Public opinion and casualties in wartime censorship*

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February 28, 2025

Abstract

How reliable are public opinion polls in wartime censorship of authoritarian regimes? Academic debates on this question have arisen with renewed vigor after the full-scale Russian invasion of Ukraine and media coverage of the substantial support for the invasion by the majority of the Russian population. We answer this question by exploiting 36 waves of public opinion polls for February 2022 - March 2024, which accounted for 51,740 responses and objective behavioral measures in subnational Russian regions and municipalities. First, we show that the ordinal geographical variation in public opinion corresponds well to the objective measures - war support is significantly lower in regions with higher anti-war protest activity, while claimed war participation is higher in regions with higher objective war participation activity. Second, we demonstrate a selective non-response in public opinion polls based on these objective measures, suggesting that the cardinal levels of war support are biased. Third, using the staggered nature of casualties by the regions, we show a strong negative effect of casualties on war support and a positive impact on the demand for a truce after correction for the selective non-response. We show that social media is the information dissemination mechanism about casualties, while other media are not. Finally, by exploiting residential addresses for a subset of dead warriors, we demonstrate that the casualties in the immediate proximity to the respondents' municipalities reduced the willingness to vote for Vladimir Putin in the 2024 presidential elections.

Keywords: Russia-Ukraine war, public opinion, casualties, media, censorship, election, authoritarianism

JEL: D72, D74, P23

*This research has was funded by Nazarbayev University under Faculty-development competitive research grants program for 2025-2027 Grant No 040225FD4707, Andrey Tkachenko. We thank Alexey Minyaylo, Elena Koneva, and Vladimir Zvonovsky for their contribution and interest in the project. We thank Andrei Yakovlev, Alexander Libman, Alexis Belianin, Koen Schoors, Nikita Zakharov, Vasily Korovkin, Philine Widmer, Laura Solanko, Zuzana Fungacova, Riccardo Franceschin, Vladimir Zabolotskiy, Georgy Tarasenko for the discussion. We thank participants of the FRIAS Conference and seminar participants at Nazarbayev University, BOFIT, and Sabanci University for their comments. We thank Amir Saimassay for his helpful research assistance.

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1 Introduction

Keeping popularity and showing trust in a leader are the key ingredients for modern informational autocracies to stay in power for a long time (Guriev and Treisman 2020, 2022). But how can popularity be demonstrated when fair elections are lacking? In informational autocracies, public opinion polls are a powerful tool to illustrate an autocrat's popularity, incentivizing manipulation in public opinion polls and creating debates on their reliability (Frye et al. 2017, 2023; Buckley et al. 2023). Academic debates on the issue have arisen with renewed vigor after the full-scale Russian invasion of Ukraine and state media claiming permanent support for the invasion by the majority of the Russian population. The wartime gives an autocrat even more power to censor independent media, use selective repressions of dissenters, and so manipulate personal popularity and war approval. Therefore, to what extent can we trust war approval based on public opinion polls in wartime censorship? Can public opinion polls reflect the causal effect of casualties on war approval and autocrat popularity?

We answer these questions using 36 waves of phone public opinion surveys in Russia conducted in February 2022 – March 2024 by state independent pollsters, which accounted for 51,740 responses, their response rate statistics, and the objective population behavioral measures at the regional and municipal levels in Russia, including (i) the list of more than 54 thousand verified dead warriors with their residential address, (ii) online search statistics for financial compensation to families for dead warriors (iii) pre-war protest potential and detentions for anti-war protests. We start with the verification of public opinion polls using triangulation (Rosenfeld 2023). We show that the ordinal geographical variation in public opinion polls is reasonable as it corresponds well to the objective measures – in regions with higher pre-war and anti-war protest activity, the war support is lower, and the demand for a truce is higher. Moreover, respondents in public opinion polls are more likely to claim war participation of their relatives in regions with higher objective war participation activity.

While triangulation partially solves the problem, the generalization of analysis based on the selected survey sample to the population is limited without understanding the selection bias. The bias may happen because of selective non-response, i.e., people do not respond to the public opinion polls not purely randomly but, e.g., because of their political views. The critical problem with the non-respondents is the absence of information about them, including their demographics and attitudes. To solve this problem, we use the advantage of mobile phone surveys in which any mobile phone number is attached to a geographical region. At the region-survey level, we use the call center statistics for the population of randomly generated mobile phone numbers and their resulting call statuses. This enables us to measure contact rate, cooperation rate, and overall response rate in survey campaigns at the regional level in dynamics for 2022-2024 and associate these outcome rates with objective regional behavioral measures such as war participation, protest activity, and other economic measures. Our primary focus is on the cooperation rate – the probability that respondents complete the interview given that they respond to the call – as a measure of a conscious interview participation decision. The purely random non-response would imply zero association between the cooperation rate and regional objective measures. In contrast, we demonstrate a selective non-response in public opinion polls – the regional income per capita and protest activity are negatively associated with the cooperation rate. This suggests that the generalization about war attitudes from the survey sample to the population should have a correction for the selective non-response, at least at the regional level.

We further apply this correction to estimate the effect of casualties on war attitudes. Using the staggered nature of casualties by the regions, we show that cumulative casualties reduce the war support and increase the demand for negotiation about a truce after re-weighting public opinion polls for the inverse of the cooperation probability, so partially correcting for the selective non-response. In contrast, the effects are smaller without re-weighting or with traditional post-stratification re-weighting based on age-gender groups. The event-study analysis for staggered treatment time by casualties justifies the causal effect. Next, we show that social media is the information dissemination mechanism about casualties, while other channels, such as traditional media, websites, YouTube, Telegram channels, and communication with relatives, are not. Finally, we use a sequence of survey waves preceding the presidential elections in March 2024 and residential addresses of dead warriors to identify the effect of casualties on the willingness to vote for Vladimir Putin. Exploiting a form of regression discontinuity in geographical location (Nikolova et al. 2022), we demonstrate that the casualties in the immediate proximity to the respondents' municipalities reduced the willingness to vote for Vladimir Putin.

Literature and contribution

The paper contributes to three strands of literature. First, our paper is related to the growing literature on the debate about the reliability of public opinion polls in wartime (La Lova 2023; Morris 2023; Reisinger et al. 2023; Rosenfeld 2023; Zavadskaya and Gerber 2023; Zvonovsky and Khodykin 2024). While other papers on this topic mostly work with preference falsification issues (Chapkovski and Schaub 2022; DeSisto et al. 2024; Frye et al. 2024), none of the existing papers on war attitudes in Russia verify the ordinal or cardinal variations, nor have they deeply studied the problem of non-response.

Second, our paper connects to the literature on the effect of conflict initiation and casualties on conflict approval and the ruler's popularity. This literature has an ambiguous conclusion, though often it lacks a clear causal identification. The local casualties of WW1 induced the growth of nationalist movements in Italy and Germany (Acemoglu et al. 2022; De Juan et al. 2024) and increased activities oriented to support veterans in British communities (Carozzi et al. 2023). As recent evidence, using data on ten OECD countries from 1990-2014, Kuijpers (2019) shows a rally-around-the-flag short-term effect, meaning that "governing parties benefit from an increase in military casualties for at least a year but get punished from 4.5 years into the intervention." The same effect was observed in the US wars (Berinsky 2019), and the war support reduction was driven mainly by the awareness of local casualties rather than national losses (Althaus et al. 2012). Recent research for 27 countries (Seo and Horiuchi 2024) shows that, in general, there is disapproval of conflict initiation. However, if the conflict entails the usage of military force, there is no negative short-term effect on the governing leader's popularity. Getmansky and Weiss (2023) uses the natural experiment induced by the 1973 Yom Kippur War and shows that war initiation reduced the support for incumbent parties and increased support for the opposition in Israel. In the case of the Russia-Ukraine war and other Russian conflicts since 2000, all demonstrate a rally-around-the-flag short-term effect (Kizilova and Norris 2024), while the causal impact of casualties on war attitudes is ambiguous. Using data from the early month of the Russia-Ukraine war in 2022, Duvanova et al. (2023) showed a positive association between casualties and protest activity. However, exploiting an online survey soon after military mobilization Zakharov and Chapkovski (2025) shows that war priming increases preferences for redistribution among war supporters. For the first year of the war, Zabolotskiy and Fomichev (2023) show that information about casualties in social media public groups reduced engagement with content referencing authorities but temporarily increased interaction with patriotic and military topics in the early months of the invasion. We contribute to this literature and study the causal effect of casualties on war attitudes and electoral preferences.

Finally, we contribute to the broad literature on the role of media in shaping political attitudes. The effect of traditional media has been extensively studied, both for democracies (DellaVigna and Kaplan 2007; Gerber et al. 2009; Durante and Knight 2012) and autocracies (Yanagizawa-Drott 2014; Adena et al. 2015; Peisakhin and Rozenas 2018; Pan et al. 2022). Specifically, literature focusing on Russia has shown that state-independent traditional media can effectively reduce government support (Enikolopov et al. 2011, 2022). More recently, social media has started to play an essential role in influencing public opinion (Bond et al. 2012) and political preferences (Guriev et al. 2021; Zhuravskaya et al. 2020; Fujiwara et al. 2024). While the opposition has used social media to organize protests (Enikolopov et al. 2020), authoritarian states also increasingly spread their messages through social media and take control of it. We contribute to this literature by showing the exclusive role of social media in disseminating information about war casualties in a setting where other traditional and online media are censored.

2 Background

The Russian full-scale invasion of Ukraine occurred on February 24, 2022, starting the largest militarized conflict in Europe since World War II. On March 04, 2022, the Russian government adopted the "War Censorship Law"[1] that allows criminal punishment for any statement about the actions of the Russian army, which is not based on what the Russian Ministry of Defense claims. Since then, the Russian traditional media, following the state-owned pollsters, have been declaring that around 70% of the Russian population supports the invasion (VCIOM 2025). On top of that, the most popular state-independent pollster, Levada Center, shows similar numbers (Center 2025). These numbers induced hot academic debates about the reliability of public opinion in wartime censorship. A self-evident argument was that the expression of war dissent is illegal, so people would lie to the question about their war attitude (preference falsification) even if they participated in the survey. On top of that, there is a big concern about survey participation, and the assumption is that people with opposing views are less likely to participate in surveys (selective non-response). Right after the invasion, several state-independent projects surveying public opinion via mobile phones appeared – Chronicles, Extreme Scan, and Russian Field – conducting their first waves in February 2022. All these projects showed that war support is not as stable as propaganda claims (Chronicles 2025; ES 2024; RF 2025), but even more importantly, the demand for negotiations for a truce becomes a dominant wish by 2024, even if the war goals are not achieved.

As the war evolved, the Russian Ministry of Defense stopped publishing information about casualties after the first week in March 2022. Mediazona together with BBC[2] initiated a project collecting information about dead warriors from posts and news in social media, federal/regional/local newspapers, and organizing volunteer visits to public cemeteries. Each case is verified and de-duplicated. By the end of 2024, the number of verified casualties on the Russian side reached 90 thousand, which is the lower non-binding bound of the toll. The alternative aggregate calculations based on the male excess mortality estimate the casualties at 165 thousand, excluding wounded soldiers and casualties of warriors drafted from the occupied territories.[3] The statistics of wars would imply that the number of wounded soldiers who cannot return to the frontier is about three times the casualties, while verified wounded from the leaked hospitals' list account for 166 thousand.[4]

[1] Federal Law of 04.03.2022 No. 32-FZ.

[2] See Mediazona. Casualties. and Mediazona. Russia 200

[3] Mediazona 2025. Three years of death.

[4] Radio Svoboda 2025. 166 thousand wounded. A database of patients from the Ministry of Defense hospitals.

There are two major types of soldiers taking part in the war. The first includes warriors signing a contract with the Ministry of Defense. The lump-sum payment for contract signing varied by region and time from 6 to 25 thousand USD, and the monthly payment varied from 1.5 to 3 thousand USD. Contract soldiers are considered to be the core of the army. However, on September 21, 2022, after a successful counter-offense of Ukraine, de-occupying significant territory in the Kharkiv region, Vladimir Putin announced a military mobilization. Officially, 300 thousand men were drafted, while alternative calculations based on excess marriages estimate the draft to include at least 500 thousand men (Mediazona 2023). The drafted soldiers, unlike contract soldiers, are not paid the lump-sum contract payment, and their monthly wage is smaller. Nevertheless, in 2024, the Ministry of Defense pushed drafted soldiers to sign contracts to reduce the social pressure from family members of drafted soldiers. Neither drafted nor contract soldiers can terminate their service until the official de-mobilization is announced (with some exceptions). In case of recognized death on the battlefield, the official family members (wife in a registered marriage, parent, or full-age child) could request compensation payment for the dead warrior, which amounts to 70 thousand USD. This potential compensation payment induced a surge of legalization of marriages in September-October 2022 after the military mobilization announcement, allowing (Mediazona 2023) to estimate the number of drafted men by regions.

On top of the war issue, the major domestic event for the regime was to conduct presidential elections on March 15-17, 2024, to demonstrate the autocrat's legitimacy. All candidates with minor anti-war or pro-truce campaigns were not registered in the ballot paper. The electoral law was amended so that opportunities for falsification were greatly expanded without the possibility of electoral monitoring. As a result, the independent media showed that the electoral campaign included the largest share of fraud in the Russian history of elections (Europe 2024).

3 Data

The paper uses several sources of data, measuring (i) public attitudes, (ii) war participation, and (iii) protest activity, as well as regional and municipal economic and population characteristics.

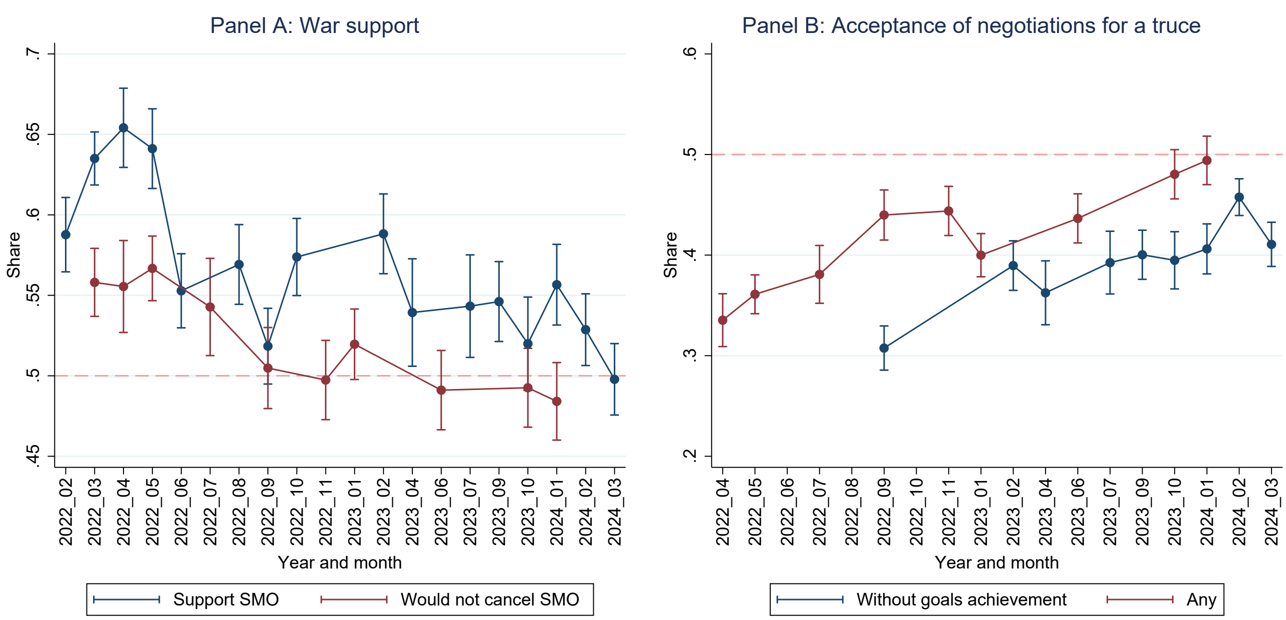
3.1 Public opinion surveys

The public opinion surveys include 36 waves conducted in February 2022 – March 2024 by three state-independent projects: 13 waves by Chronicles, 10 waves by Extreme Scan, and 13 waves by Russian Field, accounting for 51,740 responses altogether. All surveys are conducted via mobile phones (Computer Assisted Telephone Interviews), sampling 1000 – 1800 respondents per wave.

