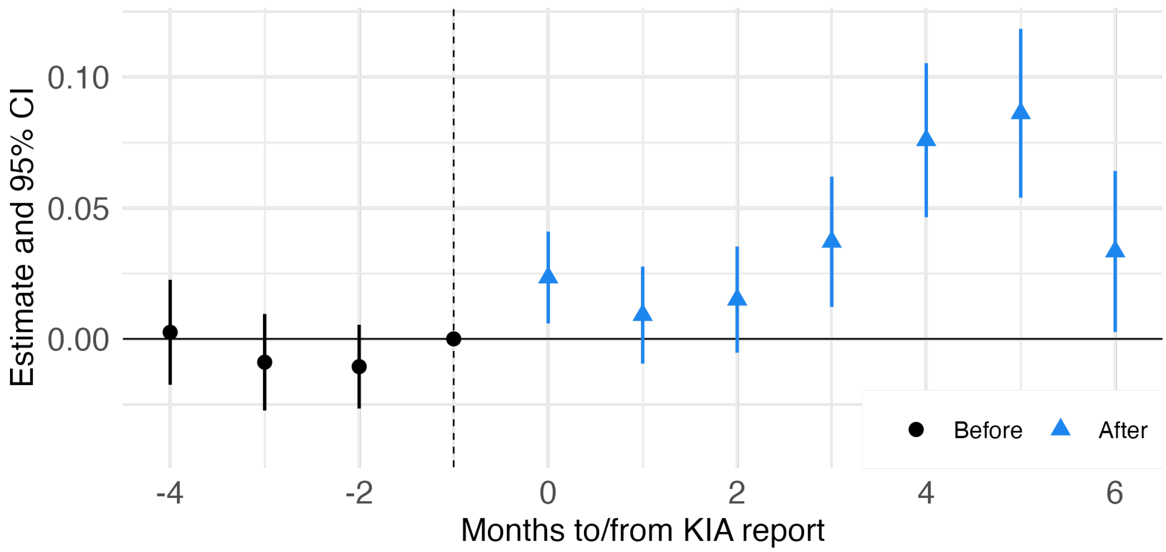
(B) Authorities (keywords)



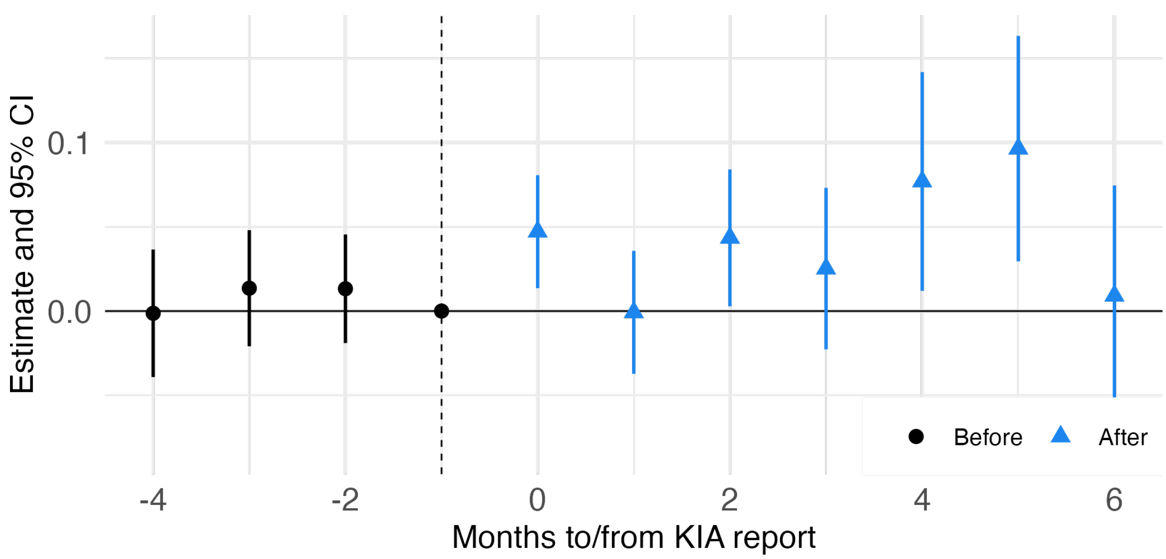
Note: Results from estimating Equation 4 with Chaisemartin and D'Haultfœuille (2024) estimator for patriotic content. Dots report the point estimates and vertical bars report the 90% confidence intervals. Dependent variable: Δ log Likes per post for Authorities topic defined with zero-shot (top) and keywords (bottom). Treatment: an additional KIA report in a municipality. Standard errors clustered at municipality.

Figure A.VI.
Dynamic effect of the KIA reports on relative engagement with patriotic content
(Chaisemartin and D'Haultfœuille 2024 estimator)

(A) Patriotism (zero-shot)



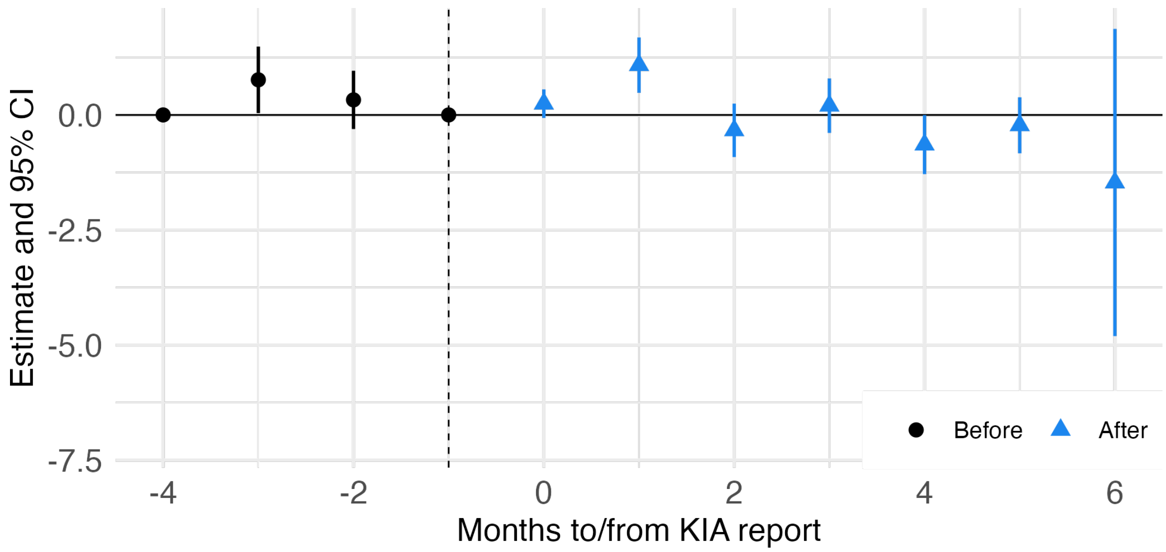
(B) Patriotism (keywords)



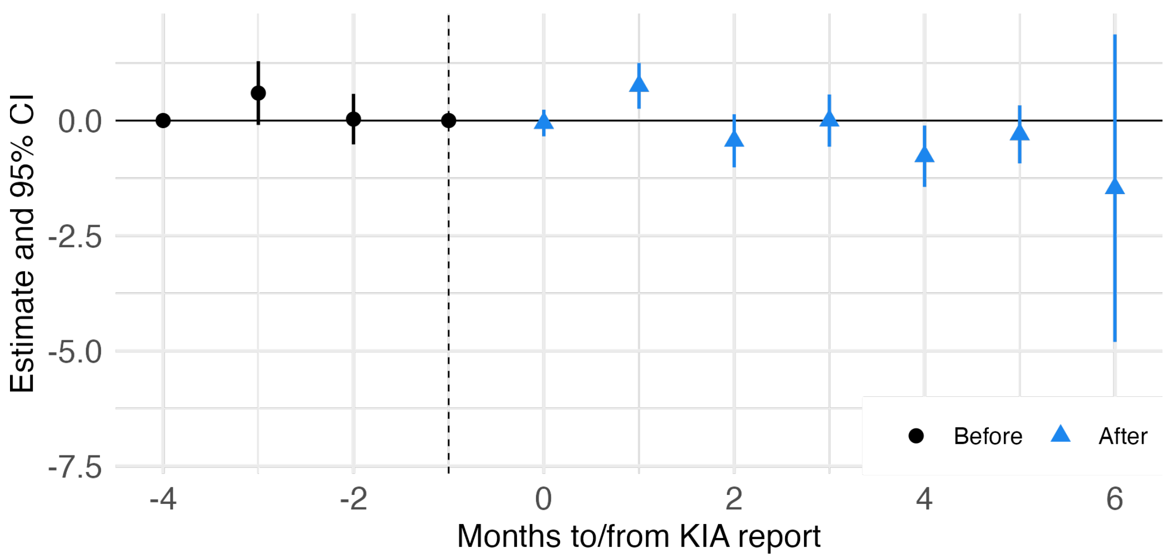
Note: Results from estimating Equation 4 with Chaisemartin and D'Haultfœuille (2024) estimator for patriotic content. Dots report the point estimates and vertical bars report the 90% confidence intervals. Dependent variable: Δ log Likes per post for Patriotism topic defined with zero-shot (top) and keywords (bottom). Treatment: an additional KIA report in a municipality. Standard errors clustered at municipality.

Figure A.VII.
Dynamic effect of the KIA reports on relative engagement with content related to the War in Ukraine (Chaisemartin and D'Haultfœuille 2024 estimator)

(A) War in Ukraine (keywords)



(B) War in Ukraine without commemoration (keywords + GPT)

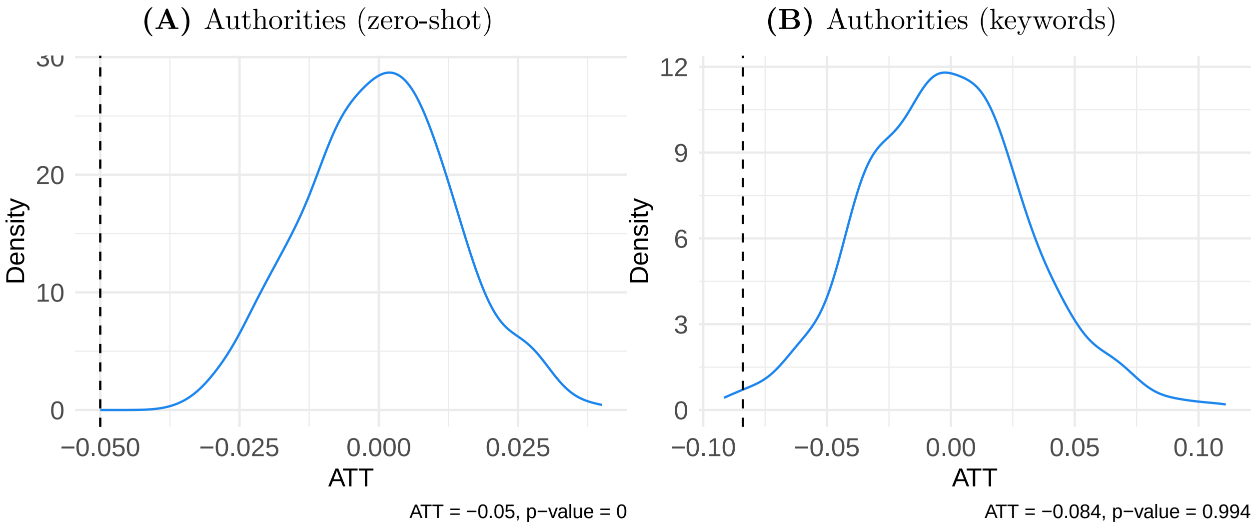


Note: Results from estimating Equation 4 with Chaisemartin and D'Haultfœuille (2024) estimator for content related to the war in Ukraine. Dots report the point estimates and vertical bars report the 90% confidence intervals. Dependent variable: Δ log Likes per post for Patriotism topic defined with zero-shot (top) and keywords (bottom). Treatment: an additional KIA report in a municipality. Standard errors clustered at municipality. Note that pre-trends are available only for up to three months before the KIA report due to the absence of the respective topic before February 2022.

