The Role of the Military-Industrial Complex in Shaping Electoral Preferences

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Abstract

In this paper, I am studying the role of the military-industrial complex of Russia in the massive rise of governmental approval after the first Russia-Ukraine conflict in 2014. I geocoded a historical dataset on the geography of Soviet defense enterprises in Russia and coupled it with the electoral data of the most precise level. I am implementing a difference-in-differences strategy, comparing geographical areas with different levels of exposure to the military enterprises, before and after the armed conflict in 2014. The results indicate that, after those events, higher exposure to a military plant was associated with significantly greater support for the current regime. One possible mechanism pertains to the local labor market: the restructuring of the industry and an increase in the volumes of production within the sector could impact the economic environment in highly exposed areas and, consequently, shape electoral outcomes in the aftermath of the conflict. The empirical analysis does not provide any evidence of electoral fraud driving the effects.

Introduction

Degree of exposure to specific sectors of the national economy can be related to political leanings of citizens and subsequent local electoral outcomes (Ebeid and Rodden, 2006). For instance, areas and regions with a significant presence of military production may exhibit distinct political patterns due to economic, social, and industrial peculiarities (Rhode et al., 2018). The presence of such entities may contribute to job creation, economic stability, and local infrastructure development, influencing the preferences and voting behavior of individuals within those communities. Additionally, defense-related issues, such as defense spending, military contracts, and national security concerns, may take on greater significance in elections, further shaping electoral outcomes in areas with exposure to defense enterprises (Williams, 2015) and leading to local rally-around-the-flag effects (Hess and Orphanides, 1995). This relationship is important for addressing the effects of economic, cultural, and institutional features on electoral decision-making.

In this paper, I am focusing on the onset of the political conflict between Russia and Ukraine in 2014, and studying the rise and big restructuring of the military-industrial complex in Russia during that period (The Government of Russia, 2015). I am investigating the relationship between the greater emphasis on the defense sector in post-conflict Russia and the concomitant shift of political leanings and a vast increase in the degree of governmental approval (see Figure 1). Using data from official administrative sources and a novel dataset of a geocoded historical archive, I am conducting a reduced-form empirical analysis by using the difference-in-differences framework to study the following questions. How the higher importance of the defense industry in Russia contributed to the massive rise of governmental support after the beginning of the first political conflict with Ukraine in 2014? Conditional on the presence of this contribution, what are the underlying mechanisms of the effect? In the empirical analysis, I am leveraging the heterogeneity of the proximity of voting polling stations to Soviet-time defense industry enterprises as the source of variation.

The findings suggest that one standard deviation of the measure of exposure to the defense industry within a municipality was associated with a two percent increase in the number of votes for the government in 2018. The decomposition analysis indicates that two sources are driving this effect: a shift in the vote share, and a change in the number of registered voters in geographical areas around defense enterprises.

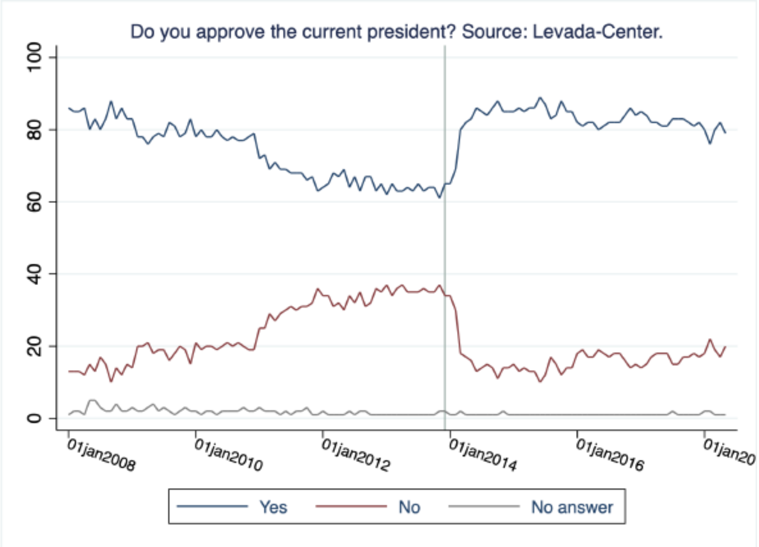


Figure 1: Presidential Approval over Time from the National Survey

Data source: Levada Analytical Center, Russian non-governmental research organization.
Note: the graph illustrates the evolution of positive and negative responses regarding the approval of the current president of Russia over time. There is a negligible fraction of refusals to answer over time.