All the surveys include questions about war support. Chronicles and Extreme Scan projects have the following wording of this question *Tell me, please, do you support or do not support the military operation of Russia on the territory of Ukraine, find it difficult to answer, or do not want to answer this question?*. The Russian Field project asks *If you had a chance to return back in time and cancel the decision about the launch of the special military operation, would you do it or not?*. Panel A of Figure 1 shows the share of respondents who support the war or would not cancel it. Both measures have a decreasing trend starting at the point significantly above 50%, and by 2024, reaching the level of around 50% or lower.

All the projects since 2022 also ask questions about acceptance of negotiations for a truce. Chronicles and Extreme Scan projects have the following wording of this question *If Vladimir Putin decides to take out the troops from Ukraine and start the negotiation without achievement of the initial goals, will you support this decision or not?*. The Russian Field project asks *Do you think Russia should continue the special military operation on the territory of Ukraine, or should it initiate the negotiation process?*. Panel B of Figure 1 shows an increasing share of respondents accepting negotiations for a truce even without goal achievements, with the shares starting from 30% in 2022 and exceeding 40% in 2024.

Figure 1: War attitudes over time



Note. The figure shows the dynamics of war support and demand for a truce from public opinion polls.

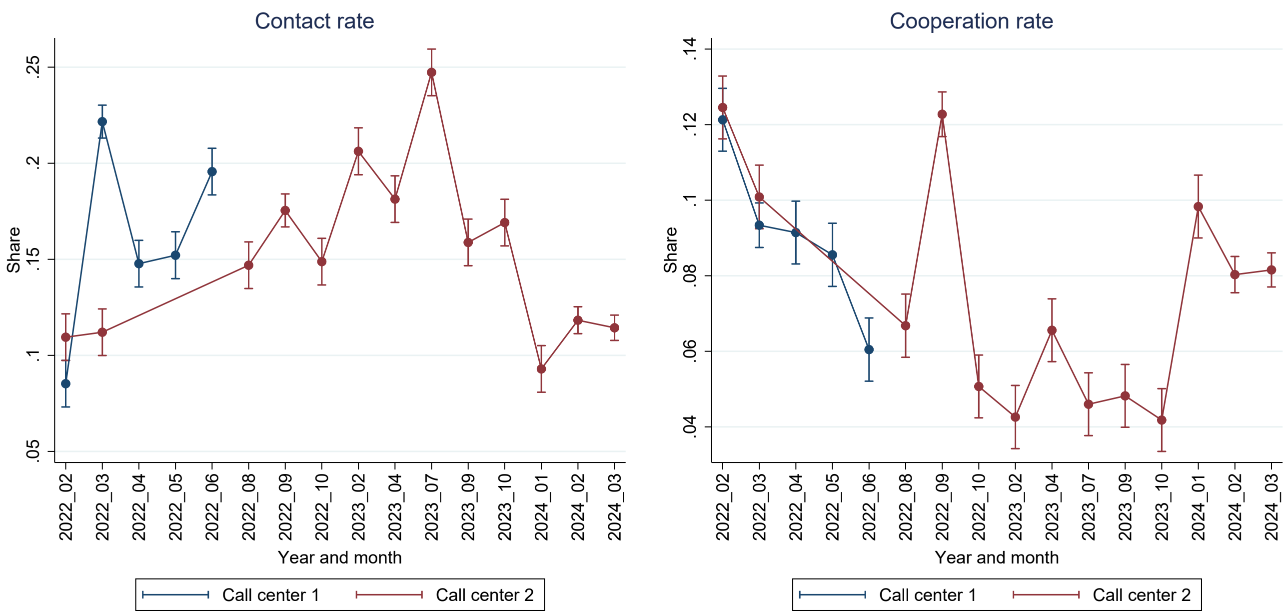
Chronicles and Extreme Scan projects occasionally ask if respondents or their relatives currently or used to participate in the war. Panel A of Table A1 in Appendix A shows the increasing trend, with the share being around 5% in 2022 and reaching 27% in 2024. Russian field also does this, adding familiars to this list of participants, and the share reaches 50%. Chronicles and Extreme Scan projects occasionally ask about the sources of information about the war, which included communication with relative, traditional media (TV, radio, newspapers), internet websites, and different popular media platforms, including YouTube, Telegram, and social media. In some waves, they ask about state-owned Russian social media Vkontakte and Odnoklassniki separately from other social media and, in some waves, about all social media together. Some media were immediately blocked after the invasion (e.g., Facebook and Instagram), and some websites have been blocked in the war's progress, so we use the question of VPN usage as a proxy for the demand for non-censored content. Finally, from January 28 to March 10, 2024, Chronicles and Extreme Scan asked about the general willingness to vote in presidential elections on March 15-17, 2024, and a preferred candidate by proposing a list of candidates under consideration by the survey wave date. Panel B of Table A1 in Appendix A shows the decreasing trend for readiness to vote for Vladimir Putin, reaching slightly above 50% the week before election days. Table A2 of Appendix A shows the descriptive statistics for the respondents' attitudes (Panel A), their source of information about the war (Panel B), and individual demographics (Panel C).

On top of completed interviews for Chronicles and Extreme Scan projects, we also have the population of randomly generated mobile phone numbers used for survey campaigns and their resulting call statuses. The mobile phone numbers were generated using the Random Digit Dialing approach, with stratification at federal districts proportional to the national population. In Russia, each phone number is connected to a region, and the Federal Communications Agency defines the mapping.[5] This enables us to calculate the contact, cooperation, and overall response rates at the region-survey campaign level.[6] Figure 2 shows the dynamics of the contact and cooperation rates. Contact rates vary by the call centers as the reach efficiency depends on the auto-dialing robotic tools and may differ in different call centers. At the same time, while respondents are reached, the cooperation rates of different call centers do not exhibit substantial differences for campaigns conducted in the same month. Moreover, the cooperation rate measures a conscious interview participation decision probability. Therefore, we mostly pay attention to the cooperation rate when discussing non-response in public opinion polls. Finally, for survey waves conducted by the Russian Field project, we impute the outcome rates probabilities at the regional level based on the closest survey campaign of Chronicles or Extreme Scan. Panel F of Table A2 in Appendix A shows the regional descriptive statistics for the contact, cooperation, and response rates.

[5]https://opendata.digital.gov.ru/registry/numeric/downloads

[6]The contact rate is the probability of responding to a call. The cooperation rate is the probability of completing the interview given a response to the call. Response rate is the multiplication of contact and cooperation rates.

Figure 2: Dynamics of the contact and cooperation rates



Note. The figure shows the dynamics of contact and cooperation rates in public opinion polls.

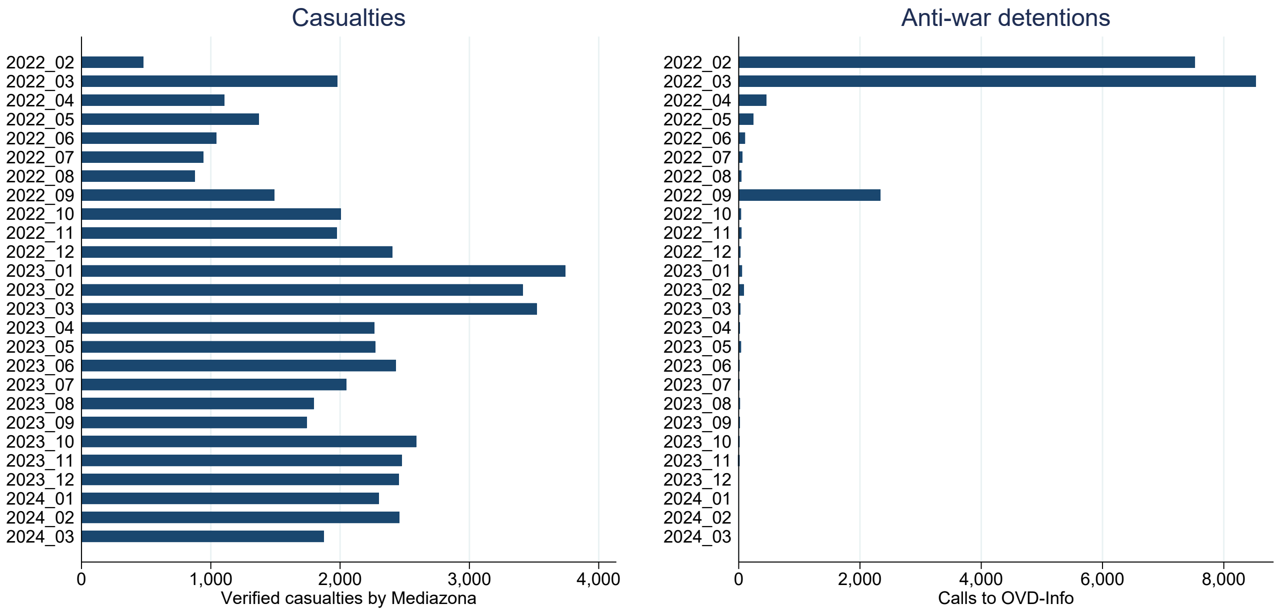
3.2 Sub-national measures of war participation and protest activity

There are several approaches we use in this paper to estimate war participation. The first is based on the Mediazona project about verified casualties discussed above. By the end of May 2024, when we received the database, it included more than 54 thousand verified entries, with March 2024 to be the last complete month. The left panel of Figure 3 shows that the dynamics of casualties is between 2 and 4 thousand monthly since 2023. Each data entry includes the region where the information about the dead warrior appeared first. By the month of each public opinion survey wave, we calculate the number of accumulated verified casualties in the region and divide it by the male regional population aged 18-49 (multiplied by 100K) to have the cumulative number of casualties by 100,000 of regional men population (of age 18-49). Figure A4 of Appendix A shows the regional distribution of this variable by March 2024. These numbers are the lower non-binding bound of real casualties by March 2024. Alternative calculations claim that the actual toll is doubled, and future data updates of Mediazona will reveal more dead warriors by that period. However, what is essential for our analysis is the date when this information becomes public because it may affect respondents' attitudes in public opinion polls.

We rely on a more granular geographical variation of casualties to identify the effect of casualties on voting preferences in January - March 2024. For 19 thousand dead warriors, the exact residential address is provided, and for the other 21 thousand dead warriors, the name of the residential municipality is known. For the survey waves of January 2024 - March 2024 conducted by Chronicles and Extreme

Scan we know the respondents' municipalities. Using Google Maps, we geolocated the respondents' municipality centers, residential addresses of dead warriors, or their residential municipalities when exact addresses were unavailable. After that, we calculated the number of casualties by March 2024 at different distances from the respondents' municipality centers.[7] Panel E of Table A2 in Appendix A shows the descriptive statistics for this mapping.

Figure 3: Casualties and anti-war detentions over time



Note. The figure shows the dynamics of verified casualties and anti-war detentions.

The second data to measure the percentage of drafted men aged 18-49 at the regional level is based on excess weddings in September-October 2022, compared to the similar months of 2019-2021 proposed and verified by (Mediazona 2023). Figure A5 of Appendix A demonstrates a substantial regional variation. The third data to measure war participation is the online search statistics for phrases related to government financial compensation to families of dead warriors via Yandex (www.wordstat.yandex.ru). At the regional-month level, we collected the total number and share of searches of the phrase *"payment dead"* for January 2021 - January 2024. Figure A6 of Appendix A shows the dynamics for Russia. There were near zero searches for this phrase until January 2022, and since February 2022, the number of searches has increased to dozens of thousands per month. All these three measures are the lower non-binding bound of the war participation.

We use two measures of the protest activity at the regional level. The first is the number of people registered on the Free Navalny website (www.free.navalny.com) to get information about the protests

[7] We excluded Moscow and Saint-Petersburg as these municipalities are too vast.

against Navalny's imprisonment, their schedule, and venues in April 2021. The number of registered people accounted for 431 thousand, and the website demonstrated their regional and municipal distribution. The second measure is based on the list of 19.5 thousand detained people for anti-war protests collected by OVD-Info. The right graph of Figure 3 shows that the majority of detentions took place right after the full-scale invasion, in February and March 2022, and right after military mobilization in September 2022. We normalize both these protest activity measures to the regional population (multiplied by 100K). We consider the first measure a *pre-war protest potential*, while the second measure is the revealed anti-war movement per 100,000 regional population. Figures A2 and A3 of Appendix A show the regional distribution.

Table A1 of Appendix A shows the descriptive statistics of war participation and protest activity variables by region, and Panel D of Table A2 of Appendix A shows the descriptive statistics of these regional variables attached to respondents in public opinion polls. Other regional and municipal variables considering regional wealth and demographics originate from the Russian Statistical Service. A source for each variable used in the analysis is provided in Table A2 of Appendix A.

4 Validation of public opinion polls

4.1 Geographical variation

We start validating public opinion polls by analyzing how individual attitudes and claimed war participation in public opinion polls correspond to geographical variation of objective measures in protest activity and war participation. We consider the following specification

$$y_{itr} = \alpha T_{[t]r} + \mathbf{X}_{itr}\beta + \mathbf{R}_{[t]r}\gamma + \lambda_t + \varepsilon_{itr} \tag{1}$$

where y_{itr} is the binary variable on war support, acceptance of negotiations for a truce, or claimed war participation, $T_{[t]r}$ is a regional measure of protest activity or war participation in the region r (in month t of survey for dynamics measures), $\mathbf{X}_{itr}$ is the set of individual controls, including gender, four age groups, four welfare groups, presence of high education, R_{rt} are regional controls: unemployment and median income per cap for year preceding the survey date, ruling party United Russia share in 2021 parliament elections, log of population by January 2022, a binary variable for regions bordering Ukraine, indicators for regions - national republics. We control for survey wave fixed effect λ_t, taking into account the overall change in dynamics of opinion as well as the difference in question wordings between Chronicles/Extreme Scan and Russian Field. Errors ε_{itr} are clustered at the regional level.

Table 1 shows the result of (1) OLS estimation for war support and acceptance of negotiations as dependent variables in associations with pre-war protest potential and anti-war detentions (Table B1 of Appendix B shows the full regression output of these regressions). The cumulative anti-war detentions by survey date and pre-war protest potential are negatively associated with war support and positively associated with the demand for negotiation for a truce. A growth of detentions by 10 people per 100K of the regional population is related to a reduction of war support by 0.74 percentage points (1.3%) and a growth of the acceptance for negotiation by 0.59 percentage points (1.53%). Similarly, a growth of registrations for Free Navalny protest in 2021 by 100 people per 100K of the regional population is related to a reduction of war support by 0.9 percentage points (1.6%) and a growth of the acceptance for negotiation by 0.7 percentage points (1.84%).

Table 1: War attitudes and protest participation

	(1)	(2)	(3)	(4)
VARIABLES	War support		Accept negotiations	
Cum detentions per 100k	-0.00074***		0.00059**	
	(0.00019)		(0.00024)	
Protest potential 2021		-0.000090***		0.000070***
		(0.000014)		(0.000022)
Observations	51,740	51,740	36,074	36,074
R-squared	0.097	0.098	0.089	0.089
Wave FE	Y	Y	Y	Y
Waves	Feb22-Mar24	Feb22-Mar24	Feb22-Mar24	Feb22-Mar24

Note. Significance levels: *** p<0.01, ** p<0.05, * p<0.10. The table shows OLS estimates for (1) with war support and acceptance of negotiations for a truce as a dependent variable. Robust standard errors clustered at the regional level are in parentheses. Table B1 of Appendix B shows the full regression output.

Table 2 shows the result of (1) OLS estimation for claimed personal or relatives' war participation as dependent variables in associations with objective war participation measures (Table B2 of Appendix B shows the complete regression output of these regressions). All three objective measures are positively associated with the claimed war participation. The growth of cumulated casualties by 100 warriors per 100K of the male regional population is related to increased claimed war participation by 3.4 percentage points (12.2%). A growth of the share of drafted men by 1 percentage point is associated with a rise in claimed war participation by 2.1 percentage points (7.55%). The growth of online searches related to the compensation for dead warriors by 100 units (per 10 M searches) in the survey month is associated with a rise in claimed war participation by 13 percentage points (46.7%). Overall, results from Tables

Table 2: Claimed and objective war participation

	(1)	(2)	(3)
VARIABLES		Participation in war	
Cum casualties per 100k	0.00034***		
	(0.00010)		
Percent of drafted men 18-49		0.021***	
		(0.0063)	
Payment dead search(per 10m)			0.0013***
			(0.00025)
Observations	11,952	11,952	11,945
R-squared	0.115	0.115	0.116
Wave FE	Y	Y	Y
Waves	May22-Jan24	May22-Jan24	May22-Jan24

Note. Significance levels: *** p<0.01, ** p<0.05, * p<0.10. The table shows OLS estimates for (1) with claimed war participation as a dependent variable. Robust standard errors clustered at the regional level are in parentheses. Table B2 of Appendix B shows the full regression output.