A.1.4 Placebo studies

Figure A.VIII.

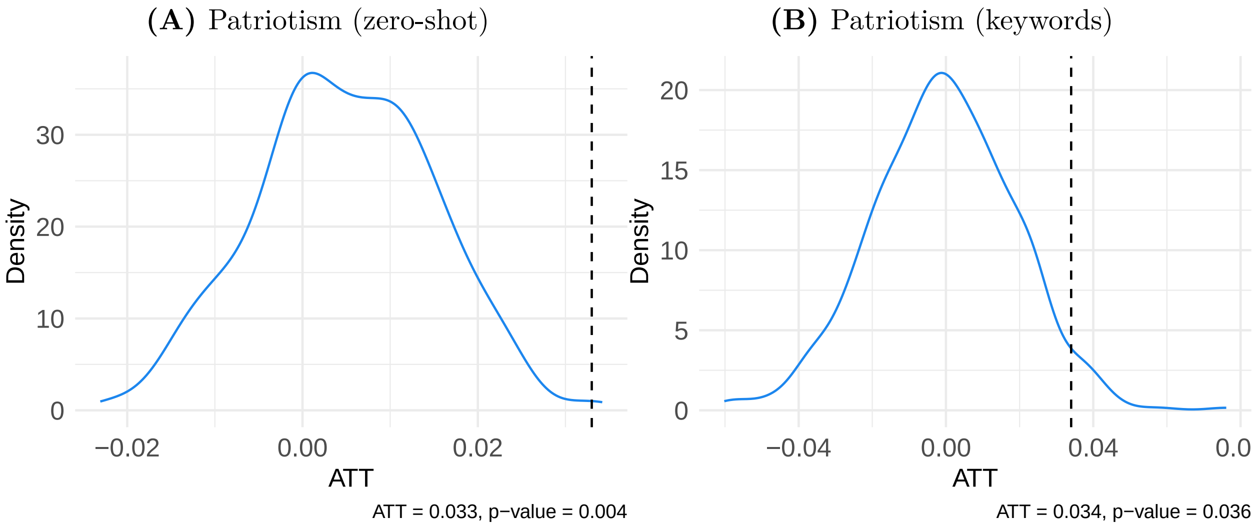
Monte-Carlo simulation for the effect of the first KIA report on engagement with pro-authorities content



Note: Dependent variable: Δ log Likes per post. Treatment: the first KIA report in a municipality. 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.

Figure A.IX.

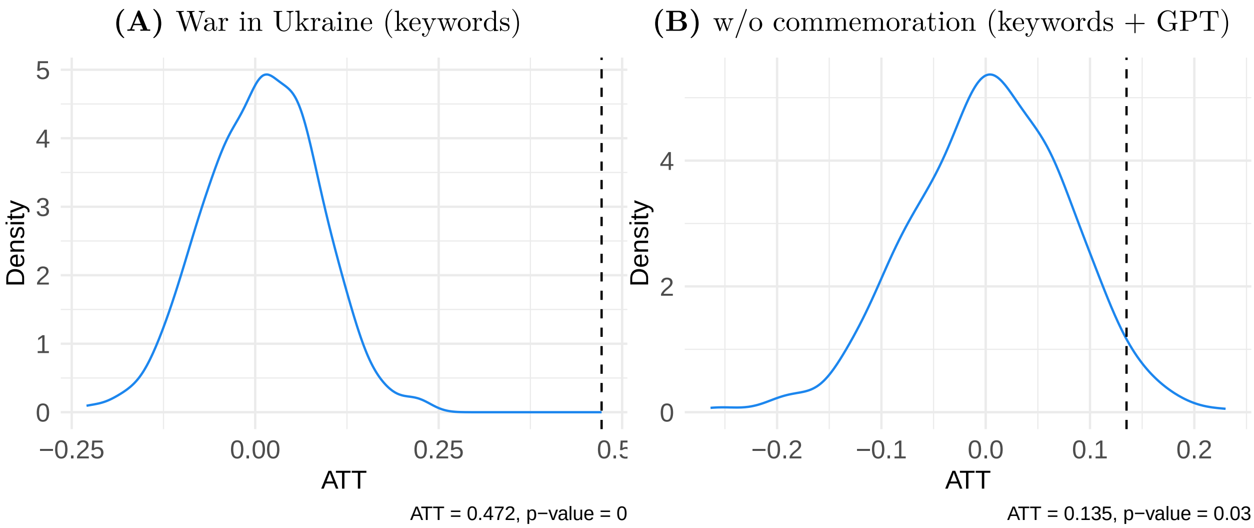
Monte-Carlo simulation for the effect of the first KIA report on relative engagement with patriotic content



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.

Figure A.X.

Monte-Carlo simulation for the effect of the first KIA report on relative engagement with content related to the war in Ukraine



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.

A.1.5 Results with balanced sample

Table A.I. Effect of the KIA reports on relative engagement with pro-authorities content (municipalities observed since September 2021)

Specification	TWFE (1)	C&SA (2)	C&SA + Controls (3)
Panel A:		Authorities (zero-shot)	
ATT	-0.034***	-0.02	-0.051**
	(0.01)	(0.016)	(0.02)
Outcome Mean	-0.419	-0.413	-0.439
Outcome SD	0.435	0.416	0.42
Observations	17359	16107	12571
Municipalities	1355	1239	967
Months	13	13	13
Panel B:		Authorities (keywords)	
ATT	-0.026	-0.073	-0.058
	(0.022)	(0.045)	(0.058)
Outcome Mean	-0.087	-0.02	-0.043
Outcome SD	0.877	0.801	0.815
Observations	15874	8684	6968
Municipalities	1353	668	536
Months	13	13	13

Note: Results from estimating Equation 3 for Authorities topic. Sample is a balanced panel of municipalities with at least one active online school group prior to September 2021. Dependent variable: Δ log Likes per post. Classification strategy in the panel header. Treatment: first KIA report in a municipality. Controls: log average Night Lights intensity, log Population, % Population age 50 or older. Standard errors in parentheses are clustered at municipality. Estimation strategy is indicated in the column header. Single, double, and triple asterisks report significance at 10%, 5%, and 1%, respectively.

Table A.II. Effect of the KIA reports on relative engagement with patriotic content (municipalities observed since September 2021)

Specification	TWFE (1)	C&SA (2)	C&SA + Controls (3)
Panel A:		Patriotism (zero-shot)	
ATT	0.014*	0.046***	0.07***
	(0.008)	(0.011)	(0.019)
Outcome Mean	0.031	0.034	0.038
Outcome SD	0.299	0.28	0.285
Observations	17359	16107	12571
Municipalities	1355	1239	967
Months	13	13	13
Panel B:		Patriotism (keywords)	
ATT	0.011	0.039*	0.079**
	(0.014)	(0.02)	(0.035)
Outcome Mean	0.348	0.36	0.369
Outcome SD	0.575	0.516	0.523
Observations	17103	14716	11479
Municipalities	1354	1132	883
Months	13	13	13

Note: Results from estimating Equation 3 for Patriotism topic. Municipalities with no active online school groups prior to September 2021 excluded from the sample. Dependent variable: Δ log Likes per post. Classification strategy in the panel header. Treatment: first KIA report in a municipality. Controls: log average Night Lights intensity, log Population, % Population age 50 or older. Standard errors in parentheses are clustered at municipality. Estimation strategy is indicated in the column header. Single, double, and triple asterisks report significance at 10%, 5%, and 1%, respectively.

Table A.III. Effect of the KIA reports on relative engagement with content related to the War in Ukraine (municipalities observed since September 2021)

Specification	TWFE (1)	C&SA (2)	C&SA + Controls (3)
Panel A:	War in Ukraine (keywords)		
ATT	0.247***	0.911*	-0.531**
	(0.064)	(0.487)	(0.236)
Outcome Mean	0.108	-0.141	-0.141
Outcome SD	0.985	1.217	1.217
Observations	3659	70	70
Municipalities	1180	10	10
Months	7	7	7
Panel B:	War in Ukraine without commemoration (keywords + GPT)		
ATT	0.042	0.484	-0.558*
	(0.057)	(0.505)	(0.29)
Outcome Mean	-0.068	-0.385	-0.385
Outcome SD	0.838	1.162	1.162
Observations	3410	63	63
Municipalities	1162	9	9
Months	7	7	7

A.1.6 Results for sentiment composition

Table A.IV. Effect of the KIA reports on engagement with positive and negative sentiment content relative to neutral sentiment

Specification	TWFE (1)	C&SA (2)	C&SA + Controls (3)
Panel A:		Positive sentiment	
ATT	0.015	0.023	0.037
	(0.014)	(0.021)	(0.03)
Outcome Mean	0.544	0.544	0.587
Outcome SD	0.649	0.649	0.666
Observations	23949	23949	18085
Municipalities	2030	2030	1531
Months	13	13	13
Panel B:		Negative sentiment	
ATT	0.024**	0.025	0.016
	(0.011)	(0.016)	(0.026)
Outcome Mean	0.269	0.269	0.293
Outcome SD	0.517	0.517	0.531
Observations	24360	24360	18387
Municipalities	2030	2030	1529
Months	13	13	13

Note: Results from estimating Equation 3 for relative engagement with content with different sentiment scores. Dependent variable: Δ log Likes per post. Classification strategy in the panel header. Treatment: first KIA report in a municipality. Controls: log average Night Lights intensity, log Population, % Population age 50 or older. Standard errors in parentheses are clustered at municipality. Estimation strategy is indicated in the column header. Single, double, and triple asterisks report significance at 10%, 5%, and 1%, respectively.

Table A.V. Effect of the KIA reports on sentiment composition

Specification	TWFE (1)	C&SA (2)	C&SA + Controls (3)
Panel A:		Positive sentiment	
ATT	-0.035***	-0.033*	-0.011
	(0.012)	(0.02)	(0.033)
Outcome Mean	-0.332	-0.332	-0.354
Outcome SD	0.689	0.689	0.697
Observations	23949	23949	18085
Municipalities	2030	2030	1531
Months	13	13	13
Panel B:		Negative sentiment	
ATT	-0.005	-0.015	-0.017
	(0.008)	(0.014)	(0.023)
Outcome Mean	-0.076	-0.076	-0.062
Outcome SD	0.441	0.441	0.438
Observations	24360	24360	18387
Municipalities	2030	2030	1529
Months	13	13	13

Note: Results from estimating Equation 3 for content composition with respect to the sentiment scores. Dependent variable: Δ log Posts. Classification strategy in the panel header. Treatment: first KIA report in a municipality. Controls: log average Night Lights intensity, log Population, % Population age 50 or older. Standard errors in parentheses are clustered at municipality. Estimation strategy is indicated in the column header. Single, double, and triple asterisks report significance at 10%, 5%, and 1%, respectively.

A.1.7 Results with sentiment score adjustment

Table A.VI. Effect of the KIA reports on relative engagement with pro-authorities content with different sentiment

Specification	TWFE (1)	C&SA (2)	C&SA + Controls (3)
Panel A:	Positive sentiment: Authorities (zero-shot)		
ATT	-0.036***	-0.062***	-0.044*
	(0.012)	(0.019)	(0.024)
Outcome Mean	-0.551	-0.551	-0.554
Outcome SD	0.588	0.588	0.589
Observations	23949	23949	23602
Municipalities	2030	2030	2002
Months	13	13	13
Panel B:	Negative sentiment: Authorities (zero-shot)		
ATT	-0.026**	-0.038**	-0.043**
	(0.011)	(0.015)	(0.02)
Outcome Mean	-0.508	-0.508	-0.51
Outcome SD	0.511	0.511	0.511
Observations	24360	24360	24010
Municipalities	2030	2030	2002
Months	13	13	13
Panel C:	Neutral sentiment: Authorities (zero-shot)		
ATT	-0.024**	-0.029*	-0.037*
	(0.01)	(0.017)	(0.021)
Outcome Mean	-0.473	-0.473	-0.474
Outcome SD	0.486	0.486	0.487
Observations	24412	24412	24059
Municipalities	2031	2031	2003
Months	13	13	13

Note: Results from estimating Equation 3 for Authorities topic with different sentiment scores. Dependent variable: Δ log Likes per post. Classification strategy in the panel header. Treatment: first KIA report in a municipality. Controls: log average Night Lights intensity, log Population, % Population age 50 or older. Standard errors in parentheses are clustered at municipality. Estimation strategy is indicated in the column header. Single, double, and triple asterisks report significance at 10%, 5%, and 1%, respectively.