This study relates to several strands of political economy and political science literature. The researchers focus on geographical peculiarities of electoral outcomes and aim to address how the geography of the voting polls is associated with the way citizens behave during elections. The key question is whether there exists a causal link between a precinct location and how a citizen living there makes an electoral choice (Ichino and Nathan, 2013; Vargas et al., 2022; Hintson and Vaishnav, 2023).

In the context of military objects, the proximity to such entities may shape the political preferences and voting behavior of individuals residing in those areas. Bautista et al. (2023) exploited the geographical variation of military bases in Chile and demonstrated that voters residing in exposed counties exhibited higher levels of political engagement and cast more votes in opposition to Pinochet's regime. Bauer et al. (2016) examined how exposure to war affects individuals' propensity to cooperate with others. The findings suggest that exposure to war-related violence and political conflicts, particularly those with pro-social motives or group identity formation, leads to higher cooperation and greater social participation. The current study builds upon these research papers by exploring the degree of exposure to the military-industrial complex during times of political tension in the Russian context. Specifically, it examines how it could shape the voting behavior and local electoral outcomes of citizens residing in highly exposed geographical areas.

Some studies particularly delve into the context of Russian elections. Peeva (2018) showed that the government of Russia gained relatively more support in places geographically close to sanctioned firms after the events of 2014. Via an empirical analysis of administrative data and public opinion surveys, the author found that the imposed sanctions contributed to a rally-around-the-flag effect, leading to increased incumbent's ratings. Finally, Enikolopov et al. (2011) studied electoral outcomes of the 1999 parliamentary elections within Russian regions with differential access to the single national TV channel that was independent from the government. The authors built their identification strategy based on geographical peculiarities of the channel availability. Empirical findings suggest that media played a significant role in influencing political persuasion, with increased exposure to state-controlled television leading to a higher likelihood of supporting the ruling party.

The contribution of this study to the present literature is attempting to explain how the degree of exposure to a specific sector of the economy, the defense sector in the current context, which was related to the increase in economic activity and concomitant growth in production volumes, could be associated with the way voters behaved during times of political tension. When a particular sector dominates the local economy, electoral outcomes and political leanings may be explained by the interests and concerns of those involved in that specific sector, especially when it becomes to be significantly favored and targeted by the government: voters tend to reciprocate monetary incentives by increasing their approval (Finan and Schechter, 2012). At the same time, the increased production might convey valuable information regarding the goals of the government to the electorate (i.e., the possibilities of a war).

The structure of this paper proceeds as follows. Section 1 describes the historical background behind the analysis and presents pieces of motivational evidence. Section 2 describes the data used in the empirical analysis. The empirical specification is presented in Section 3. I organize the empirical results in Section 4. Section 5 discusses possible channels and mechanisms of the results, and presents supporting empirical evidence. Finally, the study concludes with a summary and final remarks.

1 Background

1.1 Military-Industrial Complex

The history of the XX century in the Soviet Union, with the presence of two dreadful wars, has led to specific consequences in the production structure of the national economy. The USSR was known for its strong emphasis on the military-industrial complex: over the years, more than a third of all the financial, technical, and scientific national resources had been allocated to its development (Krylov, 2008). It was the most advantaged sector of the economy. Hence, at the time of the Soviet collapse, there existed lots of factories that were related to defense production (Kosals and Izyumov, 2011). In the 1990s, in comparison to other economic sectors, military enterprises kept conveying a strong legacy from the Soviet Union (Kosals and Izyumov, 2011). This could have an impact on the current institutional environment in the country: violence-related political features tend to demonstrate a persistent effect on individual attitudes and behaviors, even across generations (Lupu and Peisakhin, 2017).