1 and 2 demonstrate that the geographical ordinal variation in public opinion polls is reasonable.

4.2 Selective vs. random non-response

We continue validating public opinion polls by analyzing associations of contact, cooperation, and response rates with the objective measures in protest activity and war participation. We consider the following specification.

$$s_{tr} = T_{tr}\alpha + \mathbf{R}_{[t]r}\gamma + \lambda_t + \varepsilon_{tr}, \tag{2}$$

where s_{tr} are the contact rate, cooperation rate, or response rate at the regional level. T_{tr} includes cumulative detentions and cumulative casualties in region r in month t of survey. Similarly to (1), vector $\mathbf{R}_{[t]r}$ includes the set of regional characteristics (dynamic and static), and λ_t is the survey wave fixed effect. Errors are clustered at the regional level.

Table 3 shows that the contact rate is lower in regions with higher income per capita, unemployment, and cumulative casualties. Even more critical is that the cooperation rate is negatively associated with regional detentions. The latter suggests that people in regions with high protest activity are less likely to discuss war issues with unknown interviewers. This result, in connection with the fact that people from more protest-active regions were less supportive of the war, may indicate an underestimation of the share of people in the population who do not support the war based on the public opinion polls. Overall, the contact and cooperation rates analysis indicates selective non-response based on war participation and protest activity. Therefore, the generalization about war attitudes from the survey sample to the population should have a correction for the selective non-response, at least at the regional level.

Table 3: Regional contact, cooperation, and response rate

	(1)	(2)	(3)
VARIABLES	Contact rate	Cooperation rate	Response rate
Unemployment	-0.0039***	-0.00044	-0.00030***
	(0.00053)	(0.00030)	(0.000055)
Income per cap	-1.9e-06***	-5.3e-07***	-1.9e-07***
	(2.4e-07)	(9.8e-08)	(2.5e-08)
Cum detentions per 100k	-0.00023	-0.00036***	-0.000059***
	(0.00023)	(0.000076)	(0.000021)
Cum casualties per 100k	-0.000075**	-6.0e-06	-4.6e-06**
	(0.000033)	(0.000012)	(2.1e-06)
Observations	1,986	1,979	1,979
R-squared	0.628	0.444	0.484
Wave FE	Y	Y	Y
Waves	Feb22-Mar24	Feb22-Mar24	Feb22-Mar24

Note. Significance levels: *** p<0.01, ** p<0.05, * p<0.10. The table shows OLS estimates for (2). Robust standard errors clustered at the regional level are in parentheses. Table B3 of Appendix B shows the full regression output.

5 The effect of casualties on war attitudes

In this section, we study the effect of casualties on war attitudes. We use the staggered nature of casualties by Russian regions for identification. Table C1 of Appendix C shows that by March 2024, there are 5% (10%) of regions with less than 80 (120) dead warriors by 100K men population (aged 18-49), and Figure A4 of Appendix A shows the distribution by regions. These numbers are the lower non-binding bound of real casualties by March 2024, but it is essential that this information was published by the survey dates so that it may affect respondents' attitudes. We start with consideration of the following two-way fixed effect specification.

$$y_{itr} = [\alpha C_{tr}] + \left[\sum_{g=1}^{7} \alpha_g C_{gtr}\right] + \mathbf{X}_{itr}\beta + \lambda_t + \mu_r + \varepsilon_{itr}. \tag{3}$$

where y_{itr} is the binary variable on war support, acceptance of negotiations for a truce, source of information about the war, or willingness to vote for Vladimir Putin. The variable C_{tr} is the cumulative verified casualties in the region r by survey month t per 100,000 male population (aged 18-49). The vector of individual controls $\mathbf{X}_{itr}$ is similar to (1), λ_t is the survey wave fixed effect, and μ_r is the regional fixed effect. Errors ε_{itr} are clustered at the regional level. The main difference of this model compared to (1) is in the regional fixed effects, which flexibly control for regional time-invariant variation. Our main focus is on an estimate of α, which measures the effect of casualties on the dependent variables under parallel trend assumption and homogeneous treatment effect over time. Without these assumptions, TWFE estimates can only be interpreted as associations cleaned of main demographic and time-invariant regional confounding factors. We also are interested in the non-linear association between the outcome variables and the treatment exposure. Therefore, for alternative specifications, we break C_{tr} into seven groups C_{gtr} with an increment of 25 deaths per 100k male population.

In section 4, we have shown that the regional variation in war attitudes of public opinion polls is reasonable, but for the generalization of results to the population, we need to correct for the self-selection in the sample. According to the survey theory, the weight of a selected respondent should be inversely proportional to the probability of inclusion in the sample. When selective non-response occurs, this can be taken into account by re-weighting with respect to the predicted probabilities of inclusion into the sample based on an auxiliary model for weighting adjustment classes (Lohr 2021, Ch. 8.5). This approach is often feasible in medical and well-designed longitudinal household surveys because some demographic characteristics of non-respondents are known. However, in cross-sectional population surveys (especially phone and online), this approach is primarily unfeasible and often ignored because of the inability to observe non-respondents characteristics, so the common approach is to use post-stratification weighting based on the observed characteristics of respondents and population.[8] We partially resolve this issue because we know regions of non-respondents within a survey campaign and can use the information about cooperation rate and response rate from call-center statistics to calculate the probability of inclusion into the sample. Specifically, we use region-survey waves as weighting adjustment classes and calculate weights equal to the inverse predicted probabilities from model (2) for both cooperation and response rates.[9] We apply these weights to the model (3), and we also show the unweighted estimates and estimates based on traditional post-stratification weights for eight age-gender classes (Tables A2 of Appendix A shows the age intervals).

[8]Post-stratification means that the weights are chosen so that the weighted totals within disjoint sample classes equal the known population totals in these classes. Standard post-stratification classes for regionally non-representative population surveys are age-gender groups.

[9]Technically, the total weights should also include design weights based on the probability of a randomly generated number to be included in the sample for the dialing campaign. However, due to the Random Digit Dialing approach stratified at the federal level w.r.t. to the population of phone numbers and a large sample of selected numbers for dialing campaigns (from 400,000 to 1,000,000 per campaign), these probabilities are equal to the population probabilities.

For war support as a dependent variable, Panel A of Table 4 shows the results for continuous treatment exposure measure C_{tr}. Column 1 shows that for the selected sample without re-weighting, 100 casualties per 100K men population reduces the war support by 2.4 percentage points (4.3%). However, Columns 2 and 3 show that after the re-weighting for the cooperation rate (response rate), the magnitude of this effect increases by 3.5 p.p (3 p.p.), which is equivalent to 6.2% (5.3%). All these effects are significant at 1%. Notably, the post-stratification re-weighting yields an insignificant, though negative, estimate of the casualties effect (Column 4, Panel A).

Table 4: The effect of casualties on war support

	(1)	(2)	(3)	(4)
VARIABLES	War support			
	Panel A: Continuous measure of casualties			
Cum casualties per 100k	-0.00024***	-0.00035***	-0.00030***	-0.00016
	(0.000081)	(0.000090)	(0.000068)	(0.000097)
Observations	51,636	51,636	51,636	51,636
R-squared	0.102	0.099	0.102	0.109
Weight	No	Coop.Pr.	Resp.Pr.	Gend.Age
	Panel B: Casualties grouped in bins			
26-50 killed per 100k	-0.013	-0.015	-0.0059	-0.017*
	(0.0078)	(0.0092)	(0.0079)	(0.0087)
51-75 killed per 100k	-0.0061	-0.0076	-0.012	-0.0064
	(0.012)	(0.013)	(0.012)	(0.012)
76-100 killed per 100k	-0.036**	-0.041**	-0.012	-0.034**
	(0.016)	(0.017)	(0.024)	(0.017)
100-125 killed per 100k	-0.042***	-0.057***	-0.051***	-0.037**
	(0.015)	(0.017)	(0.016)	(0.017)
125-150 killed per 100k	-0.042***	-0.052***	-0.039**	-0.037**
	(0.015)	(0.018)	(0.015)	(0.017)
150+ killed per 100k	-0.051***	-0.069***	-0.056***	-0.042**
	(0.015)	(0.019)	(0.013)	(0.017)
Observations	51,636	51,636	51,636	51,636
R-squared	0.102	0.099	0.102	0.109
Weight	No	Coop.Pr.	Resp.Pr.	Gend.Age

Note. Significance levels: *** p<0.01, ** p<0.05, * p<0.10. The table shows OLS estimates for (3) with war support as a dependent variable. 0-25 killed per 100k men population is a reference category. Robust standard errors clustered at the regional level are in parentheses. Column 1 uses no weights, Column 2 uses re-weighting based on cooperation rate, Column 3 uses re-weighting based on response rate, and Column 4 uses re-weighting based on eight age-gender classes. Table C2 of Appendix C shows the full regression output.

Panel B of Table 4 shows the results for treatment exposure split into seven groups. The effect of casualties is significant only when the number of cumulative casualties by the survey data exceeds 75 dead warriors per 100K men population. Moreover, it becomes substantially stronger when the number of casualties exceeds 150 killed per 100K men population. Similarly to Panel A, the effect is the strongest after the re-weighting for the cooperation rate.

Table 5 shows estimation results for acceptance of negotiations for a truce as a dependent variable.

Table 5: The effect of casualties on acceptance of negotiations

	(1)	(2)	(3)	(4)
VARIABLES	Accept negotiations			
	Panel A: Continuous measure of casualties			
Cum casualties per 100k	0.00026***	0.00028***	0.00025**	0.00020**
	(0.000086)	(0.000092)	(0.00012)	(0.000084)
Observations	35,976	35,976	35,976	35,976
R-squared	0.094	0.098	0.091	0.098
Weight	No	Coop.Pr.	Resp.Pr.	Gend.Age
	Panel B: Casualties grouped in bins			
26-50 killed per 100k	0.012	0.022**	0.022**	0.0068
	(0.011)	(0.011)	(0.010)	(0.011)
51-75 killed per 100k	0.031**	0.034**	0.046***	0.024
	(0.015)	(0.015)	(0.010)	(0.016)
76-100 killed per 100k	0.020	0.016	0.036**	0.011
	(0.017)	(0.018)	(0.014)	(0.017)
100-125 killed per 100k	0.050***	0.050***	0.063***	0.039**
	(0.015)	(0.016)	(0.014)	(0.016)
125-150 killed per 100k	0.044***	0.052***	0.063***	0.038**
	(0.014)	(0.016)	(0.012)	(0.015)
150+ killed per 100k	0.065***	0.072***	0.086***	0.051***
	(0.015)	(0.018)	(0.014)	(0.016)
Observations	35,976	35,976	35,976	35,976
R-squared	0.095	0.099	0.092	0.098
Weight	No	Coop.Pr.	Resp.Pr.	Gend.Age

Note. Significance levels: *** p<0.01, ** p<0.05, * p<0.10. The table shows OLS estimates for (3) with war support as a dependent variable. 0-25 killed per 100k men population is a reference category. Robust standard errors clustered at the regional level are in parentheses. Column 1 uses no weights, Column 2 uses re-weighting based on cooperation rate, Column 3 uses re-weighting based on response rate, and Column 4 uses re-weighting based on eight age-gender classes. Table C3 of Appendix C shows the full regression output.

Similar to the war support, the effect is most substantial after the re-weighting for the cooperation rate. However, the difference compared to the non-weighted estimate is not as essential, which may be explained by the fact that this question is not as sensitive, and fewer respondents terminate their interview after it. Column 2 of Panel A shows that 100 casualties per 100K men population increases the demand for a truce by 2.8 percentage points (7.3%), and Panel B shows that the effect becomes substantially stronger when the number of casualties exceeds 150 killed per 100K men population. However, unlike the war support, the demand for a truce does not require so many cumulative casualties.

The main assumption of TWFE estimator to be interpreted causally is parallel pre-trends. Its testing has two natural problems: (i) no regions with zero treatment exposure, as there are casualties in all regions, (ii) no pre-war measure of war support. To solve them, we use the observation that not all the regions reached substantial casualties by March 2024. Specifically, Table C1 of Appendix C shows that for 5% of regions, casualties do not exceed 80 killed soldiers by 100k men population by March 2024. Moreover, Panel B of Table 4 shows that the association between casualties and war support appears only after substantial toll accumulation. Therefore, we can define treatment and control binary groups based on a threshold for cumulative casualties by March 2024 and treatment time based on the first month crossing the threshold. We consider three thresholds: 80, 90, and 100 killed warriors per 100k. The staggered nature of time for crossing the thresholds complicates applying the traditional event-study approach. We use the stack regression event-study design instead (Cengiz et al. 2019). Baker et al. (2022) showed that the stack regression gives unbiased estimates comparable to other modern staggered DID approaches, such as (Callaway and Sant'Anna 2021; Sun and Abraham 2021), while numerically faster.[10] For each cohort (regions treated in the same month), the stack regression approach forms a separate stack with treated regions of this cohort as a treatment group and never-treated and not-yet-treated regions as the control group. After that, the stacks are pooled together, and the traditional TWFE event-study design is applied, including stack-time and stack-region fixed effects. Given the staggered nature of regions' treatment and the non-periodical gap in the survey dates, we bin the periods by 5-6 months. All in all, we estimate the following specifications using the data with pooled stacks:

$$y_{itrs} = \sum_k \alpha_k \mathbf{I}(t - E_r = k) + [\mathbf{X}_{itrs}\beta] + \lambda_{ts} + \mu_{rs} + \varepsilon_{itrs}, \tag{4}$$

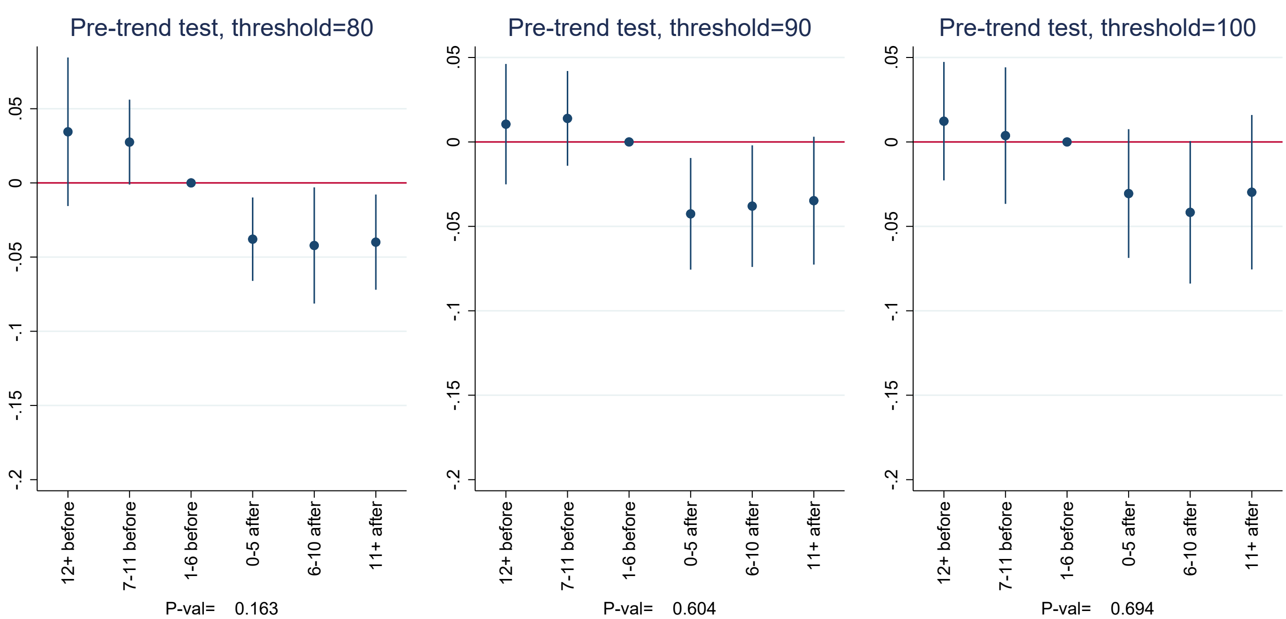
where $E_r = min(t : C_{tr} \geq threshold)$. Survey wave fixed effects λ_{ts} and region fixed effect μ_{rs} are stack specific. The main specification includes the stack-specific vector of individual demographic controls $\mathbf{X}_{itrs}$ similar to the one in (1). We also estimate (4) without individual demographics for robustness.