Table A.VII. Effect of the KIA reports on relative engagement with patriotic content with different sentiment

Specification	TWFE (1)	C&SA (2)	C&SA + Controls (3)
Panel A:	Positive sentiment: Patriotism (zero-shot)		
ATT	0.017*	0.017	0.026*
	(0.009)	(0.014)	(0.015)
Outcome Mean	-0.108	-0.108	-0.109
Outcome SD	0.387	0.387	0.387
Observations	23949	23949	23602
Municipalities	2030	2030	2002
Months	13	13	13
Panel B:	Negative sentiment: Patriotism (zero-shot)		
ATT	0.036***	0.031**	0.049***
	(0.009)	(0.013)	(0.017)
Outcome Mean	-0.023	-0.023	-0.024
Outcome SD	0.408	0.408	0.409
Observations	24360	24360	24010
Municipalities	2030	2030	2002
Months	13	13	13
Panel C:	Neutral sentiment: Patriotism (zero-shot)		
ATT	0.009	0.039***	0.06**
	(0.009)	(0.014)	(0.028)
Outcome Mean	-0.047	-0.047	-0.048
Outcome SD	0.437	0.437	0.438
Observations	24412	24412	24059
Municipalities	2031	2031	2003
Months	13	13	13

Note: Results from estimating Equation 3 for Patriotism topic with different sentiment scores. Dependent variable: Δ log Likes per post. Classification strategy in the panel header. Treatment: first KIA report in a municipality. Controls: log average Night Lights intensity, log Population, % Population age 50 or older. Standard errors in parentheses are clustered at municipality. Estimation strategy is indicated in the column header. Single, double, and triple asterisks report significance at 10%, 5%, and 1%, respectively.

A.1.8 Results with Leave-one-region-out

Figure A.XI.

Effect of the KIA reports on relative engagement with pro-authorities content (zero-shot)

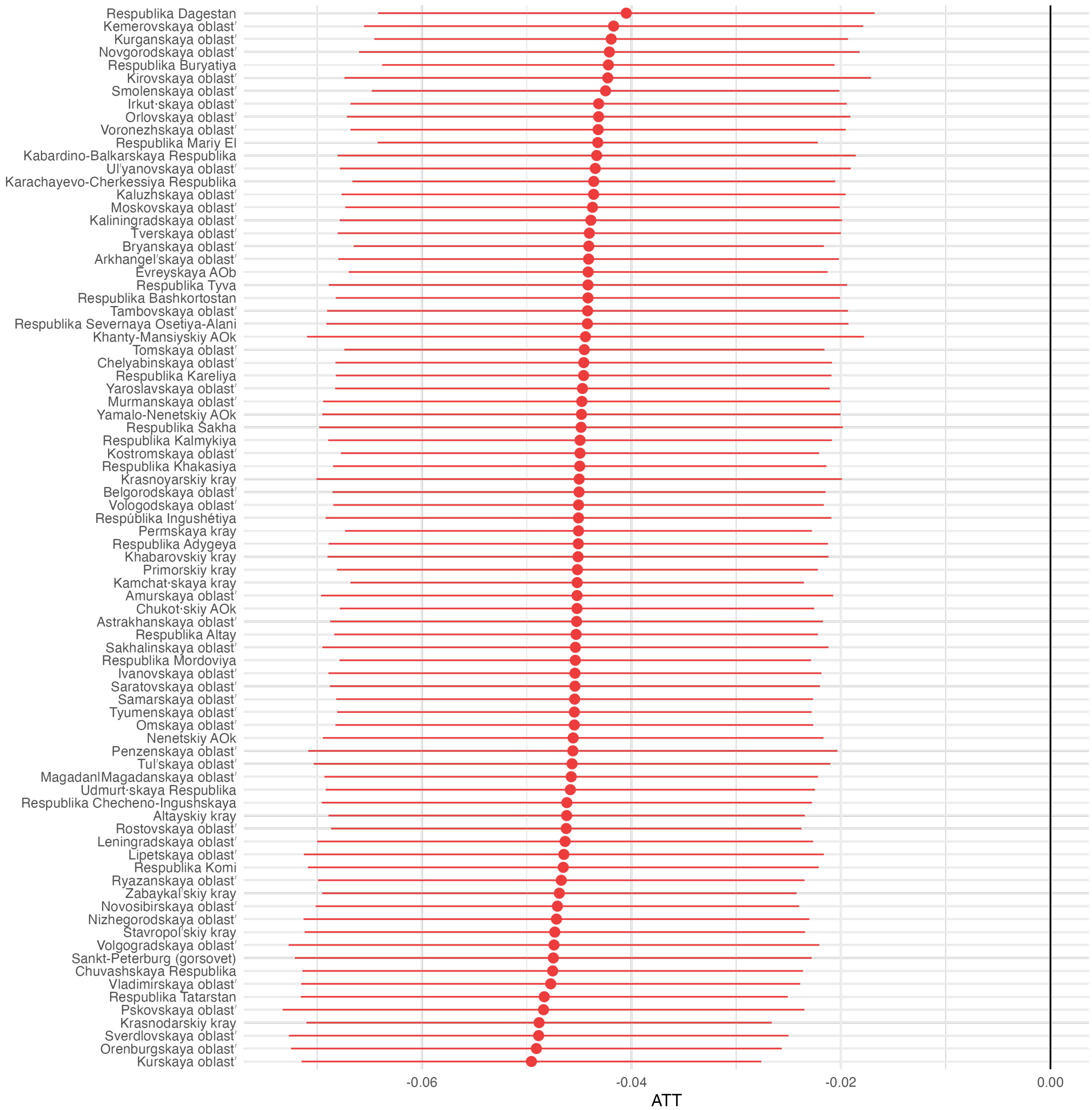


Figure A.XII.

Effect of the KIA reports on relative engagement with pro-authorities content (keywords)

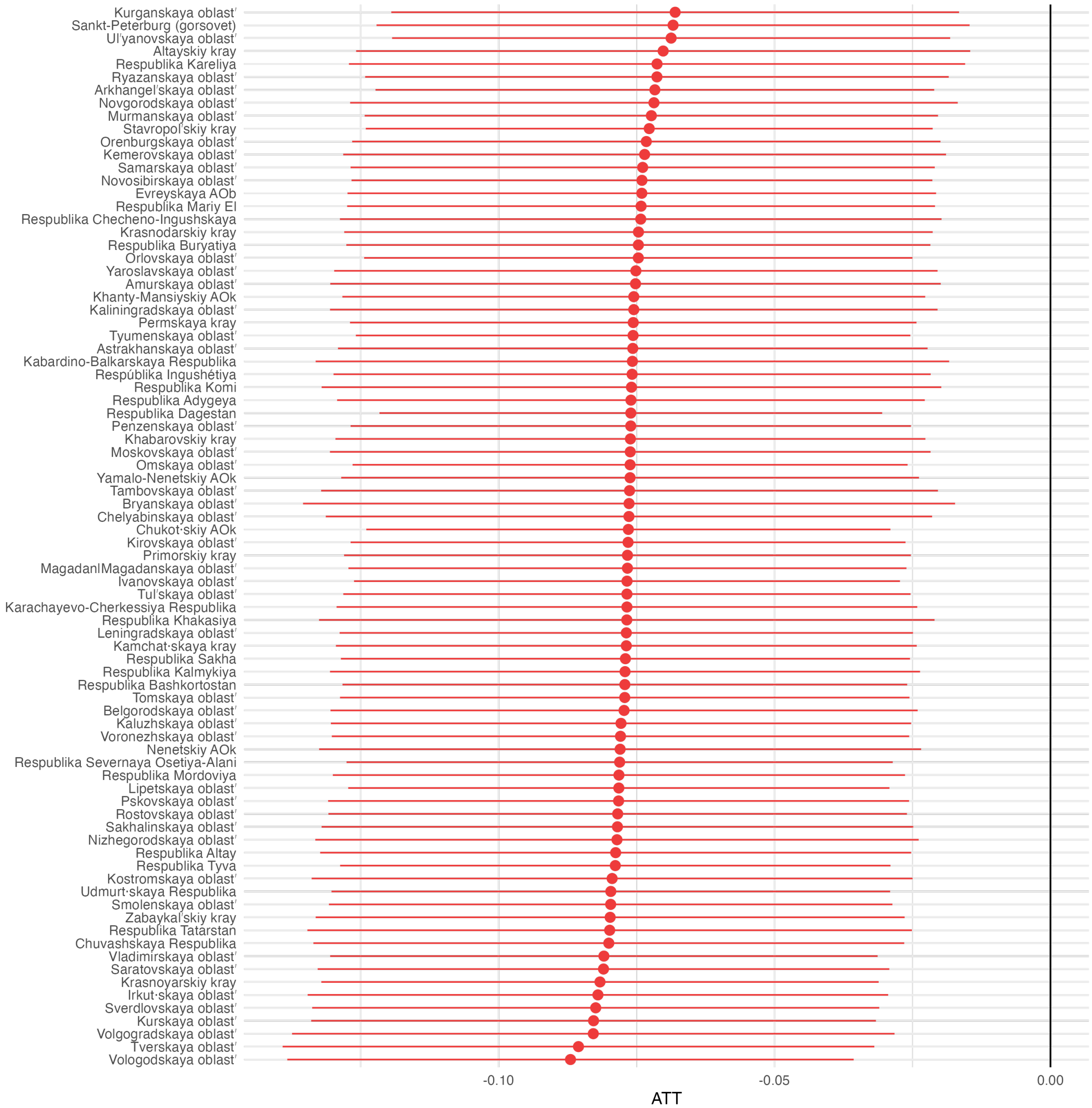


Figure A.XIII.

Effect of the KIA reports on relative engagement with patriotic content (zero-shot)