At the beginning of the XXI century, the national defense expenses contributed to the nascent revival and growth of the military-industrial sector (Kosals and Izyumov, 2011). The pattern can be observed in the evolution of military expenses in the national budget. Looking at the recent years (2006-2019), the spike in the evolution of military expenses in the Russian national budget came between 2014-2016, right after the political conflict with Ukraine in 2014 (see Figure 2). The defense budget established by the government began to increase at a faster rate. Per capita military spending was also rising, as can be inferred from Figure A4 in Appendix.

The patterns of a growing emphasis on defense production and higher importance on the industry were also documented in the official statements of the government. For example, the report of the Russian Parliament in 2014 stated that the volume of industrial output produced by the defense industry enterprises increased by 15.5% (in comparable prices of 2014), mainly due to the growth in the volume of military products. This increase was observed in all branches of the defense industry: radio-electronic industry - by 24%, aviation industry - by 17.1%, shipbuilding industry - 14.4%, ammunition and special chemicals industry - 13%, rocket and space industry - 8.6%, conventional arms industry - 5.4%. The described activities were aimed at implementing decrees and decisions of the

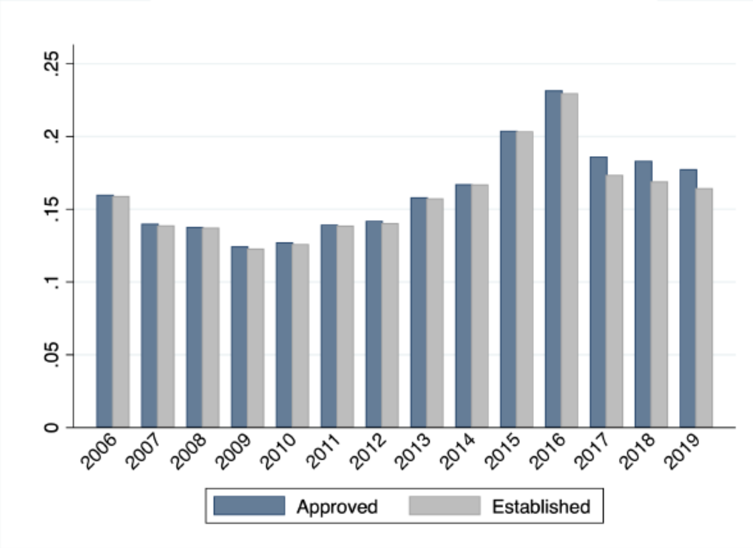


Figure 2: Share of Defense Expenses in the National Budget of Russia

Data source: Ministry of Finance of the Russian Federation.
Note: the graph plots the evolution of defense expenses in the national budget of Russia over time. "Approved" stands for approved by the Legislature for a fiscal year; "Established" stands for actual expenses.

President, the Government, and the Military Industrial Commission (The Government of Russia, 2015). This restructuring also affected the employees of the military-industrial complex: the 2014 Decree of the President awarded 228 scholarships for 114 million rubles and 683 scholarships for 239.05 million rubles " ... for outstanding achievements in the creation of breakthrough technologies and the development of modern weapons, military and special equipment, for ensuring the defense of the country and the security of the state" (The Government of Russia, 2015). From the statements of official representatives in 2013, the allocated funds were taking into account previous long-term under-financing of the defense industry, and these activities were aimed to carry out the restructuring of the military-industrial complex to the maximum extent possible (The Government of Russia, 2013).

1.2 Political Conflict of 2014

The beginning of the political conflict between Russia and Ukraine in 2014 had far-reaching implications for both countries and the broader geopolitical landscape. The conflict began following Russia's annexation of Crimea, a region that had been part of Ukraine, in March 2014. Tensions had been simmering for years, fueled by historical, ethnic, and political complexities. The Crimean conflict sparked international condemnation and led to the deterioration of relations between Russia and Ukraine, as well as strained relations with the Western countries[1] (The Washington Post, 2014; Interfax UA, 2016).