[10] Moreover, as public opinion surveys were not conducted monthly and sometimes had substantial time gaps, representing them as a balanced panel is impossible, and one needs to group periods in bins, which makes the approach of (Callaway and Sant'Anna 2021) hardly applicable.

Errors are clustered at the regional level because of the potential correlation between stacks within a region. Weights equal to the inverse cooperation rate are used.

Figure 4 shows the event-study graph for three thresholds for war support as a dependent variable. All three thresholds show the parallel pre-trends assumption holds, and after the passing threshold, the war support decreases by 4-5 percentage points.[11] Figure C1 of Appendix C shows the event-study graph for estimation without controlling for individual demographics. In this case, while parallel pre-trends may be violated for the threshold of 80 killed per 100k men population, there are no concerns for other thresholds. Table C4 of Appendix C shows the DID estimates based on the stack regressions. Crossing the threshold of 80 killed per 100k men population reduces the war support by 5.1 p.p., and this effect is 4.5 p.p. (3.7 p.p.) for the threshold of 90 (100).

Figure 4: Event-study analysis for war support: stack regression



Note. The table shows OLS estimates for (4) with war support as a dependent variable. Errors are clustered at the regional level. Re-weighting is based on the cooperation rate. Individual demographic controls are included. Each graph shows the p-value of the parallel pre-trends test, i.e., coefficients for bins "12+ before" and "7-11 before" to be equal to zero simultaneously.

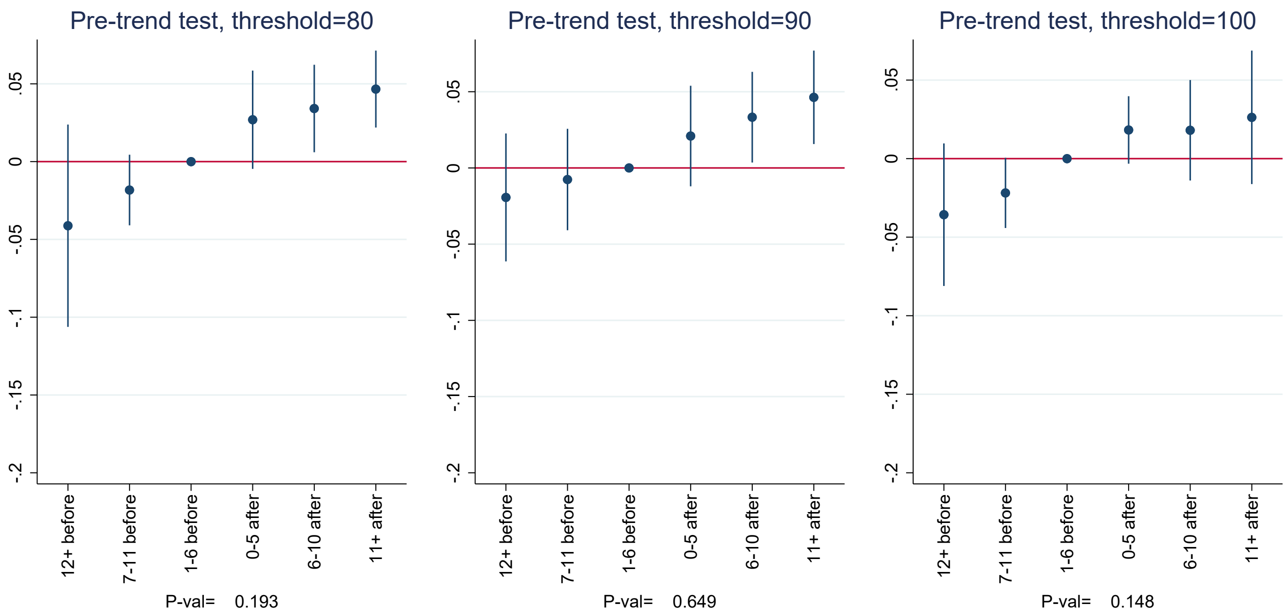
Figure C4 shows the event study analysis for the acceptance of negotiation for a truce. Similarly to the war support, the parallel trend assumption cannot be rejected for all thresholds.[12] Figure C1 of Appendix C shows the event-study graph for estimation without controlling for individual demographics, and parallel pre-trends are not rejected. Table C4 of Appendix C shows the DID estimates based on the

[11]Figure C3 of Appendix C shows that TWFE (non-stacked) event-study analysis estimates have similar dynamics.

[12]Figure C4 of Appendix C shows that TWFE (non-stacked) event-study analysis estimates have similar dynamics.

stack regressions. Crossing the threshold of 80 killed per 100k men population increases the demand for a truce by 3.8 p.p., and this effect is 3.2 p.p. (2.5 p.p.) for the threshold of 90 (100).

Figure 5: Event-study analysis for acceptance of negotiations: stack regression



Note. The table shows OLS estimates for (4) with acceptance of negotiation for a truce as a dependent variable. Errors are clustered at the regional level. Re-weighting is based on the cooperation rate. Individual demographic controls are included. Each graph shows the p-value of the parallel pre-trends test, i.e., coefficients for bins "12+ before" and "7-11 before" to be equal to zero simultaneously.

5.1 Mechanisms of the information dissemination about casualties

To study information dissemination mechanisms about casualties, we use questions about media sources respondents use to get information about the war as dependent variables in specification (3) with a continuous measure of casualties C_{tr}. Table 6 shows the results (Columns 1-8). The cumulative casualties are positively associated with the information consumption from social media only, including state-owned Vkontakte and Odnoklassniki (columns 5,6). One could not expect state-controlled TV to disseminate information about the casualties, but access to the liberation VPN technology does not help to transmit the information about casualties either. The crucial role of social media as the mechanism for information dissemination about casualties is in line with findings of Zabolotskiy and Fomichev (2023).

6 The effect of casualties on voting

We have shown that casualties negatively affected the war support and increased the demand for a truce. This, however, does not necessarily imply that people blame the war initiator – Vladimir Putin. We use a sequence of waves conducted from January 28, 2024 to March 10, 2024 (see Figure A1 of Appendix

Table 6: Casualties, Media sources about the war, VPN usage, and Voting

VARIABLES	(1) Relatives	(2) TV	(3) YouTube	(4) Telegram	(5) VK-OK	(6) Socmedia	(7) Websites	(8) VPN	(9) Vote Putin
Cum casualties per 100k	0.00015	-0.000048	0.000011	-0.00022*	0.00019**	0.00038***	0.000077	0.000050	-0.0041**
	(0.00010)	(0.00011)	(0.00015)	(0.00012)	(0.000093)	(0.00011)	(0.00010)	(0.00020)	(0.0016)
Observations	16,587	16,587	14,787	14,787	10,583	16,813	16,587	11,433	6,610
R-squared	0.075	0.164	0.079	0.157	0.144	0.188	0.076	0.140	0.073
Wave FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Region FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Waves	Feb22-Mar24	Feb22-Mar24	Feb22-Mar24	Feb22-Mar24	Feb22-Mar24	Feb22-Mar24	Feb22-Mar24	Feb22-Mar24	Jan24-Mar24

Note. Significance levels: *** p<0.01, ** p<0.05, * p<0.10. The table shows OLS estimates for (3) with an information source, VPN usage, and willingness to vote for Vladimir Putin as dependent variables. Robust standard errors clustered at the regional level are in parentheses. Table C5 of Appendix C shows the full regression output.

A) to check if the casualties affect respondents' willingness to vote for Vladimir Putin. We consider the survey outcomes rather than the official polling station statistics as the electoral campaign had the largest share of fraud in Russian history (Europe 2024).

We start from the specification (3) where we use willingness to vote for Vladimir Putin as the binary dependent variable. Column 9 of Table 6 shows the dynamics of cumulative casualties during 1.5 months of consideration are negatively associated with the willingness to vote for Vladimir Putin. Nevertheless, one can interpret this result as causal with caution, as the period is too short, and there are too few non-treated regions with low casualties by the end of January 2024, so the control group in the TWFE estimation is too small.

To understand the causal effect of casualties on voting preferences, we use a distinct approach resembling fuzzy regression discontinuity in geographical location and relying on a granular geographical variation of casualties. For 19 out of 54 thousand dead warriors, we know the exact residential address and the residential municipality's name for the other 21 thousand. We also know the respondents' municipalities for the January 2024 - March 2024 electoral surveys. Using Google Maps, we geolocated the respondents' municipality centers, residential addresses of dead warriors, or their residential municipalities when exact addresses were unavailable. After that, for each respondent, we calculated the number of casualties by the survey month in different distances of the respondent's municipality. We excluded Moscow and Saint-Petersburg as these municipalities are too vast. Panel E of Table A2 in Appendix A shows the descriptive statistics for this mapping. For this approach, we consider the following specifications:

$$y_{itrm} = \sum_{d=1}^{6} \alpha_d F(C_{tm,d} - C_{tm,d-10}) + \mathbf{X_{itrm}}\beta + \lambda_t[+\mu_r][+\mathbf{R_r}\gamma][+\mathbf{M_m}\delta] + \varepsilon_{itrm}. \tag{5}$$

Here, y_{itrm} is a binary variable indicating the willingness of responded i to vote for Vladimir Putin,

$C_{tm,d-10}$ is the absolute number of casualties from municipality m by month t in radius distance of d km ($C_{tm,0} = 0$ by definition), X_{itrm} is the vector of respondent's demographics (similar to (1) plus rural settlement type), λ_t is the wave fixed effect. Depending on specification, we also include regional fixed effects μ_r or regional vector of controls $\mathbf{R_r}$ as well as $\mathbf{M_m}$ municipal vector of controls. The vector $\mathbf{R_r}$ is identical to the one from (1), where dynamic regional measures are taken for 2023. The vector $\mathbf{M_m}$ includes the female share in the municipality by 2021 and $F(P_m)$, where P_m is a municipality population by 2021. For the main specification, we consider $F(x) = ln(x+1)$, while for the robustness check, we consider $F(x) = x$. Errors are clustered at the municipality level. Coefficients α_d estimate the effect of accumulated dead soldiers whose residences were located in the radius distance $[d-10, d)$ km to the respondent's municipality on the willingness to vote for Vladimir Putin. We consider the following set of distances (in km): 10, 20, 30, 40, 50, 100.

Table 7 shows the estimation results for (5) for the main specification calculated in logarithms. All specifications, including the most flexible one with regional fixed effects and municipal controls (Column 4), show that the casualties in immediate proximity to the respondents' municipalities reduce the willingness to vote for Vladimir Putin in the 2024 presidential elections. Namely, an increase in immediate local casualties by 50% reduces the willingness to vote for Vladimir Putin by $50 \times 0.016 = 0.8$ percentage points (1.2 p.p. in less flexible specifications), equivalent to 1.3% reduction. An alternative specification in absolute casualties in Table C7 of Appendix C shows similar results of the negative effect of casualties: 20 killed warriors in the immediate proximity of respondents municipality reduced the willingness to vote for Vladimir Putin by 0.92 - 1.2 percentage points, equivalent to 1.5% - 2%.

7 Conclusion

This paper studies the reliability of public opinion polls in wartime Russia and the effect of casualties on war attitudes and political preferences. We show that the geographical variation in public opinion is reasonable as it corresponds to the objective regional measures. However, we show selective non-response in survey participation based on political and economic regional measures, so the generalization of survey results to the population attitudes would require correction for the selection, at least at the regional level. We further show that after a proper correction for the survey participation probability, the war casualties decreased the war support, increased the demand for a truce, and reduced the willingness to vote for Vladimir Putin. We demonstrate that social media is the only information dissemination mechanism about casualties.

Table 7: The effect of casualties on the willingness to vote for Vladimir Putin

VARIABLES	(1)	(2) Vote for Vladimir Putin	(3)	(4)
Ln(cum casualt. in 10km)	-0.023***	-0.024***	-0.023***	-0.016**
	(0.0068)	(0.0065)	(0.0064)	(0.0077)
Ln(cum casualt. in 10-20km)	0.0037	0.0029	0.0052	0.0084
	(0.0075)	(0.0073)	(0.0079)	(0.0082)
Ln(cum casualt. in 20-30km)	0.00062	0.00088	-0.0095	-0.0085
	(0.0080)	(0.0078)	(0.0085)	(0.0085)
Ln(cum casualt. in 30-40km)	-0.0020	-0.0032	-0.0024	-0.0020
	(0.0080)	(0.0074)	(0.0079)	(0.0079)
Ln(cum casualt. in 40-50km)	0.0088	0.0070	0.0060	0.0059
	(0.0075)	(0.0069)	(0.0075)	(0.0076)
Ln(cum casualt. in 50-100km)	-0.0030	-0.0089	-0.0078	-0.0079
	(0.0075)	(0.0076)	(0.0098)	(0.0098)
Observations	5,403	5,403	5,403	5,403
R-squared	0.045	0.049	0.069	0.070
Wave FE	Y	Y	Y	Y
Region FE	N	N	Y	Y
Region control	N	Y	N	N
Municip control	N	N	N	Y
Waves	Jan24-Mar24	Jan24-Mar24	Jan24-Mar24	Jan24-Mar24
Weight	Coop.Pr.	Coop.Pr.	Coop.Pr.	Coop.Pr.

Note. Significance levels: *** $p<0.01$, ** $p<0.05$, * $p<0.10$. The table shows OLS estimates for (5). Robust standard errors clustered at the municipal level are in parentheses. Re-weighting based on cooperation rate. Table C6 of Appendix C shows the full regression output.

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A Appendix A

A.1 Tables of Appendix A

Table A1: Descriptive statistics of regional objective measures

Variable	Obs	Mean	Std. Dev.	Min	Max
Cum casualties per 100k	85	199.74	110.30	19.00	756.87
Percent of drafted men 18-49	85	2.21	1.15	0	5.36
Payment dead search(per 10m)	83	82.16	27.36	32.71	170
Cum detentions per 100k	78	5.37	14.00	0.19	102.69
Protest potential 2021	79	202.92	159.57	20.01	1085.02

Note. The table shows the regional descriptive statistics for protest and war participation measures.

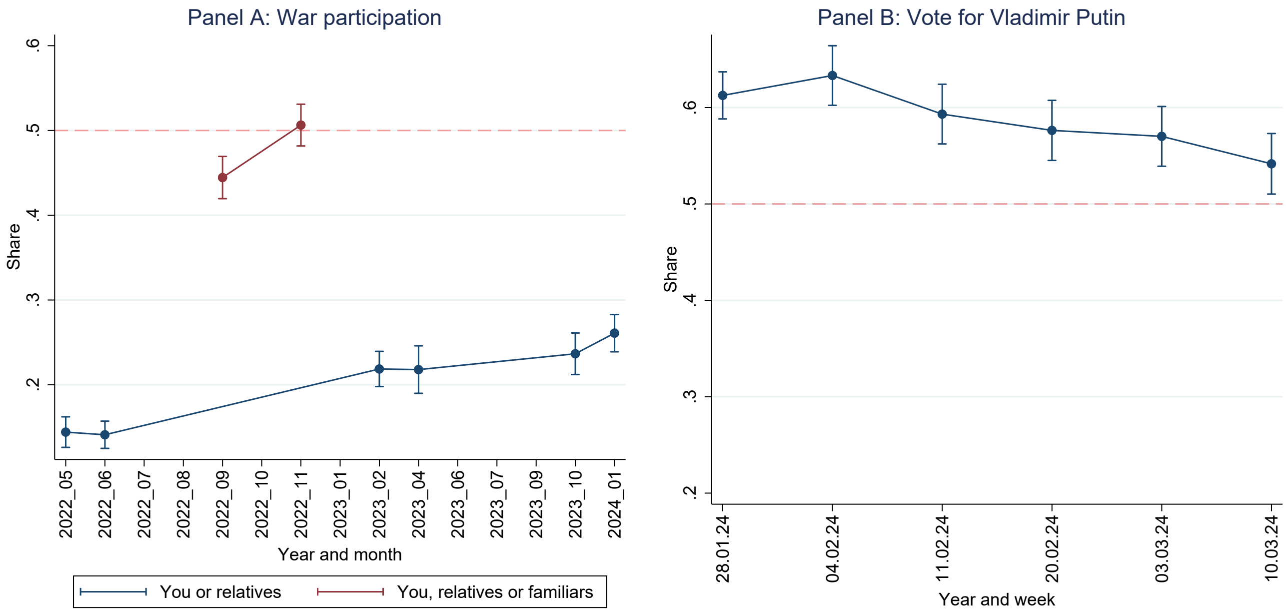
Table A2: Descriptive statistics of respondents: attitudes, media, demographics, regions, municipalities