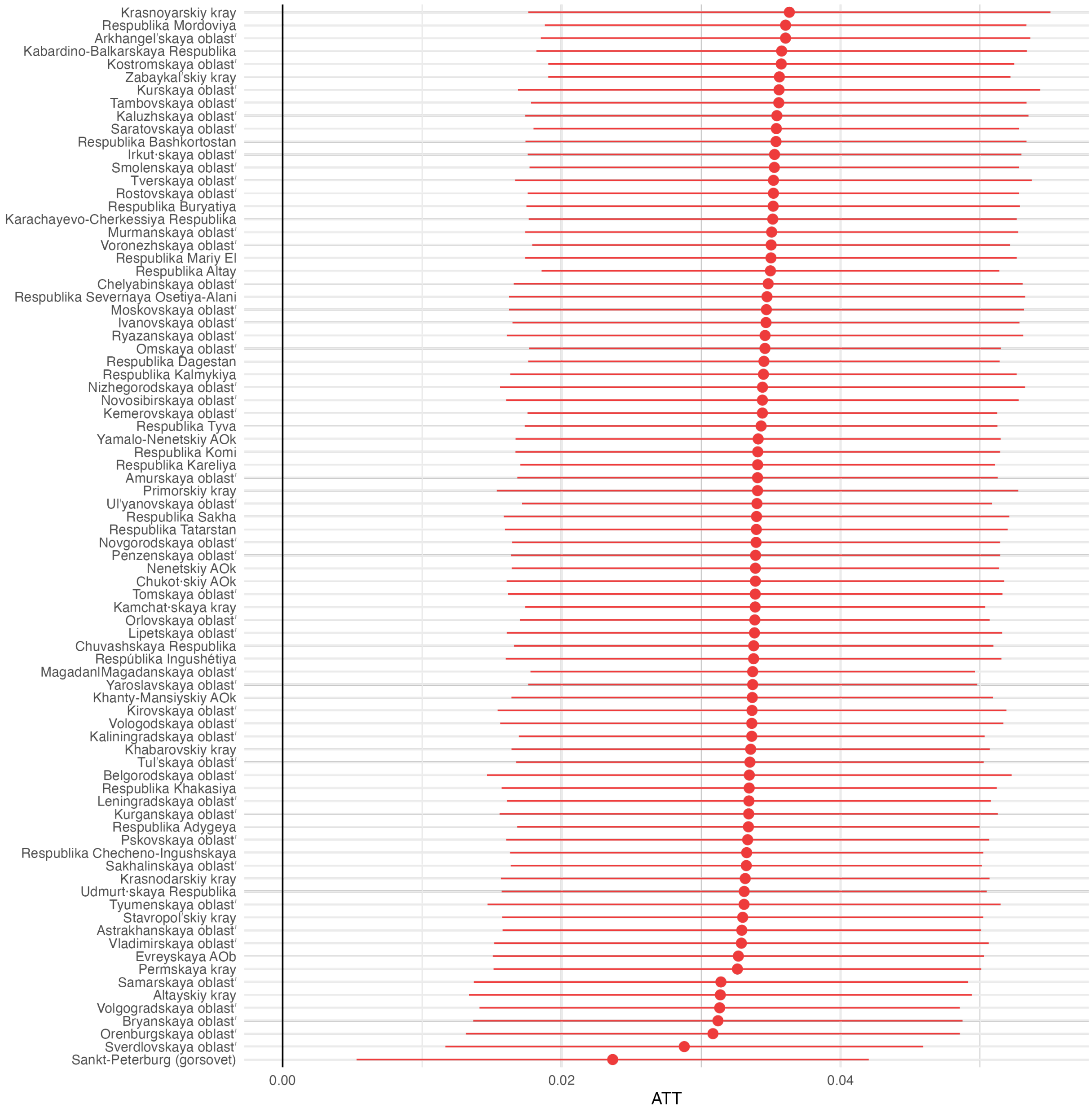
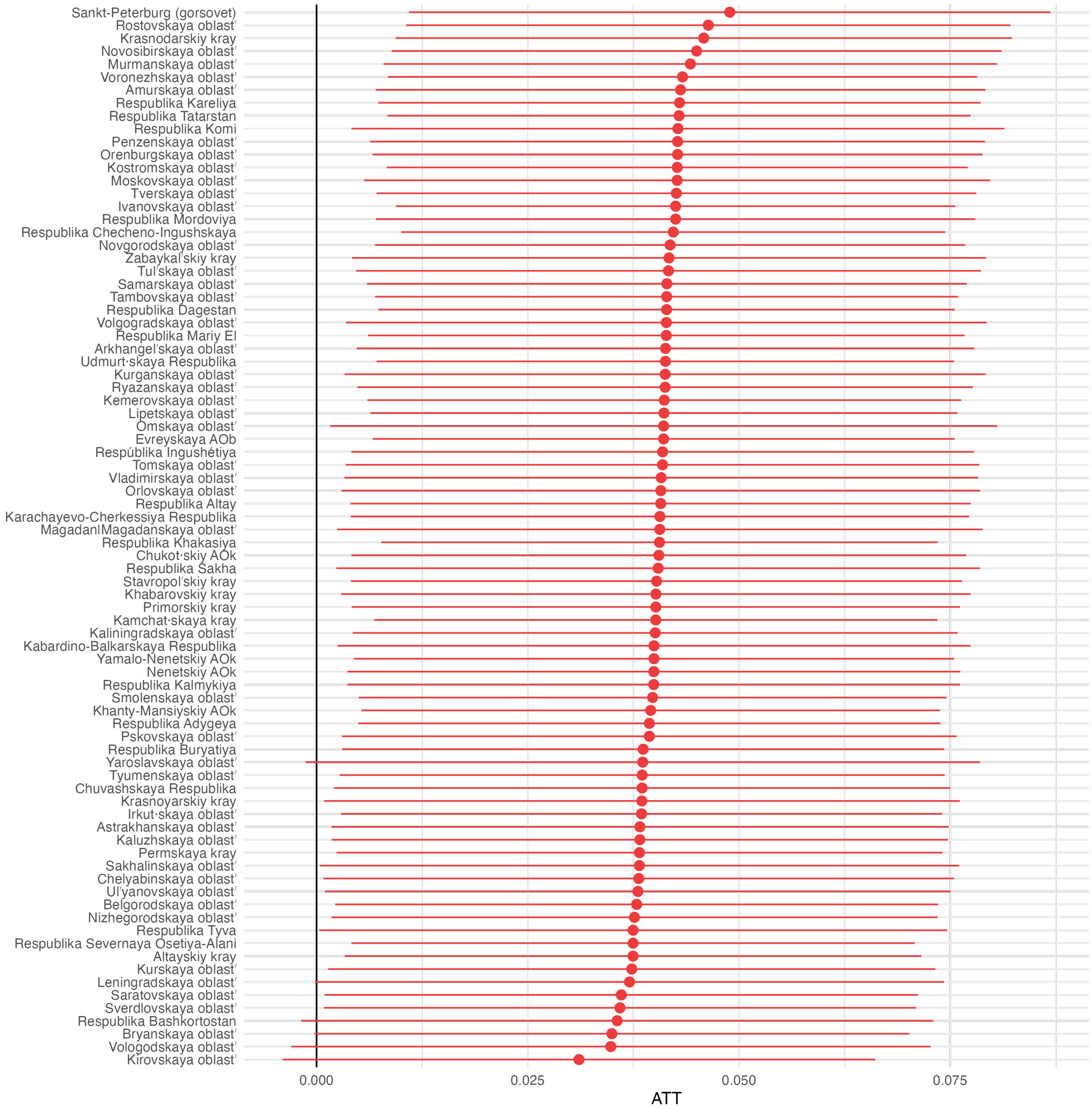


Figure A.XIV.

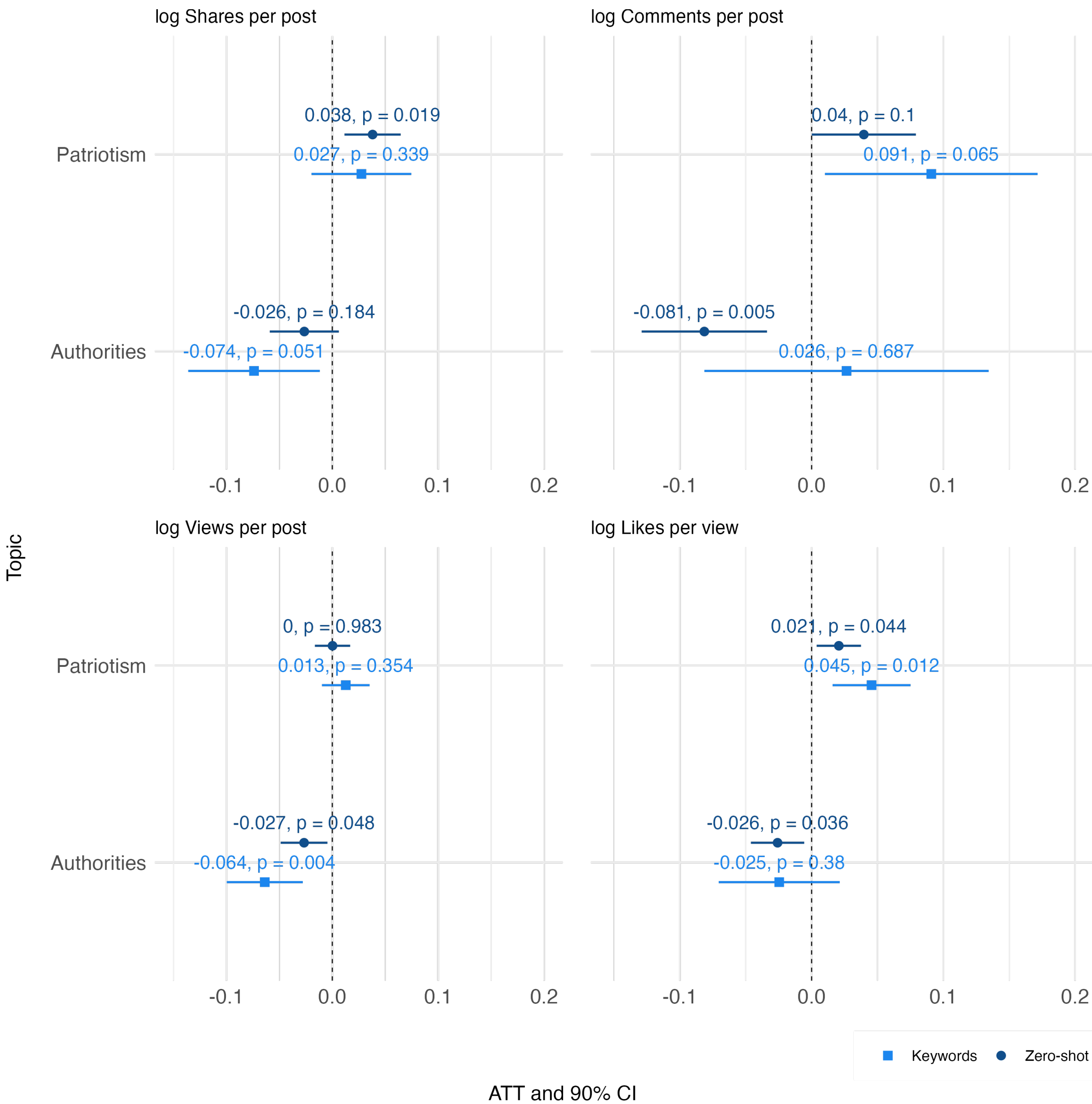
Effect of the KIA reports on relative engagement with patriotic content (keywords)



A.1.9 Results for alternative engagement metrics

Figure A.XV.

Effect of the first KIA report on alternative relative engagement metrics by topic