The conflict escalated further, when pro-Russian separatist movements emerged in eastern regions of Ukraine, leading to a series of violent clashes and the establishment of self-proclaimed separatist entities (Platonova, 2021). The Ukrainian government responded with military operations to regain control over the territories. The conflict resulted in a protracted and bloody conflict, characterized by military engagements, humanitarian crises, and significant losses (UNICEF, 2014; The Kyiv Post, 2015). The international community responded to the conflict with economic sanctions imposed on Russia and diplomatic efforts to find a resolution (European Council, 2014). This conflict also had implications for regional stability and raised concerns about the balance of power in Eastern Europe (Rynning, 2015).

These events marked a turning point in the relationship between the two countries and had profound consequences for the political, economic, and social landscape of the region. It remains a complex and unresolved issue, with ongoing diplomatic negotiations and efforts to de-escalate tensions.

After the beginning of this conflict in 2014, the military-industrial complex of Russia experienced significant shifts and developments. The conflict prompted an increase in defense spending and investment in the Russian defense industry (The Government of Russia, 2013). The government implemented policies to modernize and strengthen its military capabilities, leading to a surge in demand for military equipment and technology. This created opportunities for the domestic defense industry, which saw an expansion of production and increased contracts with the government. The conflict also brought attention to the defense sector's importance in national security and stimulated further cooperation between the military, government, and defense companies (The Government of Russia, 2013).

1.3 Political Attitudes and Electoral Outcomes

This narrative left a trace in the attitudes of citizens. Militarization of the economy and a growing emphasis on the martial sector were happening alongside shifts in the way people think about the world, which can be noticed from the national surveys (e.g., see

[1] For example, see Appendix, Figure A5.

Figure 3). For instance, from the left graph, the share of people answering "military power" as the first thing a person associates with the thought of the Russian people has increased significantly after the year 2014. At the same time, from the right graph, the same increasing pattern is observed with positive answers to the question "In your opinion, is the world afraid of Russia or not?". This evidence indicates that there was a notable increase in militaristic attitudes following the onset of the political conflict in 2014.

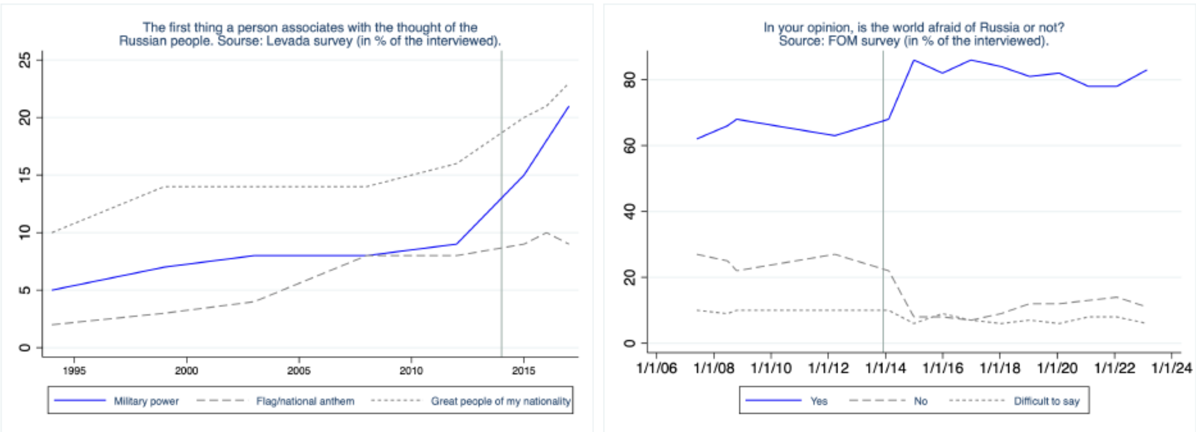


Figure 3: Evolution of Attitudes over Time in Russia

Data source: Levada Analytical Center, Russian non-governmental research organization.
Note: the left panel plots the evolution of answers "military power", "flag/national anthem", and "great people of my nationality" to the question "What is the first thing a person associates with the thought of the Russian people?" over time. The right panel plots the evolution of positive and negative answer percentages to the question "In your opinion, is the world afraid of Russia or not?" (with some fraction left unanswered).