Variable	Obs	Mean	Std. Dev.	Min	Max	Source
Panel A: Attitudes of respondents						
War support	51,740	0.563	0.496	0	1	Ch, ES, RF
Accept negotiations	36,074	0.385	0.487	0	1	Ch, ES, RF
Vote for Putin	5,438	0.609	0.488	0	1	Ch, ES
Panel B: Sources of information about the SMO						
Relatives	16,585	0.283	0.450	0	1	Ch, ES
TV	16,585	0.658	0.474	0	1	Ch, ES
YouTube	14,785	0.241	0.428	0	1	Ch, ES
Telegram	14,785	0.248	0.432	0	1	Ch, ES
VK-OK	10,581	0.205	0.404	0	1	Ch, ES
Soc.media	16,811	0.279	0.449	0	1	Ch, ES
Websites	16,585	0.306	0.461	0	1	Ch, ES
VPN	11,431	0.180	0.384	0	1	Ch, ES
Panel C: Individual demographics of respondents						
Female	51,740	0.500	0.500	0	1	Ch, ES, RF
Age 18-29	51,740	0.144	0.351	0	1	Ch, ES, RF
Age 30-44	51,740	0.363	0.481	0	1	Ch, ES, RF
Age 45-59	51,740	0.261	0.439	0	1	Ch, ES, RF
Age 60+	51,740	0.233	0.423	0	1	Ch, ES, RF
Welfare: Low	51,740	0.202	0.401	0	1	Ch, ES, RF
Welfare: below medium	51,740	0.308	0.462	0	1	Ch, ES, RF
Welfare: medium	51,740	0.262	0.440	0	1	Ch, ES, RF
Welfare: above medium	51,740	0.142	0.350	0	1	Ch, ES, RF
Welfare: missing	51,740	0.086	0.281	0	1	Ch, ES, RF
High education	51,740	0.510	0.471	0	1	Ch, ES, RF
High education(missing)	51,740	0.125	0.330	0	1	Ch, ES, RF
War participation	11,952	0.278	0.448	0	1	Ch, ES, RF
Panel D: Regional characteristics of respondents						
Cum casualties per 100k	51,740	55.4	71.3	0	774.1	Mediazona
Percent of drafted men 18-49	51,740	1.9	1.0	0	5.4	Mediazona
Payment dead search(per 10m)	51,225	39.8	29.3	-29.3	271.8	Yandex
Cum detentions per 100k	51,740	12.7	24.1	0	102.7	OVD-Info
Protest potential 2021	51,740	307.2	286.0	0	1085.0	Wiki
Unemployment	51,740	4.3	2.4	1.5	31.1	Rosstat
Income per cap	51,740	33805	14065	15185	81223	Rosstat
Border region	51,740	0.125	0.330	0	1	Map
National republic	51,740	0.121	0.326	0	1	Map
United Russia share 2021	51,740	45.5	13.6	24.5	96.1	Wiki
Regional population (M)	51,740	3.775	3.561	0.045	12.635	Fedstat
Panel E: Municipal characteristics of respondents						
Rural settlement	5,438	0.191	0.393	0	1	Ch, ES
Municip:Female share	5,438	0.536	0.017	0.430	0.566	Tocho.st
Municip:Population	5,438	346512	417144	1840	1588665	Tocho.st
Cum casualt. in 10km	5,438	58.6	60.0	0	243	Mediazona
Cum casualt. in 10-20km	5,438	21.8	30.0	0	278	Mediazona
Cum casualt. in 20-30km	5,438	20.1	37.7	0	420	Mediazona
Cum casualt. in 30-40km	5,438	26.2	55.8	0	433	Mediazona
Cum casualt. in 40-50km	5,438	24.3	37.6	0	394	Mediazona
Cum casualt. in 50-100km	5,438	154.8	167.4	0	1124	Mediazona
Panel F: Outcome rate statistics of call centers						
Contact rate	1,979	0.152	0.070	0.014	0.413	Ch, ES
Cooperation rate	1,979	0.082	0.045	0	0.333	Ch, ES
Response rate	1,979	0.012	0.008	0	0.069	Ch, ES

Note. The table shows the descriptive statistics on attitudes and demographics (Panels A-C) for survey respondents with attached regional and municipal statistics (Panels B,D). Panel E shows the call-centers' outcome rate statistics.

A.2 Figures of Appendix A

Figure A1: Claimed war participation and vote for Vladimir Putin



Note. The figure shows the dynamics of claimed war participation in public opinion polls and willingness to vote for Vladimir Putin.