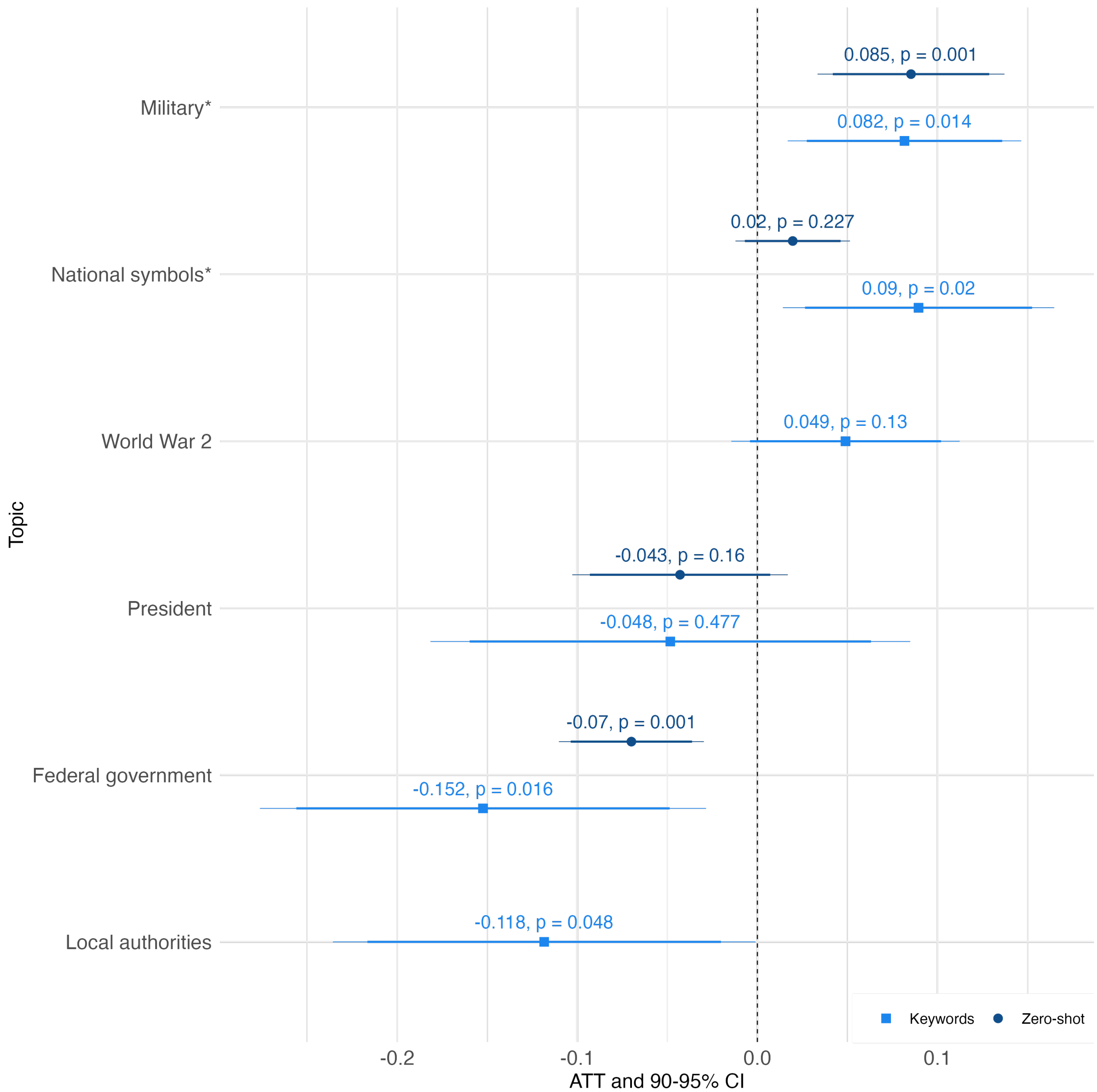


Note: Results from estimating Equation 3 for alternative relative engagement metrics by topic. Topic outlined on the vertical axis. Dependent variable in the panel header. Classification strategy: keywords (squares) or zero-shot (circles). Estimation strategy: Callaway and Sant'Anna (2021) with controls. Treatment: first KIA report in a municipality. Controls: log average Night Lights intensity, log Population, % Population age 50 or older. Standard errors clustered at municipality.

A.2 Heterogeneity

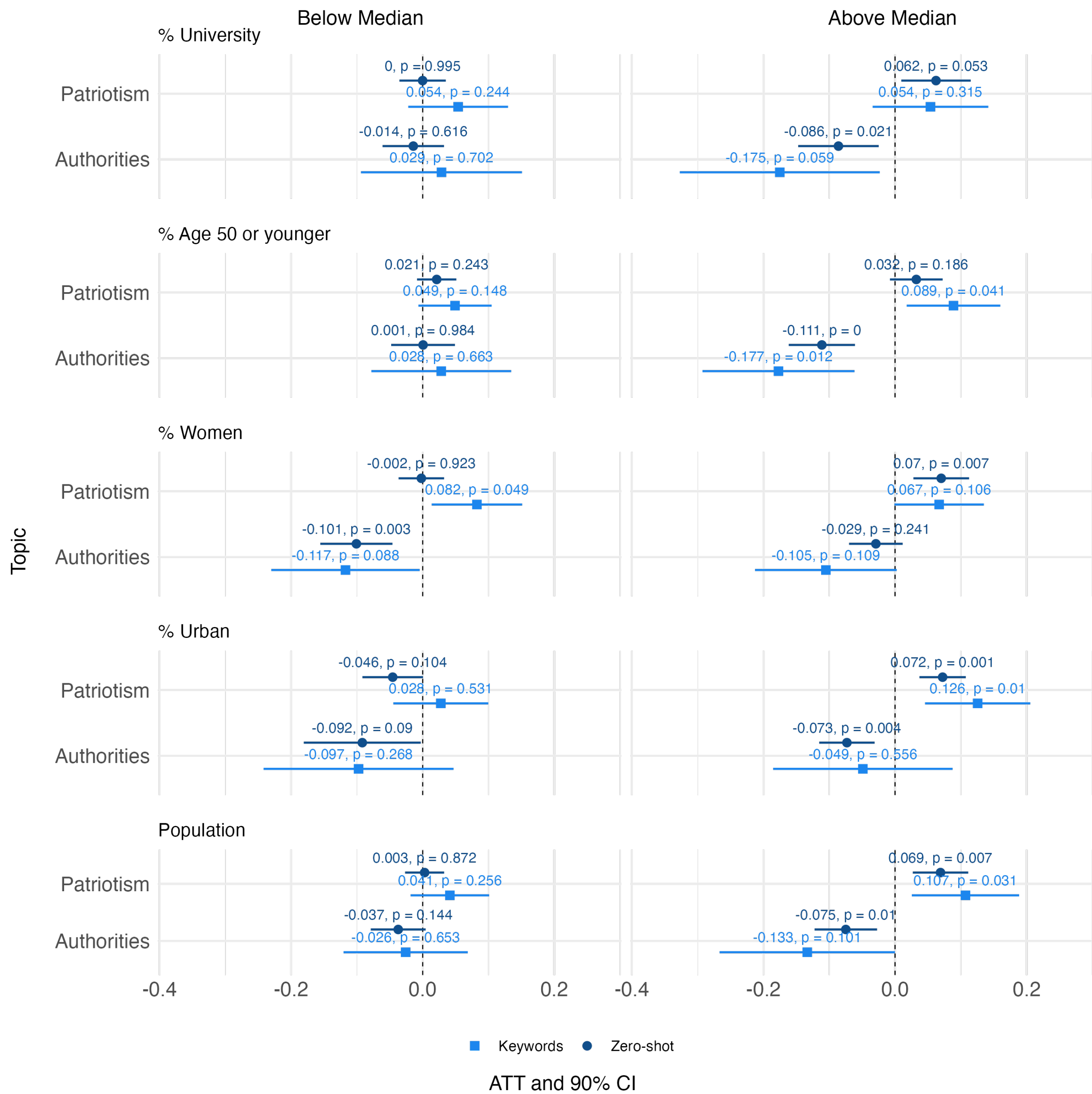
Figure A.XVI.

Effect of the KIA reports on relative engagement by detailed topic



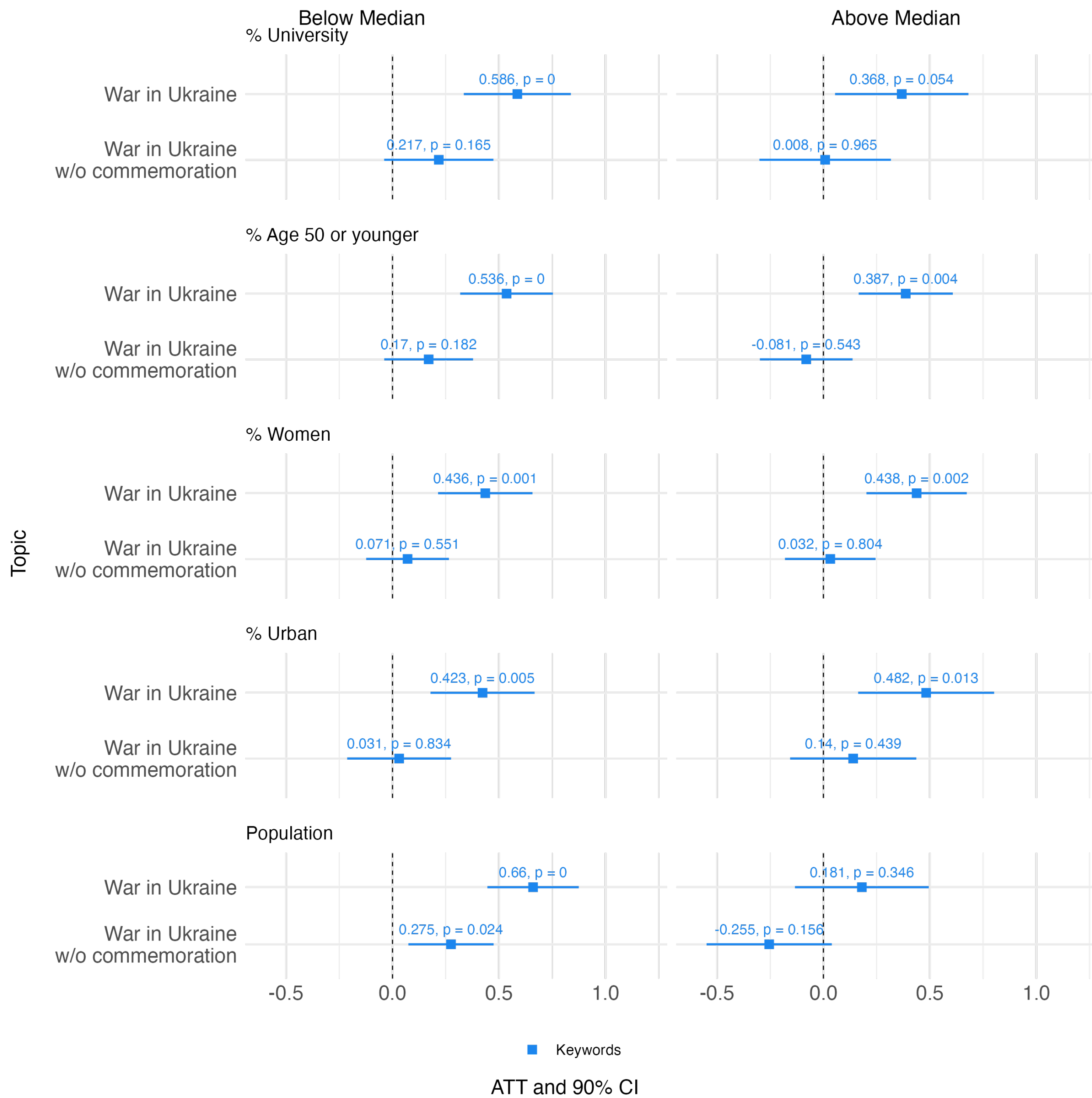
Note: Results from estimating Equation 3 for relative engagement by detailed topic. Topic outlined on the vertical axis. For *National symbols*, zero-shot label is *Patriotism*, and for *Military* the label is *War*. Dependent variable: Δ log Likes per post. Classification strategy: keywords (squares) or zero-shot (circles). Estimation strategy: Callaway and Sant'Anna (2021) with controls. Treatment: first KIA report in a municipality. Controls: log average Night Lights intensity, log Population, % Population age 50 or older. Horizontal bars denote the confidence intervals. Standard errors are clustered at municipality.

Figure A.XVII.
Effect heterogeneity by municipality characteristics for relative engagement with pro-authorities and patriotic content



Note: Results from estimating Equation 3 for relative engagement; heterogeneity by municipality characteristics. Each panel presents separate estimation results on subsamples split at the median of the variable indicated in the header. Dependent variable: Δ log Likes per post. Classification strategy: keywords (squares) or zero-shot (circles). Estimation strategy: Callaway and Sant'Anna (2021) with controls. Treatment: first KIA report in a municipality. Controls: log average Night Lights intensity, log Population, % Population age 50 or older. Horizontal bars denote the confidence intervals. Standard errors are clustered at municipality.

Figure A.XVIII.
Effect heterogeneity by municipality characteristics for relative engagement with content related to the war in Ukraine



Note: Results from estimating Equation 3 for relative engagement; heterogeneity by municipality characteristics. Each panel presents separate estimation results on subsamples split at the median of the variable indicated in the header. Dependent variable: Δ log Likes per post. Classification strategy: keywords (squares) or zero-shot (circles). Estimation strategy: Callaway and Sant'Anna (2021) with controls. Treatment: first KIA report in a municipality. Controls: log average Night Lights intensity, log Population, % Population age 50 or older. Horizontal bars denote the confidence intervals. Standard errors are clustered at municipality.