Along with that, the support of the government and of the overall political situation in the country has been increasing with time (see Figure 1). Before the beginning of the described events, in the most recent 2012 presidential election, the incumbent candidate won with a share of 63.60%, while after – in the 2018 election – with a share of 76.69%.[2] The full list of candidates and electoral outcomes over the years is presented in Table A2 in Appendix. Electoral statistics and political surveys are not fully trustworthy (Enikolopov et al., 2013), especially in autocratic regimes (Egorov and Sonin, 2021; Guriev and Treisman, 2022), but it gives some understanding of the dynamics in the political views and attitudes. The rise in governmental approval in Russia in 2018 reflected the complexity of political, economic, and social factors, shaping the perceptions and attitudes of the population towards the government.

[2]The turnout has increased only slightly (2%). Source: Central Electoral Commission, Russia.

Overall, the events of 2014 were correlated with a significant rise in governmental approval in Russia. There was a notable surge in patriotic sentiment among the citizens (Carnegie Endowment for International Peace, 2019; Vedomosti, 2019). The conflict served to rally support behind the government, resulting in a temporary boost in approval ratings (see Figure 1). In this study, I aim to address this relationship empirically, using the data I describe in the subsequent section.

2 Data

The data I employ for the empirical analysis are coming from three separate sources. The first part constitutes the electoral data (Central Electoral Commission of Russian Federation, 2021). This dataset is comprehensive and contains voting results of all the Russian federal elections. The data are collected at the most disaggregated level – polling station – a specific place, often a school, where an election takes place. It captures all the electoral outcomes, as well as the number of registered voters, and the turnout.

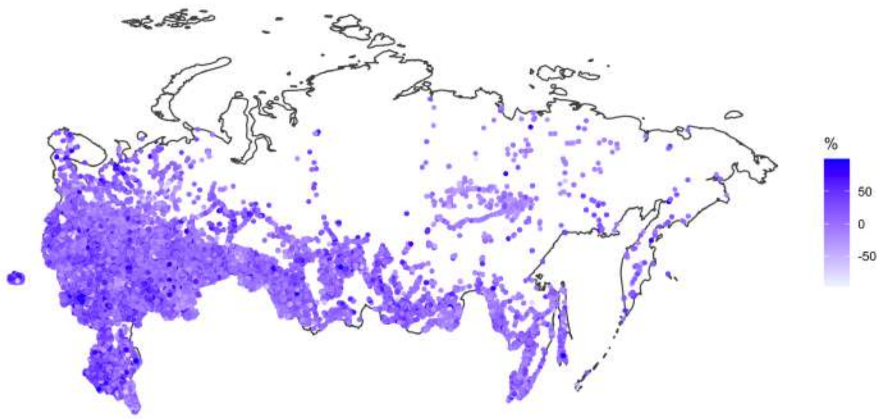


Figure 4: Spatial Heterogeneity of the Shift in Incumbent Votes in 2012-18

Data source: Central Electoral Commission of Russia and Geographic Information Systems Laboratory.
Note: observations are restricted to the range from a -100% to a 100% change.

The second part includes geographical coordinates of Russian voting polling stations over the years. Their addresses come from the GIS (Geographic Information Systems)

Laboratory, and further Google API services are used to obtain the station-level coordinates (GIS-Lab, 2021). For instance, if we merge the datasets of 2012 and 2018 years, we can obtain the following graph: Figure 4 above depicts the spatial distribution of a growth rate in incumbent vote share from 2012 to 2018 on the map of Russia. It can be inferred that this measure varies greatly by location, and it represents a crucial motivation for the current analysis. The research question raised in this study is based on this geographical heterogeneity, and it aims to investigate if the proximity to defense industry entities contributed to this geographical variation in electoral leanings.

Finally, the third dataset contains information on the defense factories, research, and design establishments of the Soviet Union – the addresses, names of the representatives, dates of opening, and closure, if observed (Dexter and Rodionov, 2022). I geocode the addresses into coordinates using the Google API services. In Figure 5 below, these enterprises are plotted on the map of Russia.