Figure A2: Protest potential 2021

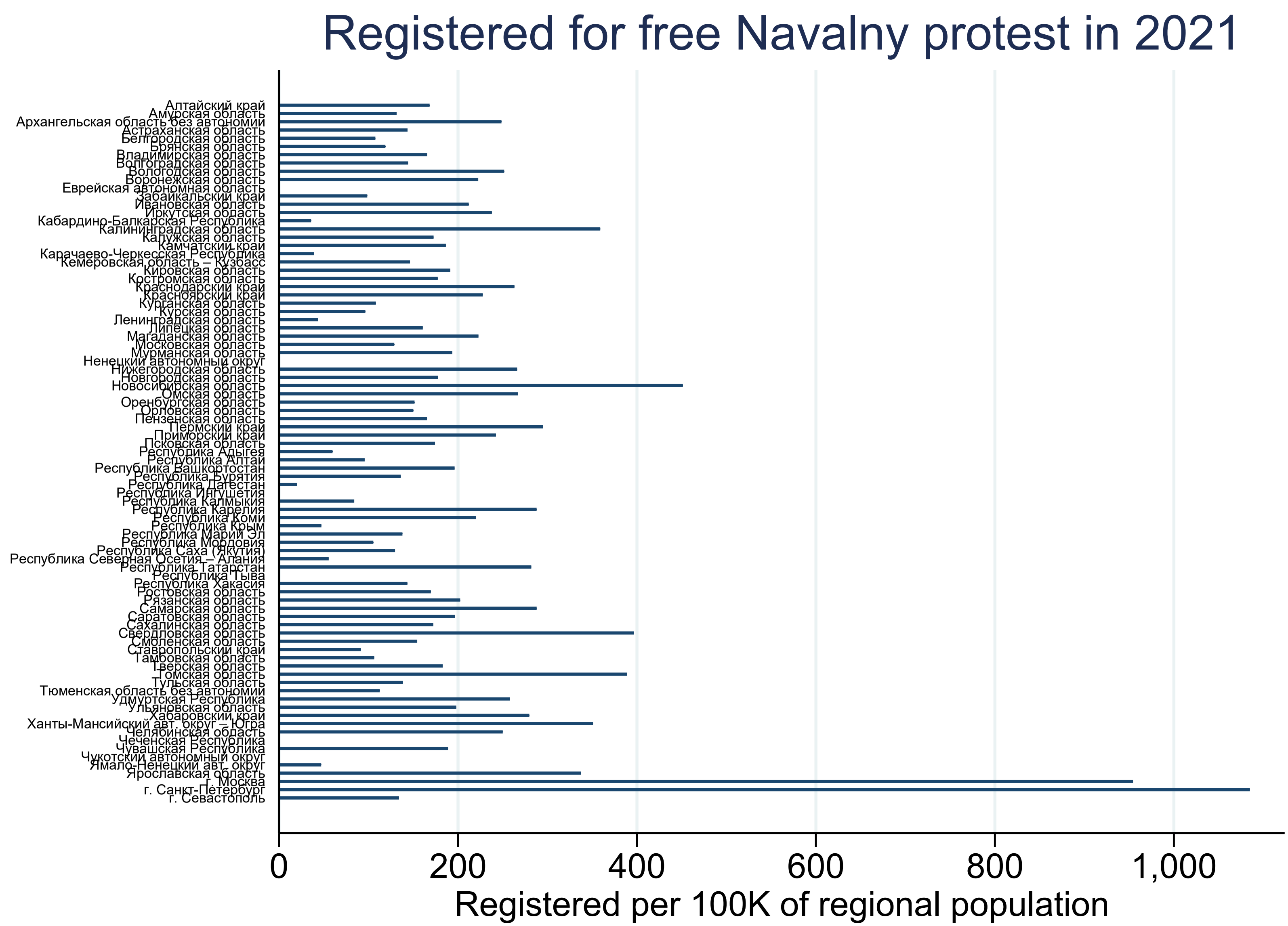


Figure A3: Anti-war detentions by regions

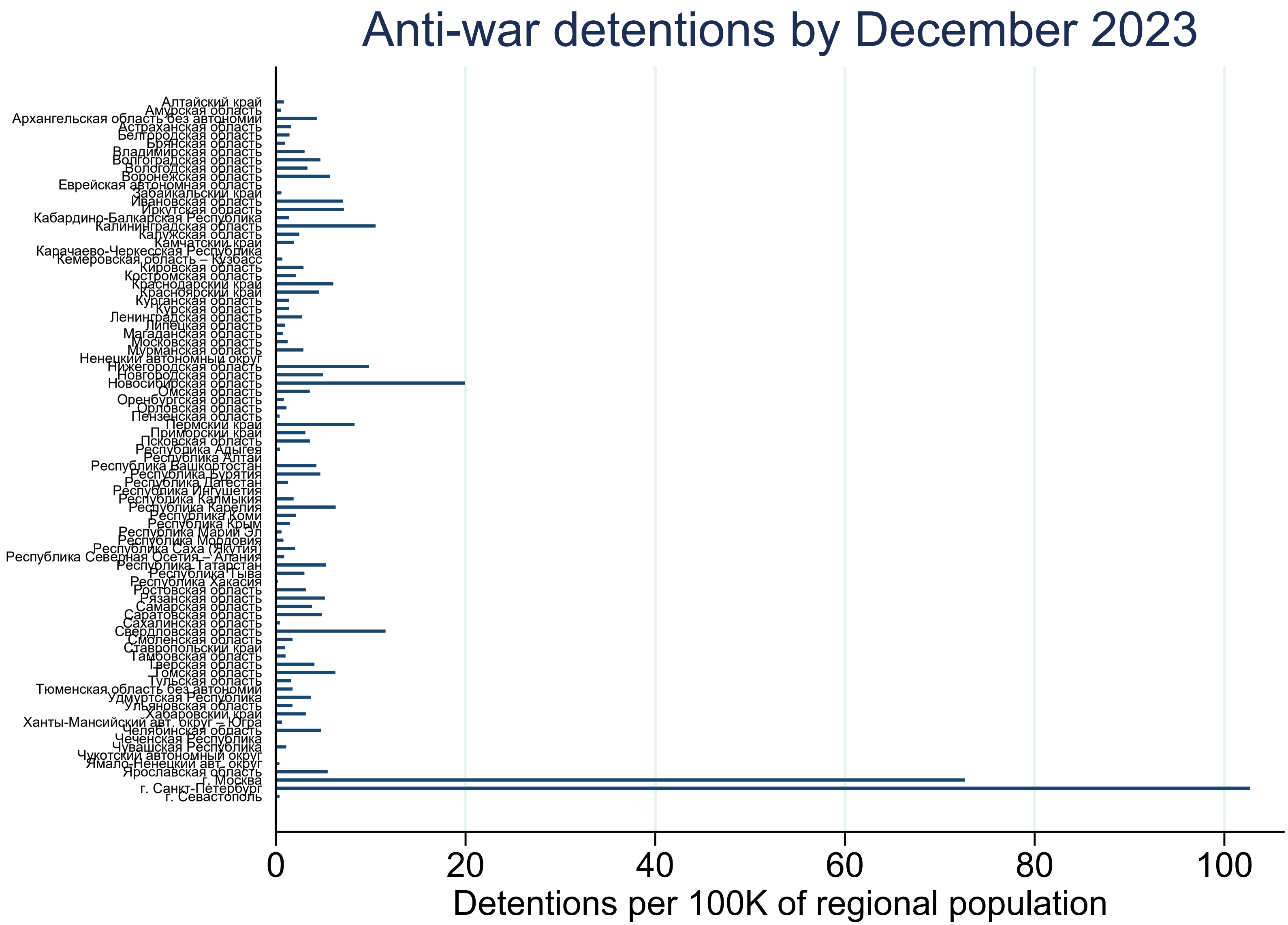


Figure A4: Casualties by regions

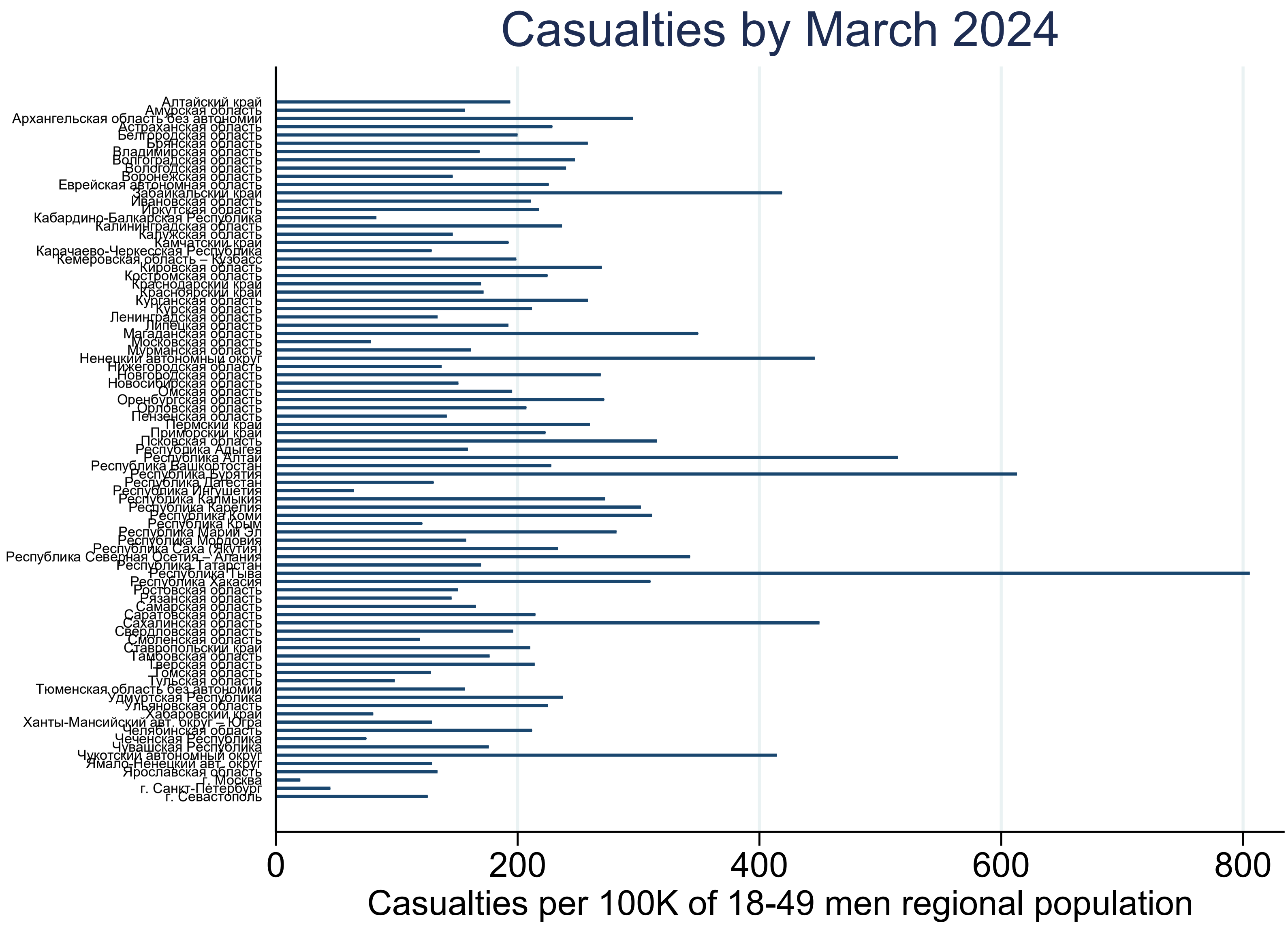


Figure A5: Percentage of drafted men

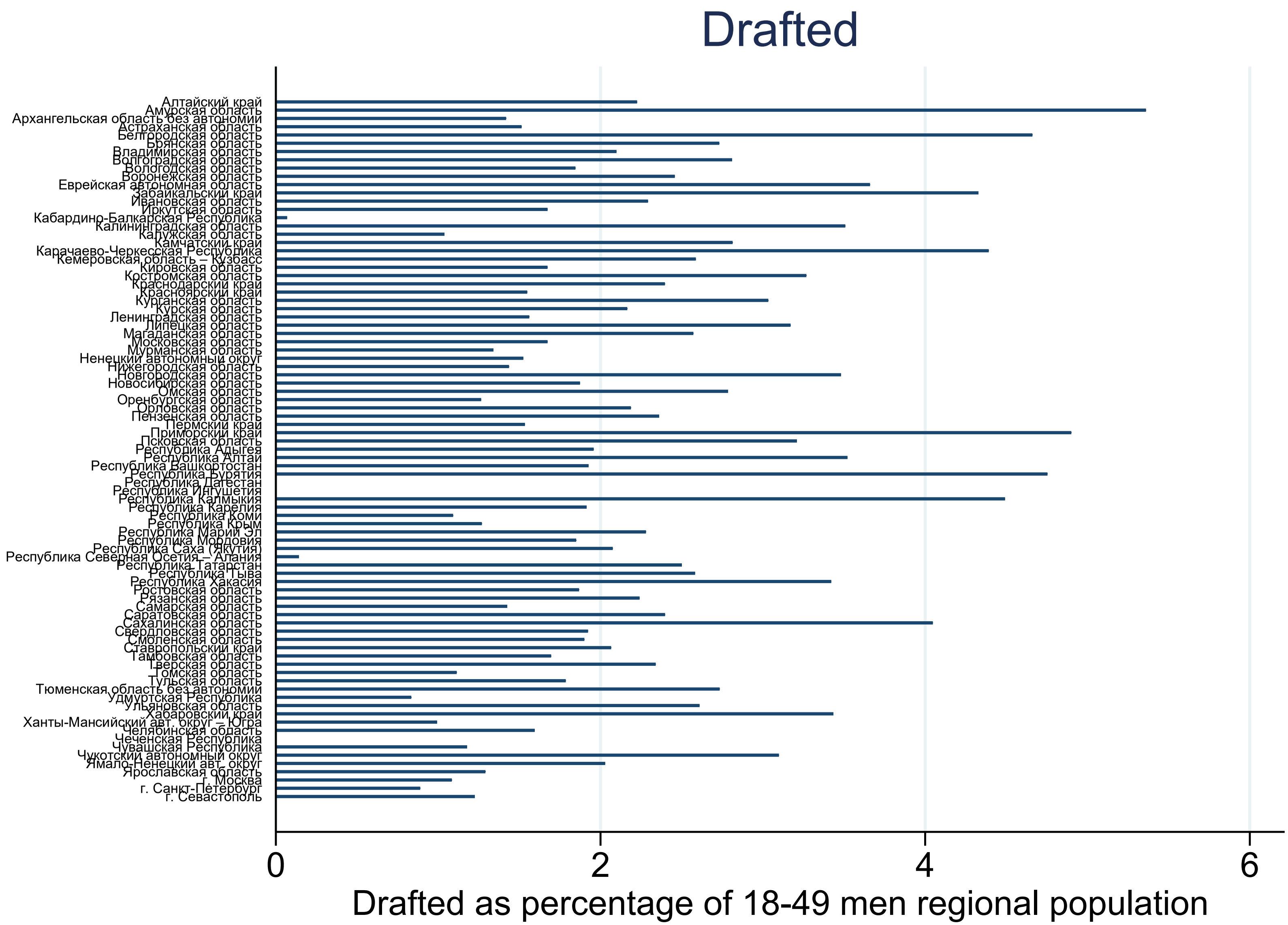
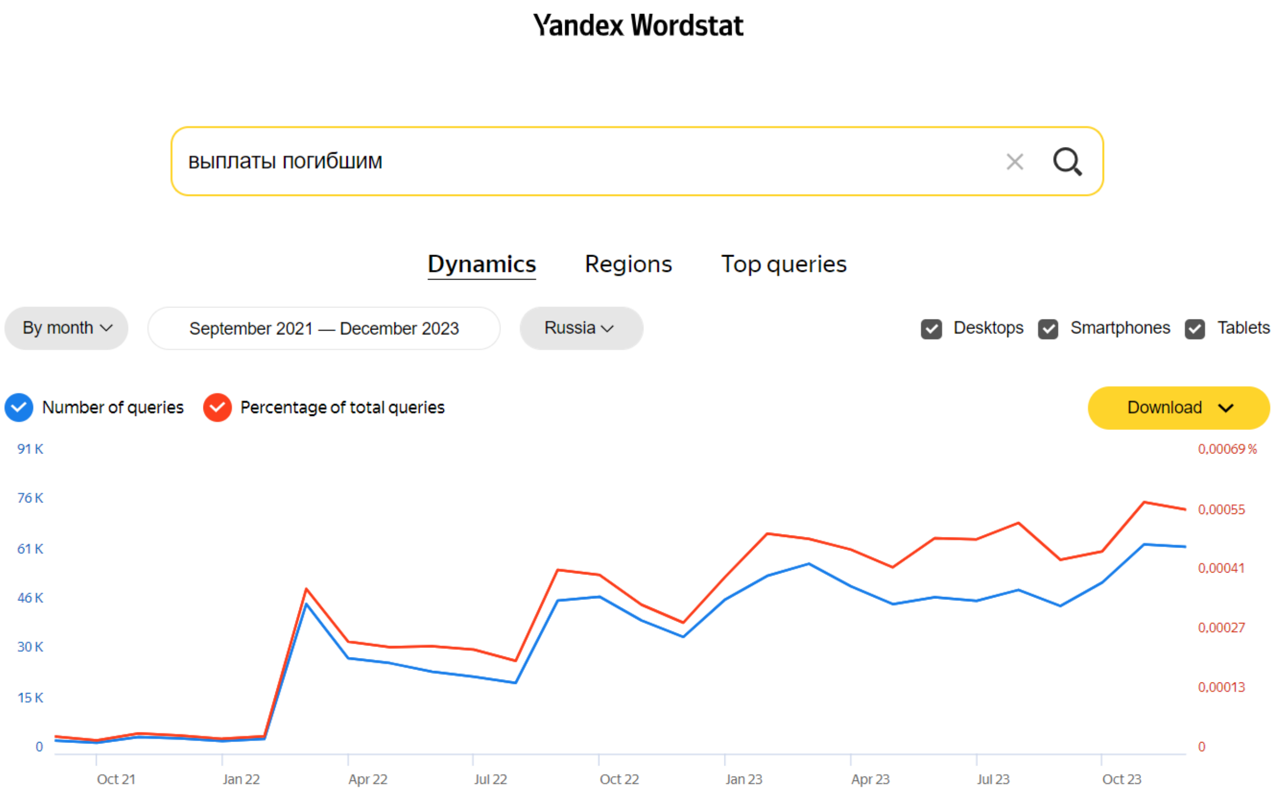


Figure A6: Yandex search for "Payment dead"



B Appendix B

B.1 Tables of Appendix B

Table B1: War attitudes and protest participation

	(1)	(2)	(3)	(4)
VARIABLES	War support		Accept negotiations	
Female	-0.097***	-0.097***	0.13***	0.13***
	(0.0050)	(0.0050)	(0.0059)	(0.0059)
Age 18-29	-0.38***	-0.38***	0.31***	0.31***
	(0.010)	(0.010)	(0.0097)	(0.0096)
Age 30-44	-0.23***	-0.23***	0.18***	0.18***
	(0.0089)	(0.0089)	(0.0080)	(0.0079)
Age 45-59	-0.098***	-0.098***	0.066***	0.066***
	(0.0088)	(0.0088)	(0.0068)	(0.0068)
Welfare: below medium	0.091***	0.091***	-0.049***	-0.049***
	(0.0073)	(0.0073)	(0.0084)	(0.0084)
Welfare: medium	0.13***	0.13***	-0.081***	-0.081***
	(0.0073)	(0.0074)	(0.010)	(0.010)
Welfare: above medium	0.17***	0.17***	-0.10***	-0.10***
	(0.0098)	(0.0097)	(0.0097)	(0.0097)
Welfare: missing	0.048***	0.048***	-0.13***	-0.13***
	(0.0097)	(0.0096)	(0.013)	(0.014)
High education	-0.023***	-0.022***	-0.026***	-0.026***
	(0.0081)	(0.0081)	(0.0070)	(0.0070)
High education(missing)	-0.072***	-0.076***	0.19***	0.19***
	(0.021)	(0.022)	(0.015)	(0.014)
Unemployment	-0.0013	-0.0018	0.0044**	0.0048**
	(0.0025)	(0.0024)	(0.0022)	(0.0022)
Income per cap	1.1e-07	3.7e-07	-1.3e-07	-2.8e-07
	(3.5e-07)	(3.5e-07)	(3.9e-07)	(4.1e-07)
Border region	0.048***	0.048***	-0.047***	-0.047***
	(0.013)	(0.011)	(0.012)	(0.012)
National republic	-0.049***	-0.045***	0.059***	0.056***
	(0.015)	(0.014)	(0.011)	(0.011)
UR share	0.00031	0.000019	-0.00011	0.000100
	(0.00047)	(0.00046)	(0.00041)	(0.00042)
ln(population)	-0.018***	-0.015***	0.013**	0.011**
	(0.0048)	(0.0042)	(0.0059)	(0.0054)
Cum detentions per 100k	-0.00074***		0.00059**	
	(0.00019)		(0.00024)	
Protest potential 2021		-0.000090***		0.000070***
		(0.000014)		(0.000022)
Observations	51,740	51,740	36,074	36,074
R-squared	0.097	0.098	0.089	0.089
Wave FE	Y	Y	Y	Y
Waves	Feb22-Mar24	Feb22-Mar24	Feb22-Mar24	Feb22-Mar24

Note. Significance levels: *** p<0.01, ** p<0.05, * p<0.10. The table shows OLS estimates for (1) with war support and acceptance of negotiations for a truce as a dependent variable. Robust standard errors clustered at the regional level are in parentheses.

Table B2: Claimed and objective war participation

	(1)	(2)	(3)
VARIABLES		Participation in war	
Female	-0.024***	-0.024***	-0.024***
	(0.0067)	(0.0067)	(0.0067)
Age 18-29	0.082***	0.083***	0.082***
	(0.012)	(0.012)	(0.012)
Age 30-44	0.098***	0.098***	0.098***
	(0.0094)	(0.0092)	(0.0093)
Age 45-59	0.070***	0.070***	0.070***
	(0.011)	(0.011)	(0.011)
Welfare: below medium	0.00084	0.0018	0.0020
	(0.013)	(0.013)	(0.013)
Welfare: medium	-0.0028	-0.0014	-0.0014
	(0.013)	(0.012)	(0.013)
Welfare: above medium	0.047***	0.048***	0.049***
	(0.015)	(0.015)	(0.016)
Welfare: missing	0.015	0.016	0.016
	(0.024)	(0.024)	(0.024)
High education	-0.026***	-0.026***	-0.026***
	(0.0078)	(0.0078)	(0.0077)
Unemployment	0.014***	0.016***	0.014***
	(0.0032)	(0.0037)	(0.0030)
Income per cap	-7.2e-07	-1.0e-06**	-8.2e-07*
	(4.7e-07)	(4.8e-07)	(4.6e-07)
Border region	-0.00095	-0.0058	-0.0045
	(0.016)	(0.015)	(0.015)
National republic	-0.017	-0.0063	0.0010
	(0.015)	(0.017)	(0.014)
UR share	0.0013***	0.0012**	0.0011***
	(0.00043)	(0.00047)	(0.00040)
ln(population)	0.00015	0.0061	0.011
	(0.0088)	(0.0094)	(0.0081)
Cum casualties per 100k	0.00034***		
	(0.00010)		
Percent of drafted men 18-49		0.021***	
		(0.0063)	
Payment dead search(per 10m)			0.0013***
			(0.00025)
Observations	11,952	11,952	11,945
R-squared	0.115	0.115	0.116
Wave FE	Y	Y	Y
Waves	May22-Jan24	May22-Jan24	May22-Jan24

Note. Significance levels: *** p<0.01, ** p<0.05, * p<0.10. The table shows OLS estimates for (1) with claimed war participation as a dependent variable. Robust standard errors clustered at the regional level are in parentheses.

Table B3: Regional contact, cooperation, and response rate

	(1)	(2)	(3)
VARIABLES	Contact rate	Cooperation rate	Response rate
Unemployment	-0.0039***	-0.00044	-0.00030***
	(0.00053)	(0.00030)	(0.000055)
Income per cap	-1.9e-06***	-5.3e-07***	-1.9e-07***
	(2.4e-07)	(9.8e-08)	(2.5e-08)
Border region	0.025***	0.0035	0.0025**
	(0.0082)	(0.0046)	(0.0011)
National republic	-0.015***	-0.0044	-0.0025***
	(0.0055)	(0.0044)	(0.00064)
UR share	0.00046**	-0.00060***	-0.000038**
	(0.00019)	(0.00011)	(0.000019)
ln(population)	0.0035	0.0079***	0.00095**
	(0.0040)	(0.0017)	(0.00039)
Operators HHI	-0.15***	0.043**	-0.0057**
	(0.018)	(0.019)	(0.0028)
Cum detentions per 100k	-0.00023	-0.00036***	-0.000059***
	(0.00023)	(0.000076)	(0.000021)
Cum casualties per 100k	-0.000075**	-6.0e-06	-4.6e-06**
	(0.000033)	(0.000012)	(2.1e-06)
Observations	1,986	1,979	1,979
R-squared	0.628	0.444	0.484
Wave FE	Y	Y	Y
Waves	Feb22-Mar24	Feb22-Mar24	Feb22-Mar24

Note. Significance levels: *** p<0.01, ** p<0.05, * p<0.10. The table shows OLS estimates for (2). Robust standard errors clustered at the regional level are in parentheses.

C Appendix C

C.1 Tables of Appendix C

Table C1: Dynamics of casualties by percentiles of regions

Year-Month	5% percent	10% percent	20% percent	median	95% percent
2022m2	0.0	0.0	0.4	1.2	8.1
2022m3	1.7	2.3	3.9	7.8	26.8
2022m4	2.0	4.7	6.3	11.8	31.6
2022m5	4.8	8.1	9.6	16.2	50.7
2022m6	5.6	9.4	13.5	20.4	61.3
2022m7	6.7	12.0	15.8	24.4	64.1
2022m8	8.1	13.2	18.4	27.2	72.5
2022m9	11.5	16.0	22.0	33.8	81.0
2022m10	15.9	20.8	27.8	42.2	96.7
2022m11	20.4	27.3	33.2	50.1	102.9
2022m12	25.8	33.6	39.7	59.5	116.5
2023m1	32.1	39.7	52.3	71.0	147.5
2023m2	40.1	46.6	60.2	81.0	174.4
2023m3	46.1	52.8	68.3	93.8	232.6
2023m4	52.6	58.0	72.2	103.5	244.2
2023m5	56.5	61.3	78.6	114.9	253.5
2023m6	58.7	66.8	83.4	124.6	278.9
2023m7	60.9	73.8	88.2	131.8	295.5
2023m8	63.7	78.4	93.9	136.9	310.1
2023m9	66.0	83.6	98.2	146.3	310.8
2023m10	69.1	90.4	106.3	157.2	339.1
2023m11	71.4	93.7	112.3	167.8	361.0
2023m12	72.5	104.1	118.4	175.5	371.7
2024m1	74.6	109.1	121.6	186.8	390.5
2024m2	76.4	114.6	128.3	195.4	414.4
2024m3	78.6	119.1	133.7	198.8	445.7

Note. The table shows the dynamics of casualties per 100k men population (aged 18-49) split by regional percentiles.