A.3 Descriptives

A.3.1 Text analysis of posts

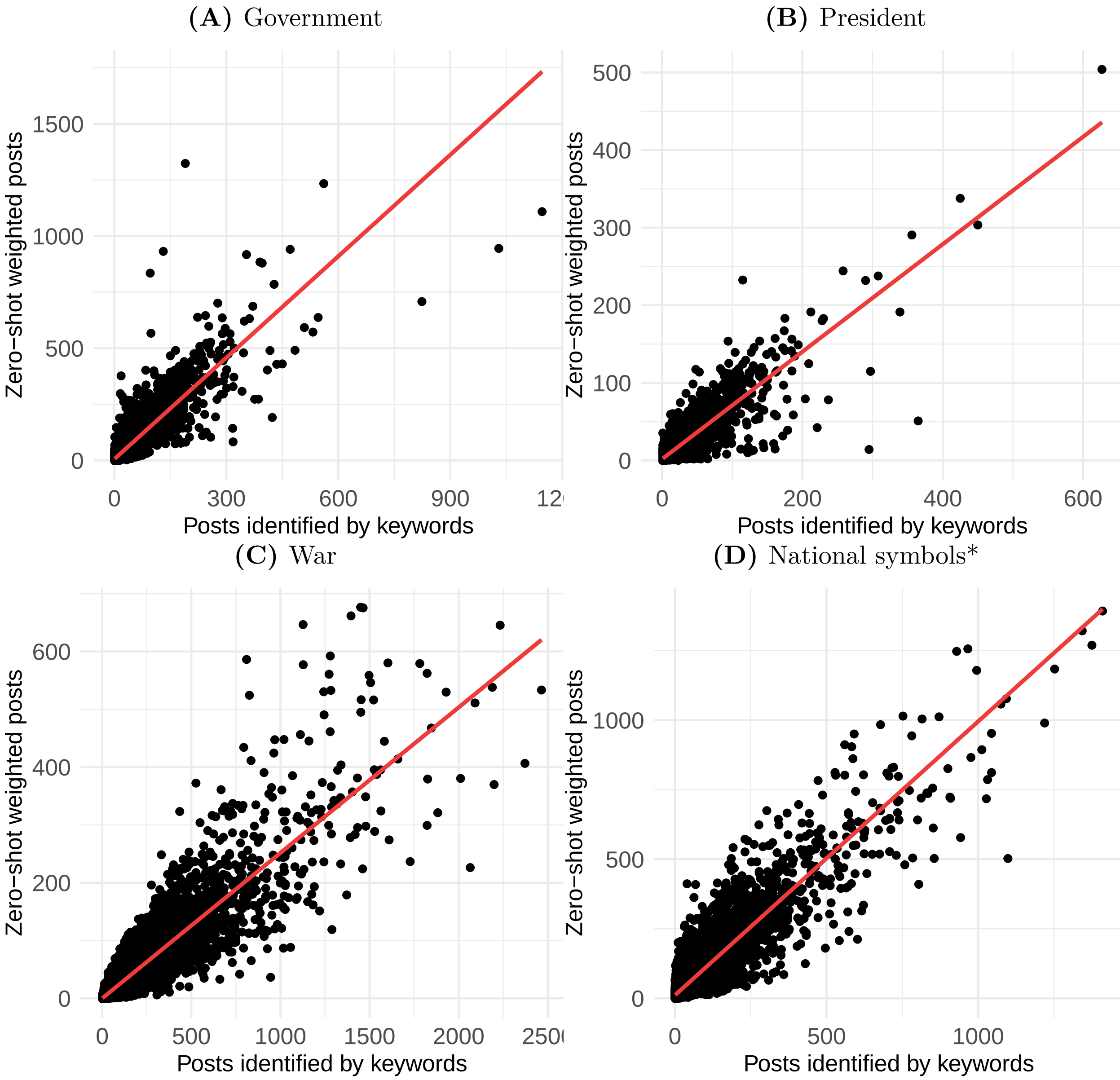
Table A.VIII. Keyword topic frequencies

Topic	Mean
Neutral	0.4556765
War	0.3360547
President	0.0548907
Government	0.0565058
Patriotism	0.1213173
WW2	0.1900880
War in Ukraine (SMO)	0.0135381
Ukraine	0.0145751

Table A.IX. 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

Figure A.XIX.
Posts identified by keywords and zero-shot



Note: Number of posts in municipality-month identified by keywords on horizontal axis. Number of posts weighted by the zero-shot quasi-probabilities on the vertical axis. Zero-shot label for the *National symbols* is *Patriotism.*

Table A.X. Keywords by topic

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
Commemoration	Died, gave his life, was killed
Authorities	
President	president, Putin
Government	deputy, parliament, state duma, minister, ministry
Local authorities	head of region, governor
Patriotism	
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
National symbols	flag, national anthem, conversations†, lesson of bravery, heroism, duty

Note: 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.

A.3.2 War fatality reports

Figure A.XX.
Days between a soldier's death and a death act

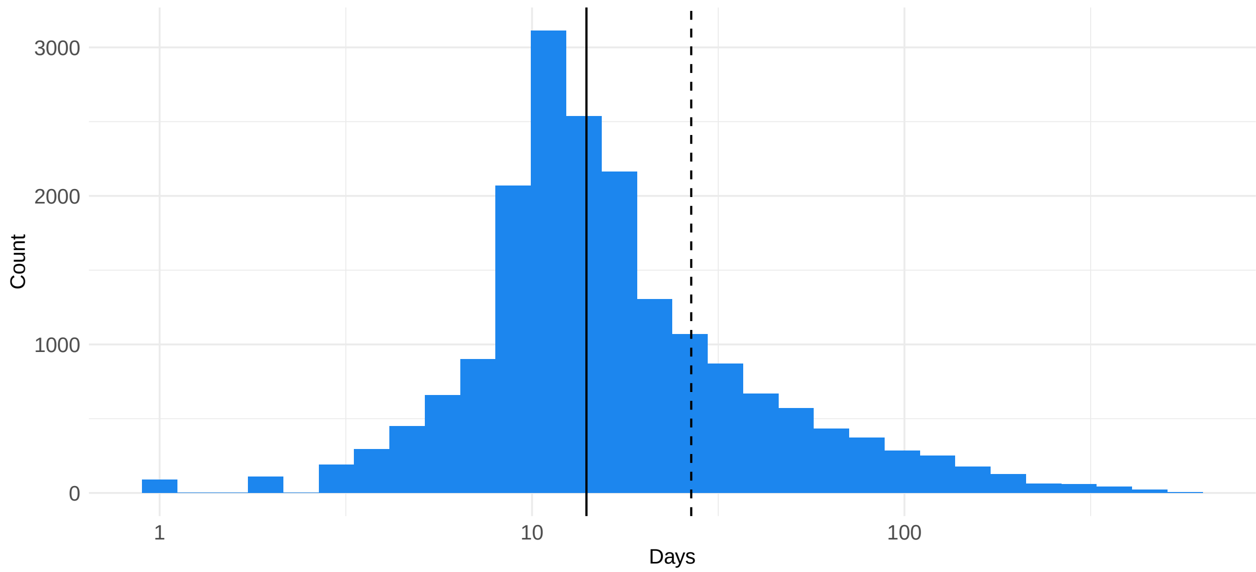
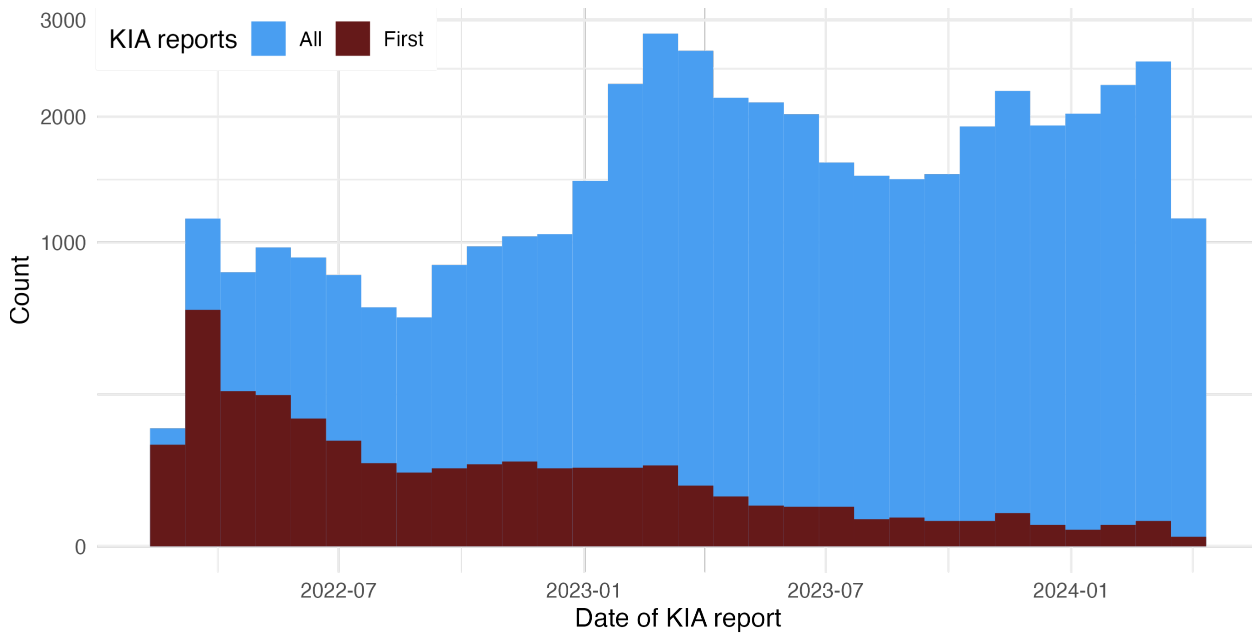


Figure A.XXI.
Dynamics of monthly KIA reports

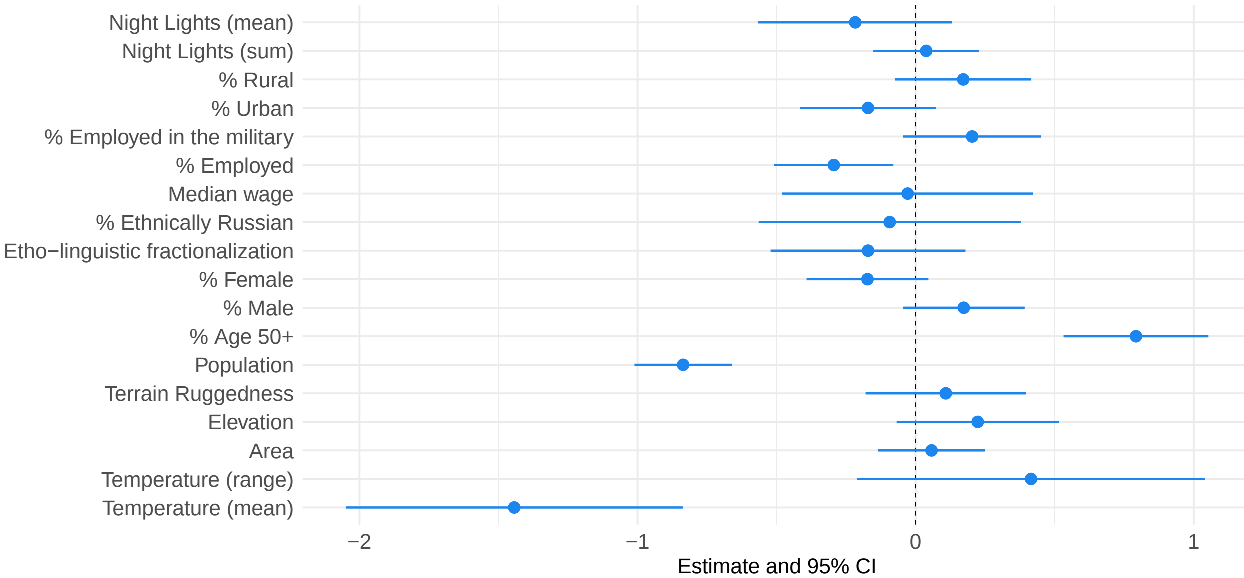


Note: Blue bars denote the total number of KIA reports in a given month. Red bars denote the number of municipalities that received the first KIA report in a given month.