Table C2: The effect of casualties on war support

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	War support							
Female	-0.097***	-0.10***	-0.10***	-0.10***	-0.097***	-0.10***	-0.10***	-0.10***
	(0.0050)	(0.0049)	(0.0043)	(0.0047)	(0.0050)	(0.0049)	(0.0043)	(0.0047)
Age 18-29	-0.38***	-0.37***	-0.38***	-0.38***	-0.38***	-0.37***	-0.38***	-0.38***
	(0.010)	(0.018)	(0.013)	(0.011)	(0.010)	(0.018)	(0.012)	(0.011)
Age 30-44	-0.23***	-0.24***	-0.24***	-0.23***	-0.23***	-0.24***	-0.24***	-0.23***
	(0.0088)	(0.011)	(0.013)	(0.0092)	(0.0087)	(0.011)	(0.013)	(0.0091)
Age 45-59	-0.10***	-0.10***	-0.11***	-0.094***	-0.10***	-0.10***	-0.11***	-0.094***
	(0.0086)	(0.011)	(0.014)	(0.0088)	(0.0086)	(0.011)	(0.014)	(0.0087)
Welfare: below medium	0.091***	0.087***	0.081***	0.092***	0.091***	0.087***	0.081***	0.092***
	(0.0073)	(0.0093)	(0.014)	(0.0069)	(0.0073)	(0.0093)	(0.014)	(0.0069)
Welfare: medium	0.13***	0.15***	0.12***	0.13***	0.13***	0.15***	0.12***	0.13***
	(0.0074)	(0.027)	(0.012)	(0.0081)	(0.0074)	(0.027)	(0.012)	(0.0081)
Welfare: above medium	0.17***	0.13***	0.15***	0.17***	0.17***	0.13***	0.15***	0.17***
	(0.0098)	(0.033)	(0.011)	(0.0098)	(0.0097)	(0.033)	(0.012)	(0.0097)
Welfare: missing	0.048***	0.044***	0.055***	0.048***	0.048***	0.044***	0.055***	0.048***
	(0.0098)	(0.012)	(0.013)	(0.011)	(0.0098)	(0.012)	(0.013)	(0.011)
High education	-0.024***	-0.058*	-0.025***	-0.019**	-0.024***	-0.058*	-0.024***	-0.019**
	(0.0079)	(0.033)	(0.0083)	(0.0080)	(0.0080)	(0.033)	(0.0083)	(0.0080)
High education (missing)	-0.065***	-0.067***	-0.052**	-0.072***	-0.064***	-0.067***	-0.054**	-0.069***
	(0.021)	(0.021)	(0.023)	(0.019)	(0.021)	(0.021)	(0.023)	(0.020)
Cum casualties per 100k	-0.00024***	-0.00035***	-0.00030***	-0.00016				
	(0.000081)	(0.000090)	(0.000068)	(0.000097)				
26-50 killed per 100k					-0.013	-0.015	-0.0059	-0.017*
					(0.0078)	(0.0092)	(0.0079)	(0.0087)
51-75 killed per 100k					-0.0061	-0.0076	-0.012	-0.0064
					(0.012)	(0.013)	(0.012)	(0.012)
76-100 killed per 100k					-0.036**	-0.041**	-0.012	-0.034**
					(0.016)	(0.017)	(0.024)	(0.017)
100-125 killed per 100k					-0.042***	-0.057***	-0.051***	-0.037**
					(0.015)	(0.017)	(0.016)	(0.017)
125-150 killed per 100k					-0.042***	-0.052***	-0.039**	-0.037**
					(0.015)	(0.018)	(0.015)	(0.017)
150+ killed per 100k					-0.051***	-0.069***	-0.056***	-0.042**
					(0.015)	(0.019)	(0.013)	(0.017)
Observations	51,636	51,636	51,636	51,636	51,636	51,636	51,636	51,636
R-squared	0.102	0.099	0.102	0.109	0.102	0.099	0.102	0.109
Wave FE	Y	Y	Y	Y	Y	Y	Y	Y
Region FE	Y	Y	Y	Y	Y	Y	Y	Y
Waves	Feb22-Mar24	Feb22-Mar24	Feb22-Mar24	Feb22-Mar24	Feb22-Mar24	Feb22-Mar24	Feb22-Mar24	Feb22-Mar24
Weight	No	Coop.Pr.	Resp.Pr.	Gend.Age	No	Coop.Pr.	Resp.Pr.	Gend.Age

Note. Significance levels: *** p<0.01, ** p<0.05, * p<0.10. The table shows OLS estimates for (3) with war support as a dependent variable. Robust standard errors clustered at the regional level are in parentheses.

Table C3: The effect of casualties on acceptance of negotiations

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	Accept negotiations							
Female	0.14***	0.11***	0.13***	0.14***	0.14***	0.11***	0.13***	0.14***
	(0.0060)	(0.027)	(0.0074)	(0.0061)	(0.0060)	(0.027)	(0.0074)	(0.0061)
Age 18-29	0.30***	0.37***	0.31***	0.30***	0.30***	0.37***	0.31***	0.30***
	(0.0099)	(0.058)	(0.018)	(0.010)	(0.0099)	(0.058)	(0.018)	(0.010)
Age 30-44	0.18***	0.15***	0.19***	0.18***	0.18***	0.15***	0.19***	0.18***
	(0.0080)	(0.032)	(0.0100)	(0.0090)	(0.0079)	(0.032)	(0.0098)	(0.0090)
Age 45-59	0.066***	0.063***	0.064***	0.067***	0.066***	0.063***	0.064***	0.067***
	(0.0067)	(0.0096)	(0.011)	(0.0072)	(0.0067)	(0.0096)	(0.011)	(0.0073)
Welfare: below medium	-0.048***	-0.055***	-0.055***	-0.049***	-0.048***	-0.055***	-0.055***	-0.049***
	(0.0081)	(0.013)	(0.016)	(0.0077)	(0.0081)	(0.013)	(0.015)	(0.0077)
Welfare: medium	-0.080***	-0.063***	-0.080***	-0.079***	-0.080***	-0.064***	-0.080***	-0.079***
	(0.0099)	(0.013)	(0.017)	(0.0100)	(0.0099)	(0.012)	(0.017)	(0.0100)
Welfare: above medium	-0.10***	-0.13***	-0.099***	-0.10***	-0.10***	-0.13***	-0.099***	-0.100***
	(0.0097)	(0.032)	(0.016)	(0.0096)	(0.0096)	(0.032)	(0.016)	(0.0096)
Welfare: missing	-0.12***	-0.12***	-0.12***	-0.13***	-0.12***	-0.12***	-0.12***	-0.13***
	(0.014)	(0.016)	(0.020)	(0.014)	(0.014)	(0.016)	(0.020)	(0.014)
High education	-0.025***	-0.0048	-0.028***	-0.026***	-0.025***	-0.0048	-0.028***	-0.026***
	(0.0067)	(0.022)	(0.0081)	(0.0072)	(0.0068)	(0.023)	(0.0081)	(0.0072)
High education (missing)	0.19***	0.19***	0.19***	0.18***	0.19***	0.18***	0.18***	0.18***
	(0.014)	(0.016)	(0.015)	(0.017)	(0.014)	(0.017)	(0.016)	(0.018)
Cum casualties per 100k	0.00026***	0.00028***	0.00025**	0.00020**				
	(0.000086)	(0.000092)	(0.00012)	(0.000084)				
26-50 killed per 100k					0.012	0.022**	0.022**	0.0068
					(0.011)	(0.011)	(0.010)	(0.011)
51-75 killed per 100k					0.031**	0.034**	0.046***	0.024
					(0.015)	(0.015)	(0.010)	(0.016)
76-100 killed per 100k					0.020	0.016	0.036**	0.011
					(0.017)	(0.018)	(0.014)	(0.017)
100-125 killed per 100k					0.050***	0.050***	0.063***	0.039**
					(0.015)	(0.016)	(0.014)	(0.016)
125-150 killed per 100k					0.044***	0.052***	0.063***	0.038**
					(0.014)	(0.016)	(0.012)	(0.015)
150+ killed per 100k					0.065***	0.072***	0.086***	0.051***
					(0.015)	(0.018)	(0.014)	(0.016)
Observations	35,976	35,976	35,976	35,976	35,976	35,976	35,976	35,976
R-squared	0.094	0.098	0.091	0.098	0.095	0.099	0.092	0.098
Wave FE	Y	Y	Y	Y	Y	Y	Y	Y
Region FE	Y	Y	Y	Y	Y	Y	Y	Y
Waves	Apr22-Mar24	Apr22-Mar24	Apr22-Mar24	Apr22-Mar24	Apr22-Mar24	Apr22-Mar24	Apr22-Mar24	Apr22-Mar24
Weight	No	Coop.Pr.	Resp.Pr.	Gend.Age	No	Coop.Pr.	Resp.Pr.	Gend.Age

Note. Significance levels: *** p<0.01, ** p<0.05, * p<0.10. The table shows OLS estimates for (3) with acceptance of negotiations for a truce as a dependent variable. Robust standard errors clustered at the regional level are in parentheses.

Table C4: The effect of exceeding casualties threshold on war support and acceptance of negotiations. Stack regression.

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES		War support			Accept negotiations	
Female	-0.090***	-0.089***	-0.088***	0.084**	0.080*	0.076*
	(0.0040)	(0.0039)	(0.0037)	(0.040)	(0.042)	(0.045)
Age 18-29	-0.38***	-0.38***	-0.38***	0.41***	0.42***	0.42***
	(0.025)	(0.024)	(0.022)	(0.076)	(0.080)	(0.083)
Age 30-44	-0.26***	-0.26***	-0.25***	0.15***	0.15***	0.14***
	(0.015)	(0.014)	(0.014)	(0.046)	(0.047)	(0.048)
Age 45-59	-0.12***	-0.11***	-0.11***	0.070***	0.068***	0.064***
	(0.017)	(0.017)	(0.017)	(0.014)	(0.015)	(0.015)
Welfare: below medium	0.083***	0.083***	0.076***	-0.062***	-0.060***	-0.059***
	(0.014)	(0.013)	(0.013)	(0.020)	(0.018)	(0.017)
Welfare: medium	0.15***	0.15***	0.15***	-0.063***	-0.065***	-0.066***
	(0.035)	(0.037)	(0.034)	(0.017)	(0.017)	(0.015)
Welfare: above medium	0.12***	0.12**	0.11**	-0.15***	-0.15***	-0.15***
	(0.044)	(0.048)	(0.051)	(0.043)	(0.045)	(0.049)
Welfare: missing	0.056***	0.062***	0.057***	-0.16***	-0.17***	-0.17***
	(0.0098)	(0.012)	(0.011)	(0.018)	(0.018)	(0.018)
High education	-0.090**	-0.091*	-0.092*	0.021	0.021	0.028
	(0.045)	(0.047)	(0.048)	(0.038)	(0.039)	(0.043)
Treat.Group*Treat.Time	-0.051***	-0.045***	-0.037**	0.038***	0.032***	0.025**
	(0.012)	(0.014)	(0.015)	(0.012)	(0.011)	(0.011)
Observations	458,915	490,225	533,109	283,407	302,851	331,381
R-squared	0.109	0.108	0.107	0.118	0.119	0.118
Wave-Stack FE	Y	Y	Y	Y	Y	Y
Region-Stack FE	Y	Y	Y	Y	Y	Y
Weight	Coop.Pr.	Coop.Pr.	Coop.Pr.	Coop.Pr.	Coop.Pr.	Coop.Pr.
Threshold	80	90	100	80	90	100

Note. Significance levels: *** p<0.01, ** p<0.05, * p<0.10. The table shows OLS estimates for stack DID regression similar to the event-study stack specification (4). War support and acceptance of negotiations for a truce are dependent variables. Robust standard errors clustered at the regional level are in parentheses.

Table C5: Casualties, Media sources about the war, VPN usage, and Voting

VARIABLES	(1) Relatives	(2) TV	(3) YouTube	(4) Telegram	(5) VK-OK	(6) Socmedia	(7) Websites	(8) VPN	(9) Vote Putin
Female	0.010	0.046***	-0.098***	-0.026***	0.043***	0.040***	-0.037***	0.042***	0.095***
	(0.0075)	(0.0066)	(0.0063)	(0.0075)	(0.010)	(0.0086)	(0.0064)	(0.0079)	(0.010)
Age 18-29	0.13***	-0.50***	0.076***	0.25***	0.18***	0.25***	0.11***	0.34***	-0.24***
	(0.0092)	(0.013)	(0.012)	(0.014)	(0.013)	(0.013)	(0.013)	(0.019)	(0.026)
Age 30-44	0.11***	-0.31***	0.051***	0.18***	0.12***	0.17***	0.095***	0.19***	-0.15***
	(0.0078)	(0.010)	(0.0074)	(0.011)	(0.012)	(0.0085)	(0.011)	(0.013)	(0.017)
Age 45-59	0.081***	-0.14***	0.067***	0.12***	0.061***	0.10***	0.096***	0.086***	-0.090***
	(0.0075)	(0.0087)	(0.0100)	(0.0078)	(0.0084)	(0.0071)	(0.0083)	(0.0091)	(0.014)
Welfare: below medium	0.00091	0.025***	0.011	0.038***	0.0058	0.021***	0.045***	0.024***	0.057***
	(0.0089)	(0.0091)	(0.0091)	(0.0071)	(0.010)	(0.0074)	(0.010)	(0.0080)	(0.021)
Welfare: medium	0.0070	0.020*	0.029**	0.094***	-0.015	0.012	0.067***	0.056***	0.097***
	(0.0095)	(0.010)	(0.012)	(0.0088)	(0.011)	(0.0096)	(0.011)	(0.010)	(0.023)
Welfare: above medium	0.0057	0.021*	0.0045	0.077***	0.0020	0.0087	0.040***	0.045***	0.13***
	(0.010)	(0.011)	(0.011)	(0.010)	(0.013)	(0.0081)	(0.010)	(0.0085)	(0.023)
Welfare: missing	-0.014	0.0069	-0.066***	-0.0056	-0.017	-0.033**	-0.031*	0.0063	0.056*
	(0.017)	(0.017)	(0.019)	(0.016)	(0.019)	(0.016)	(0.016)	(0.016)	(0.029)
High education	0.030***	-0.070***	0.052***	0.099***	-0.025***	0.025***	0.093***	0.086***	-0.070***
	(0.0064)	(0.0087)	(0.0061)	(0.0068)	(0.0088)	(0.0069)	(0.0081)	(0.0075)	(0.011)
Rural	-0.012	0.033***	-0.046***	-0.065***	-0.017*	-0.026***	-0.056***	-0.066***	0.034**
	(0.011)	(0.0085)	(0.0091)	(0.0069)	(0.0099)	(0.0079)	(0.0099)	(0.0089)	(0.014)
Cum casualties per 100k	0.00015	-0.000048	0.000011	-0.00022*	0.00019**	0.00038***	0.000077	0.000050	-0.0041**
	(0.00010)	(0.00011)	(0.00015)	(0.00012)	(0.000093)	(0.00011)	(0.00010)	(0.00020)	(0.0016)
Observations	16,587	16,587	14,787	14,787	10,583	16,813	16,587	11,433	6,610
R-squared	0.075	0.164	0.079	0.157	0.144	0.188	0.076	0.140	0.073
Wave FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Region FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Waves	Feb22-Mar24	Feb22-Mar24	Feb22-Mar24	Feb22-Mar24	Feb22-Mar24	Feb22-Mar24	Feb22-Mar24	Feb22-Mar24	Jan24-Mar24

Note. Significance levels: *** p<0.01, ** p<0.05, * p<0.10. The table shows OLS estimates for (3) with an information source, VPN usage, and willingness to vote for Vladimir Putin as dependent variables. Robust standard errors clustered at the regional level are in parentheses.

Table C6: The effect of casualties on the willingness to vote for Vladimir Putin.

	(1)	(2)	(3)	(4)
VARIABLES		Vote for Vladimir Putin		
Ln(cum casualt. in 10km)	-0.023***	-0.024***	-0.023***	-0.016**
	(0.0068)	(0.0065)	(0.0064)	(0.0077)
Ln(cum casualt. in 10-20km)	0.0037	0.0029	0.0052	0.0084
	(0.0075)	(0.0073)	(0.0079)	(0.0082)
Ln(cum casualt. in 20-30km)	0.00062	0.00088	-0.0095	-0.0085
	(0.0080)	(0.0078)	(0.0085)	(0.0085)
Ln(cum casualt. in 30-40km)	-0.0020	-0.0032	-0.0024	-0.0020
	(0.0080)	(0.0074)	(0.0079)	(0.0079)
Ln(cum casualt. in 40-50km)	0.0088	0.0070	0.0060	0.0059
	(0.0075)	(0.0069)	(0.0075)	(0.0076)
Ln(cum casualt. in 50-100km)	-0.0030	-0.0089	-0.0078	-0.0079
	(0.0075)	(0.0076)	(0.0098)	(0.0098)
Female	0.085***	0.087***	0.091***	0.091***
	(0.014)	(0.014)	(0.014)	(0.014)
Age 18-29	-0.23***	-0.23***	-0.23***	-0.23***
	(0.024)	(0.024)	(0.024)	(0.024)
Age 30-44	-0.12***	-0.12***	-0.12***	-0.12***
	(0.018)	(0.018)	(0.018)	(0.018)
Age 45-59	-0.081***	-0.085***	-0.083***	-0.083***
	(0.018)	(0.018)	(0.018)	(0.018)
Welfare: below medium	0.043*	0.048**	0.050**	0.051**
	(0.023)	(0.023)	(0.023)	(0.023)
Welfare: medium	0.081***	0.090***	0.088***	0.089***
	(0.026)	(0.025)	(0.025)	(0.025)
Welfare: above medium	0.14***	0.15***	0.14***	0.14***
	(0.030)	(0.030)	(0.030)	(0.030)
Welfare: missing	0.038	0.042	0.051	0.052*
	(0.032)	(0.032)	(0.031)	(0.032)
High education	-0.053***	-0.052***	-0.054***	-0.054***
	(0.013)	(0.013)	(0.013)	(0.013)
Rural	0.0052	-0.0052	-0.0046	-0.0039
	(0.020)	(0.020)	(0.020)	(0.020)
Reg:Unemployment		0.0041		
		(0.0036)		
Reg:Income per cap		-1.6e-06		
		(1.1e-06)		
Reg:Border		0.045**		
		(0.021)		
Reg:National repub		0.0033		
		(0.026)		
Reg:UR share		0.0011*		
		(0.00063)		
Reg:Ln(population)		0.0062		
		(0.013)		
Municip:Female share				-0.0090
				(0.58)
Municip:Ln(population)				-0.012
				(0.0082)
Observations	5,403	5,403	5,403	5,403
R-squared	0.045	0.049	0.069	0.070
Wave FE	Y	Y	Y	Y
Region FE	N	N	Y	Y
Region control	N	Y	N	N
Municip control	N	N	N	Y
Waves	Jan24-Mar24	Jan24-Mar24	Jan24-Mar24	Jan24-Mar24
Weight	Coop.Pr.	Coop.Pr.	Coop.Pr.	Coop.Pr.

Note. Significance levels: *** p<0.01, ** p<0.05, * p<0.10. The table shows OLS estimates for (5). Robust standard errors clustered at the municipal level are in parentheses. Re-weighting is based on the cooperation rate.

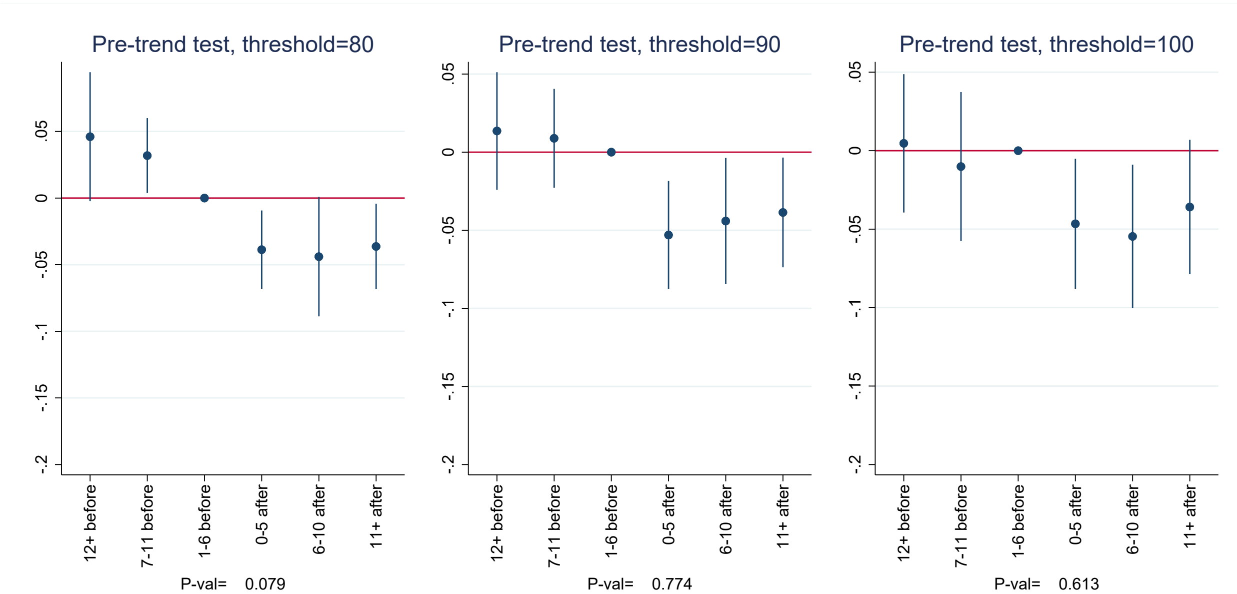
Table C7: The effect of casualties on the willingness to vote for Vladimir Putin. Specification with absolute casualties.

	(1)	(2)	(3)	(4)
VARIABLES		Vote for Vladimir Putin		
Cum casualt. in 10km	-0.00051***	-0.00053***	-0.00060***	-0.00046**
	(0.00016)	(0.00015)	(0.00014)	(0.00020)
Cum casualt. in 10-20km	0.00029	0.00024	0.00034	0.00042
	(0.00037)	(0.00033)	(0.00035)	(0.00034)
Cum casualt. in 20-30km	-0.00034	-0.00031	-0.00046*	-0.00046*
	(0.00027)	(0.00027)	(0.00028)	(0.00028)
Cum casualt. in 30-40km	1.3e-06	0.000035	0.000022	0.000023
	(0.00018)	(0.00019)	(0.00019)	(0.00019)
Cum casualt. in 40-50km	0.00013	0.000060	0.000016	0.000015
	(0.00019)	(0.00018)	(0.00018)	(0.00018)
Cum casualt. in 50-100km	-0.000039	-0.000041	-0.000068	-0.000071
	(0.000040)	(0.000046)	(0.000065)	(0.000065)
Female	0.085***	0.087***	0.091***	0.091***
	(0.014)	(0.014)	(0.014)	(0.014)
Age 18-29	-0.22***	-0.23***	-0.23***	-0.23***
	(0.024)	(0.024)	(0.024)	(0.024)
Age 30-44	-0.12***	-0.12***	-0.12***	-0.12***
	(0.018)	(0.018)	(0.018)	(0.018)
Age 45-59	-0.081***	-0.085***	-0.083***	-0.083***
	(0.018)	(0.018)	(0.018)	(0.018)
Welfare: below medium	0.042*	0.046**	0.048**	0.048**
	(0.023)	(0.023)	(0.023)	(0.023)
Welfare: medium	0.079***	0.089***	0.086***	0.086***
	(0.026)	(0.025)	(0.025)	(0.025)
Welfare: above medium	0.14***	0.15***	0.14***	0.14***
	(0.030)	(0.030)	(0.030)	(0.030)
Welfare: missing	0.037	0.042	0.050	0.050
	(0.032)	(0.032)	(0.031)	(0.031)
High education	-0.052***	-0.053***	-0.054***	-0.054***
	(0.014)	(0.013)	(0.013)	(0.013)
Rural	0.022	0.011	0.011	0.0093
	(0.019)	(0.018)	(0.018)	(0.019)
Reg:Unemployment		0.0047		
		(0.0034)		
Reg:Income per cap		-1.4e-06		
		(1.2e-06)		
Reg:Border		0.040*		
		(0.021)		
Reg:National repub		0.0029		
		(0.026)		
Reg:UR share		0.00100		
		(0.00064)		
Reg:Ln(population)		0.0082		
		(0.014)		
Municip:Female share				-0.43
				(0.54)
Municip:Population				-2.2e-08
				(3.0e-08)
Observations	5,403	5,403	5,403	5,403
R-squared	0.045	0.049	0.070	0.070
Wave FE	Y	Y	Y	Y
Region FE	N	N	Y	Y
Region control	N	Y	N	N
Municip control	N	N	N	Y
Waves	Jan24-Mar24	Jan24-Mar24	Jan24-Mar24	Jan24-Mar24
Weight	Coop.Pr.	Coop.Pr.	Coop.Pr.	Coop.Pr.

Note. Significance levels: *** p<0.01, ** p<0.05, * p<0.10. The table shows OLS estimates for (5). Robust standard errors clustered at the municipal level are in parentheses. Reweighting is based on the cooperation rate.

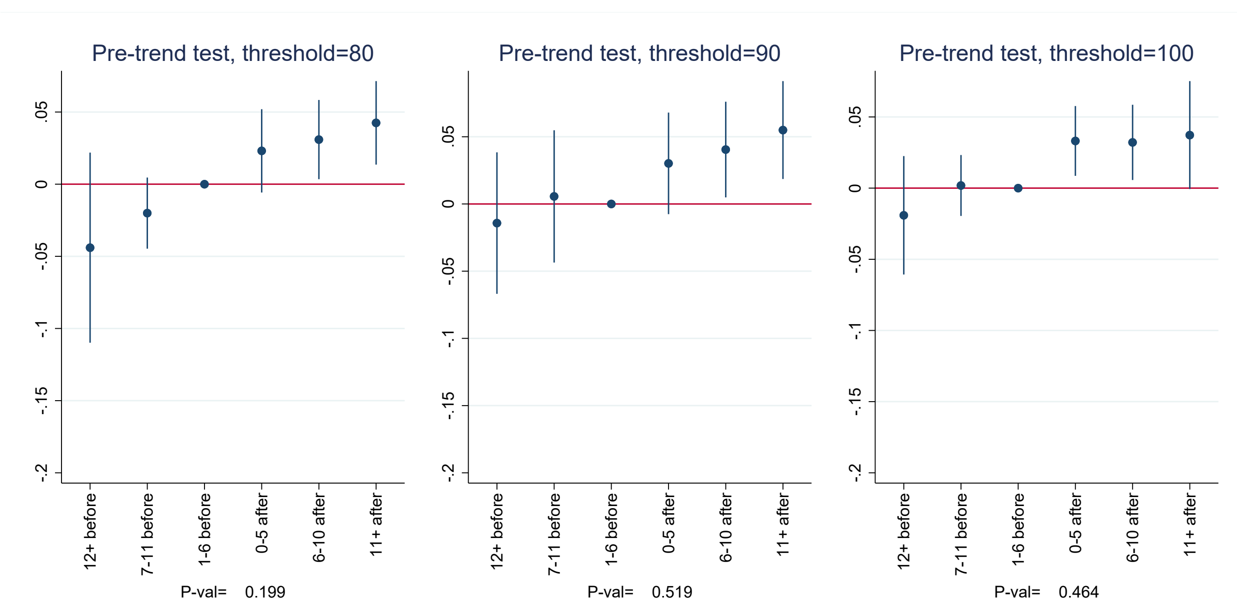
C.2 Figures of Appendix C

Figure C1: Event-study analysis for war support. Stack regression without individual controls.



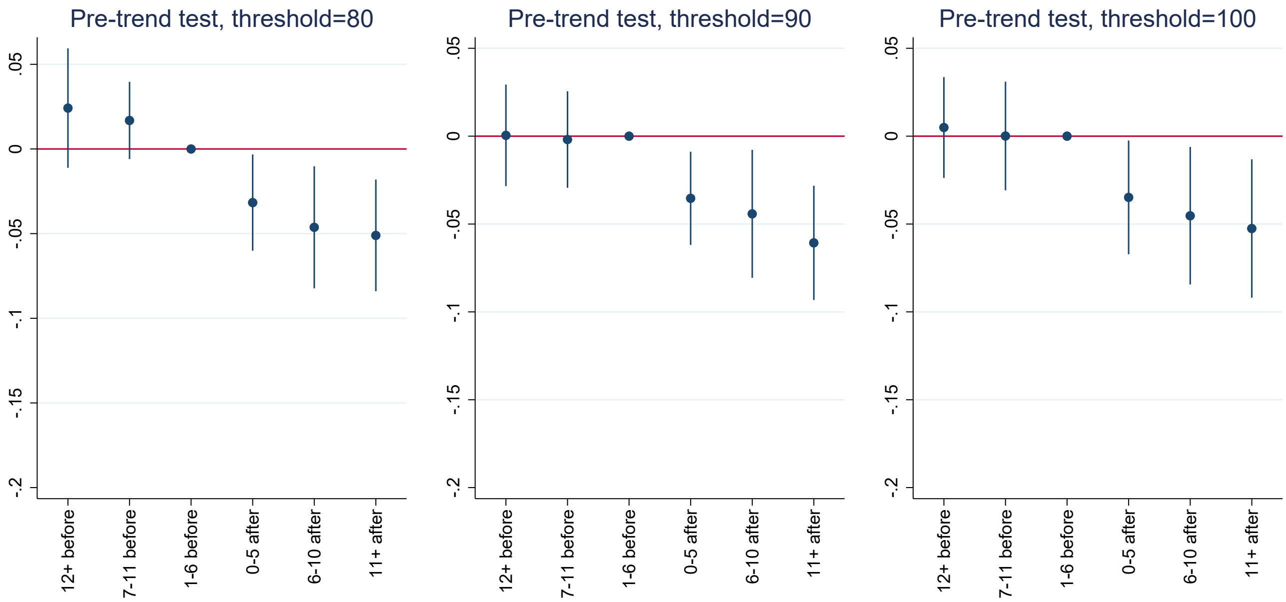
Note. The table shows OLS estimates for (4) with the war support as a dependent variable. Errors are clustered at the regional level. Re-weighting is based on the cooperation rate. Individual demographic controls are excluded. Each graph shows the p-value of the parallel pre-trends test, i.e., coefficients for bins "12+ before" and "7-11 before" to be equal to zero simultaneously.

Figure C2: Event-study analysis for acceptance of negotiations. Stack regression without individual controls



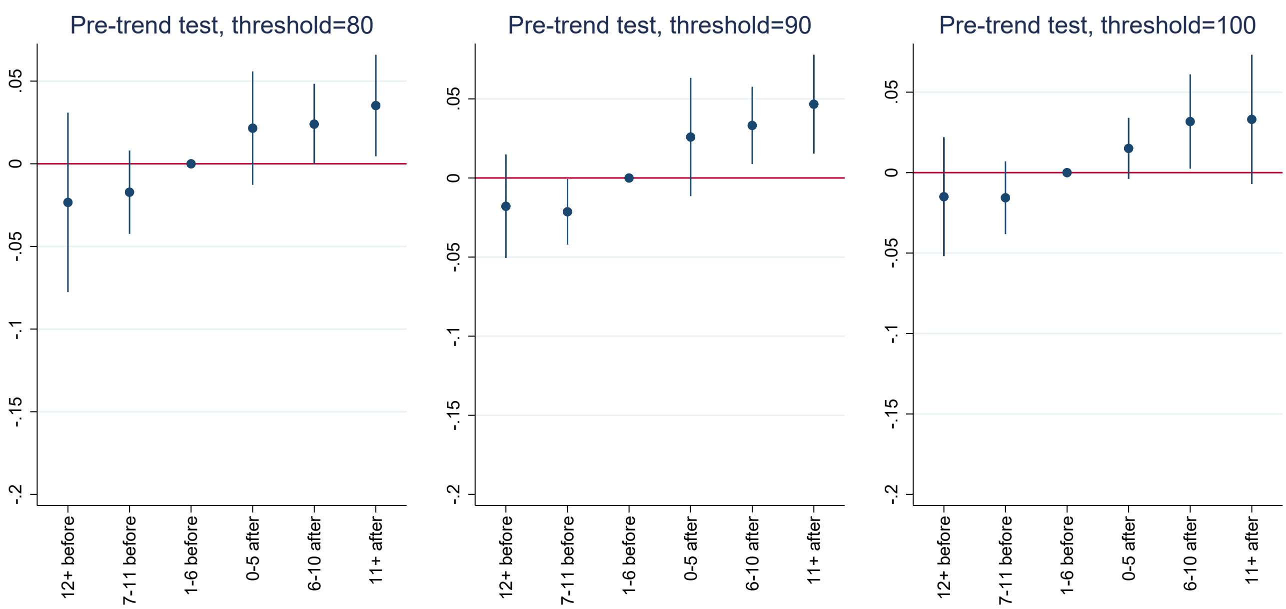
Note. The table shows OLS estimates for (4) with acceptance of negotiation for a truce as a dependent variable. Errors are clustered at the regional level. Re-weighting is based on the cooperation rate. Individual demographic controls are excluded. Each graph shows the p-value of the parallel pre-trends test, i.e., coefficients for bins "12+ before" and "7-11 before" to be equal to zero simultaneously.

Figure C3: TWFE event-study analysis for war support



Note. The table shows OLS estimates for the traditional two-way fixed effect event-study approach with war support as a dependent variable. Errors are clustered at the regional level. Re-weighting is based on the cooperation rate. Individual demographic controls are included.

Figure C4: TWFE event-study analysis for acceptance of negotiations



Note. The table shows OLS estimates for the traditional two-way fixed effect event-study approach with acceptance of negotiations for a truce as a dependent variable. Errors are clustered at the regional level. Re-weighting is based on the cooperation rate. Individual demographic controls are included.