Table A.XI. Municipality summary statistics

Variable	N	Mean	SD	Min	Max
Temperature (mean)	2522	3.24	4.02	-16	13
Temperature (range)	2522	30.78	6.00	17	60
Area	2522	6944.86	32438.95	1	1028475
Elevation	2522	249.31	317.75	-28	2635
Terrain Ruggedness	2522	99.12	151.55	2	1542
Population	2482	56032.53	115307.52	718	1625631
% Age 50+	1870	0.30	0.07	0	1
% Male	1942	0.48	0.02	0	1
% Female	1942	0.52	0.02	0	1
Etho-linguistic fractionalization	1640	0.23	0.21	0	1
% Ethnically Russian	1640	0.74	0.32	0	1
Median wage	2099	41935.53	26703.83	0	234565
% Employed	1884	0.18	0.18	0	4
% Employed in the military	1962	0.12	0.07	0	1
% Urban	1346	0.61	0.28	0	1
% Rural	1346	0.39	0.28	0	1
Night Lights (sum)	2522	72066.54	507526.41	164	17445113
Night Lights (mean)	2522	10.61	28.98	0	292

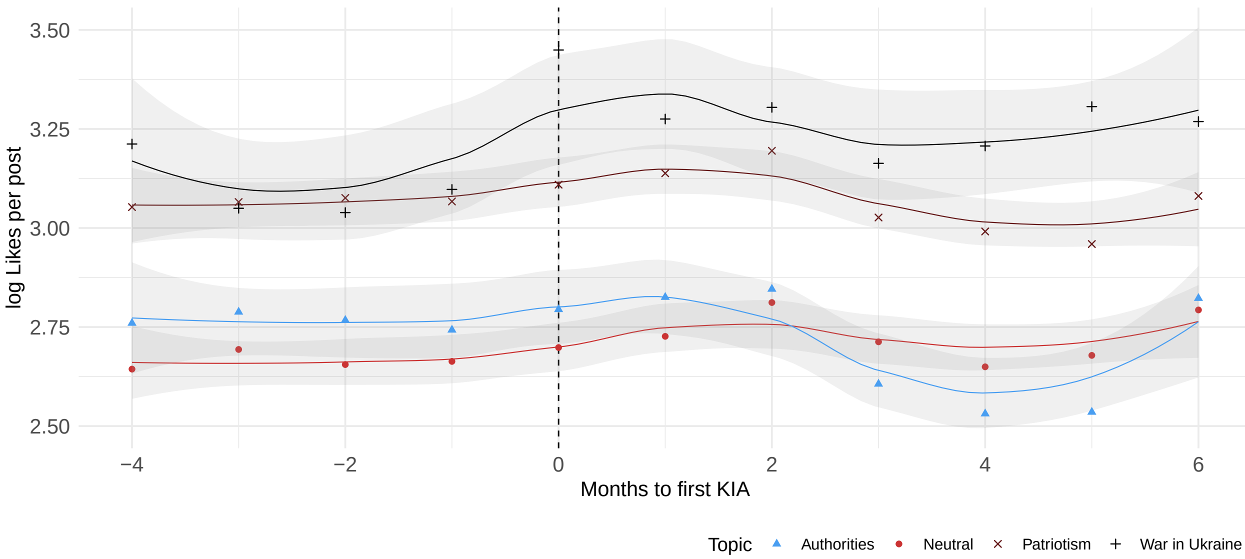
Figure A.XXII.
Correlates of the KIA report treatment with covariates



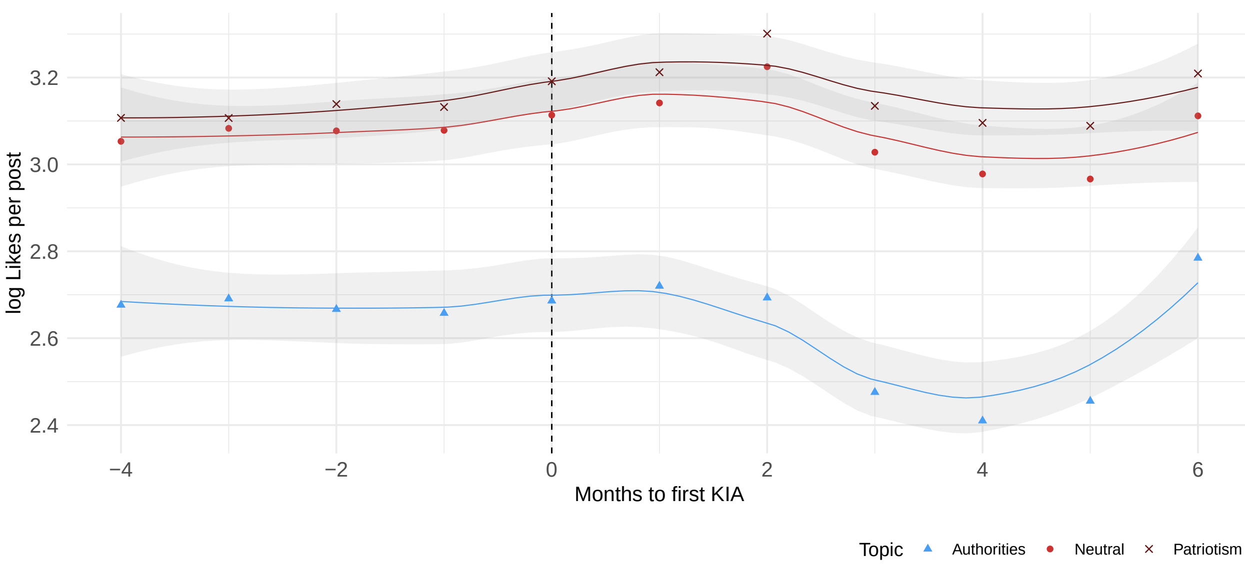
Note: Dependent variable: Month of the first KIA report. Independent variables: Covariates defined along the vertical axis and region fixed effect. Dots show the standardized coefficient from a separate regression. Negative coefficients correspond to earlier treatment time. Standard errors clustered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

Figure A.XXIII.
SM engagement around the date of the first KIA report

(A) Keyword topics



(B) Zero-shot topics



A.3.3 Obituaries classification

To identify the obituaries, we first use keyword analysis based on the keywords for the War in Ukraine topic and keywords related to death, e.g., died, killed, etc. We then feed the identified posts, more than 47 thousand in total, into the GPT model using the following prompt:

You are a classification assistant. Analyze the post below and return [the following] fields:

- *Died in Ukraine*: *Yes* if the post clearly states the person died in Ukraine during the SVO (2022 or later); otherwise, *No*.
- *Name mentioned*: *Yes* if the full name of the deceased is present; otherwise, *No*.
- *Date of death*: Return in *DD-MM-YYYY* format if known. If only month and year are available, use the 15th of the month. Return *NA* if unknown.
- *Name*: Full name in Cyrillic (nominative case), or *NA* if not present.
- *Award*: *Yes* only if a specific military award is clearly mentioned as being awarded to the deceased; otherwise, *No*.
- *Death announcement*: *Yes* if the post primarily announces or mourns the death; otherwise, *No*.
- *Commemoration*: *Yes* if a formal commemorative act (e.g., memorial desk, school plaque) is described; *No* otherwise.
- *Possible graduate*: *Yes* if a school-related tribute implies the deceased was a graduate or related to staff/students; *No* otherwise.
- *Central topic*: *Yes* if the deceased is the primary subject of the post; *No* if a side mention.
- *Grief score*: Integer from 1 to 5; 1 = No grief, 5 = Highly emotional mourning.
- *Propaganda score*: Integer from 1 to 10.

1	Neutral
2–3	Light patriotic tone
4–5	Clear patriotic framing
6–7	Nationalistic emphasis
8–9	Ideological, symbolic heroism
10	Full-scale propaganda

We then recode the Propaganda score into 5 bins to have more well-distributed variable. We assign 0 to 1-5; 1 to 6; 2 to 7; 3 to 8; 4 to 9-10.

A.3.4 Demographics

Figure A.XXIV.
Map of population in Russian municipalities

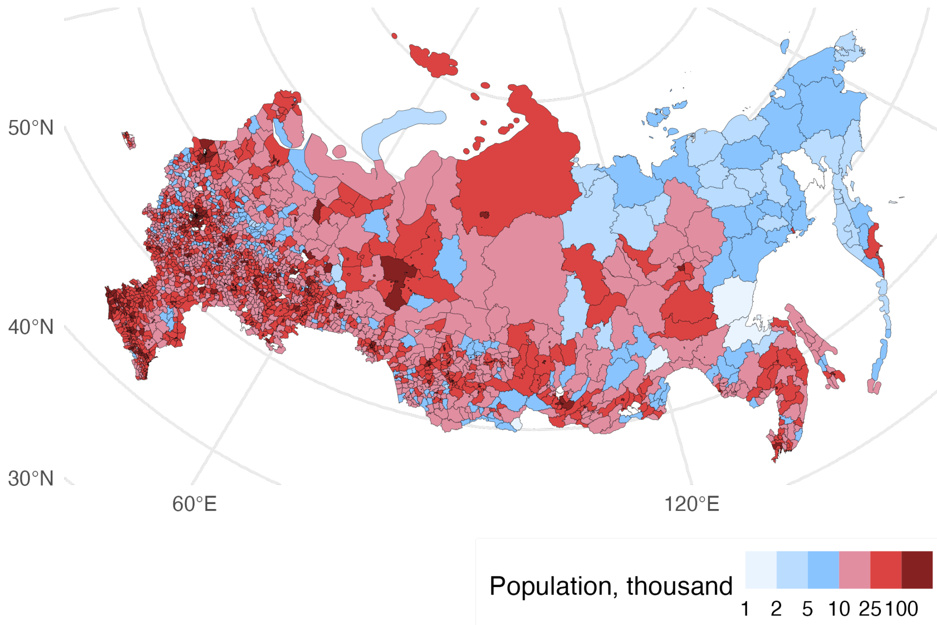
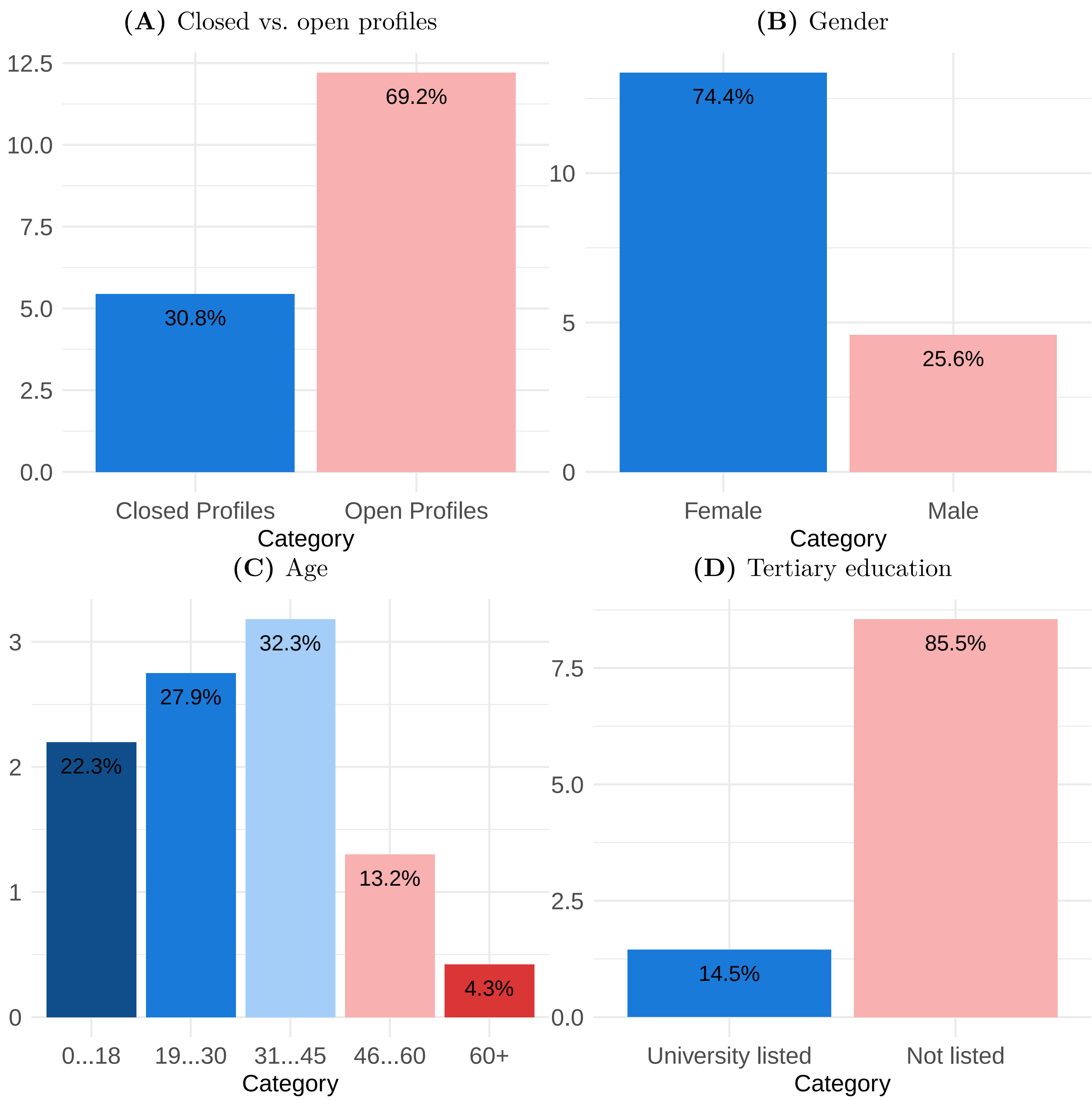


Figure A.XXV.

Demographic characteristics of school groups' subscribers



A.4 Supplemental Information

A.4.1 Example posts in schools groups

Figure A.XXVI.
Patriotic Post

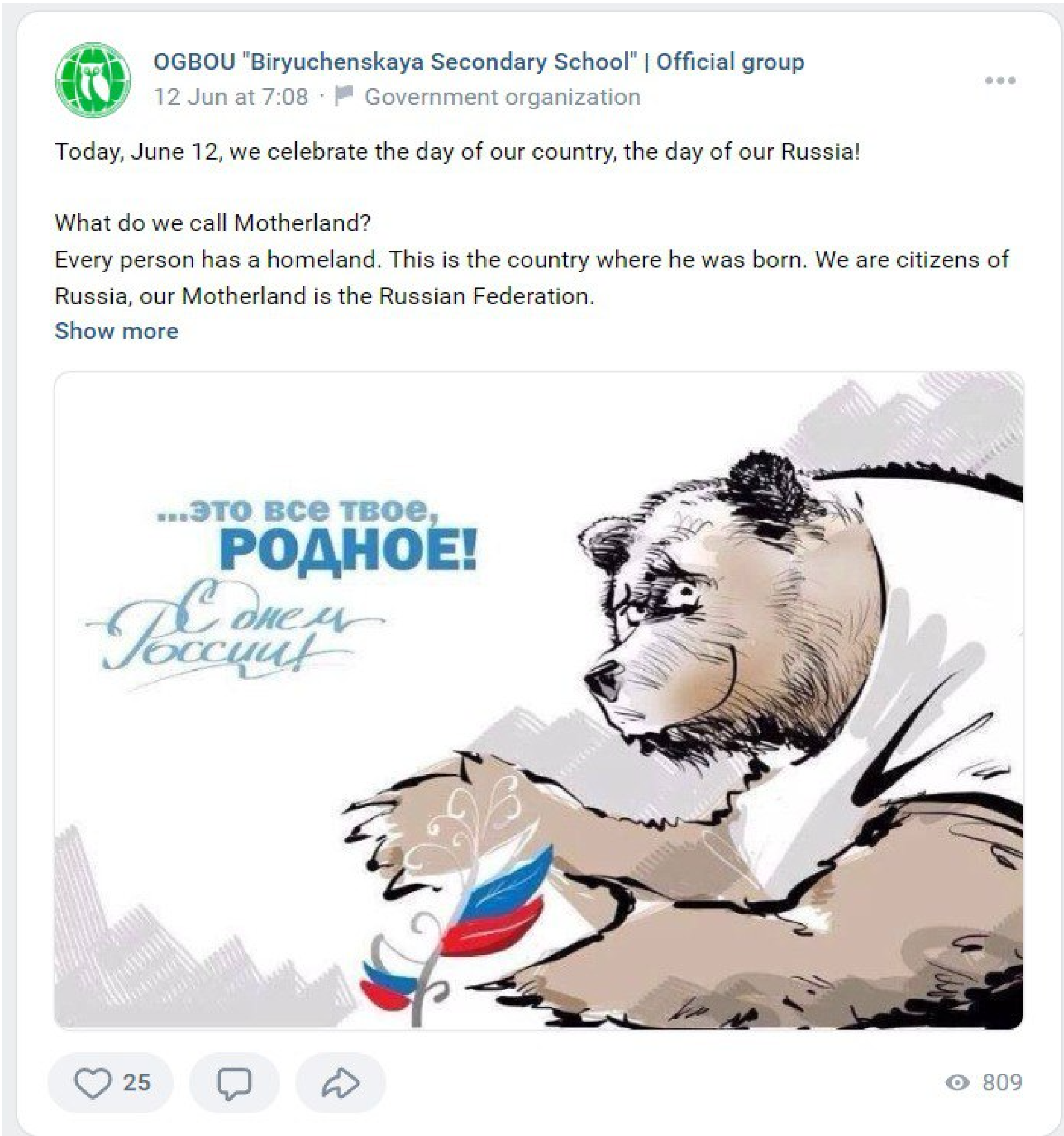


Figure A.XXVII.
Authorities Post

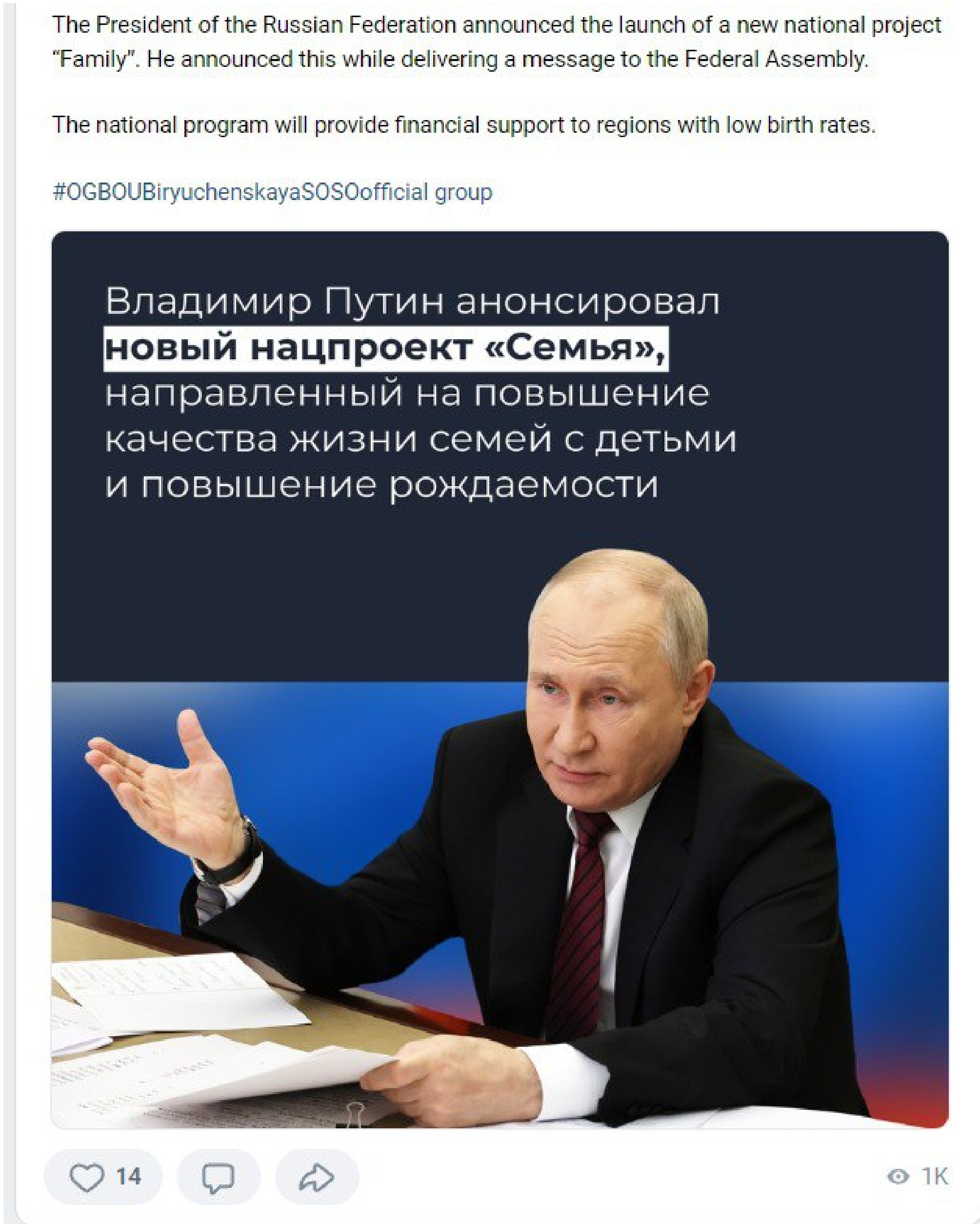
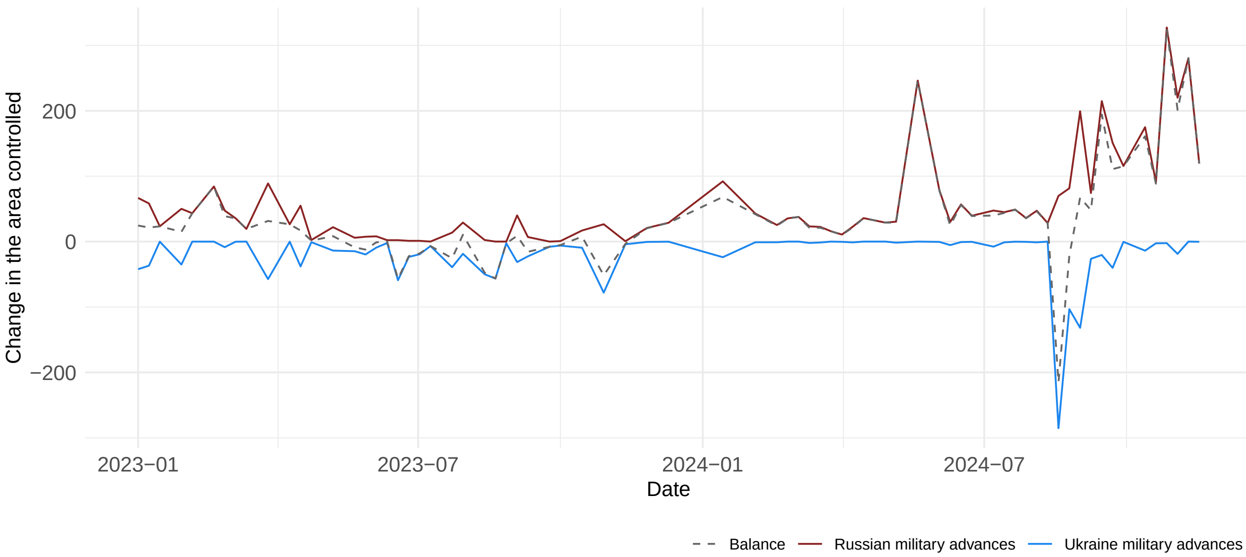


Figure A.XXVIII.
Special Military Operation Post

A.4.2 Battlefield dynamics

Figure A.XXIX.
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.4.3 Wordclouds

Figure A.XXX.

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

Figure A.XXXI.

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

Figure A.XXXII.

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

Figure A.XXXIII.

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

Figure A.XXXIV.

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

A.4.4 Social bots in school groups

{#fig-bots}

A.4.5 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.[19] In the context of the Russian-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.[20]

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.[21] The 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.[22]

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."[23]

[19] 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)

[20] 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.)

[21] 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 of death of a citizen"

[22] 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).

[23] 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)