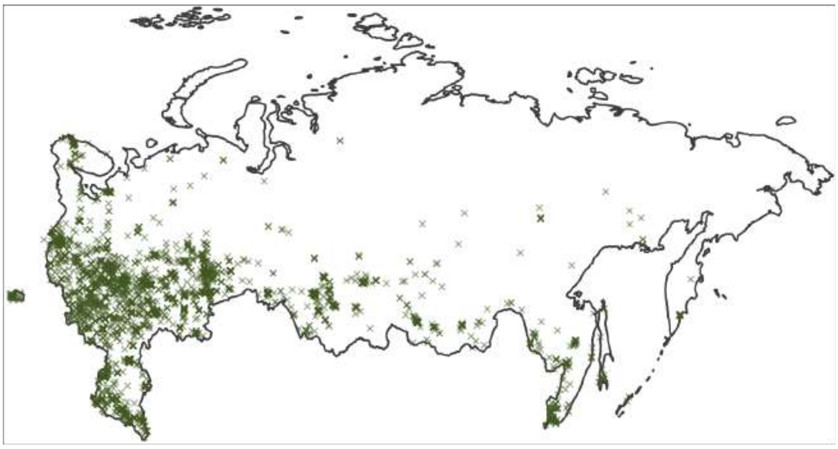


Figure 5: Soviet Enterprises of the Defense Industry in Russia

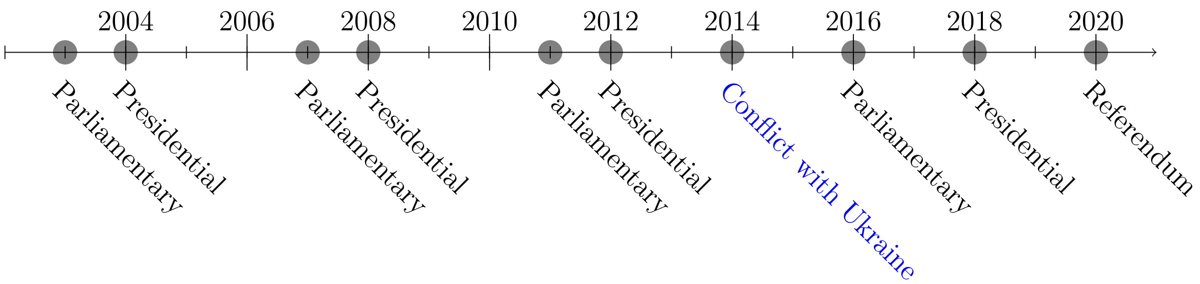
Data source: Dexter and Rodionov (2022).

The factories tend to be more prevalent in the South-Western region of the map, which is attributed to the sparsely populated territories in the North-Eastern part of the country (Geo-ref.net, 2021). For this reason, voting polls also tend to appear less frequently there (see Figure 4).

Finally, demographics and labor market characteristics at the municipal level come from the Rosstat database (Federal State Statistics Service of Russian Federation, 2022).

3 Empirical Strategy

The timeline of the federal-level Russian elections that I use in this study is presented below. Table A2 in Appendix displays the specific electoral outcomes over the years. Importantly, throughout the entire period of the analysis, one single party (the "United Russia") consistently emerged as the winner of the federal elections, subsequently forming the ruling government.



In this thesis, I am focusing only on the presidential elections of the years 2004, 2008, 2012, 2018, and the Russian constitutional referendum in 2020. By removing the parliamentary elections, I take into consideration that people may behave differently when selecting a head of state compared to choosing a party for the parliament. By including the 2020 election, I aim to expand the range of existing periods. For this election, to measure governmental approval, I am considering the number of votes in favor of constitutional modifications which were initiated by the incumbent political party.

Onward, I refer to the "exposure" of a polling station to a defense enterprise as being located within a minimum distance of 6 kilometers from the closest enterprise. Robustness checks exploring various thresholds for this distance are provided in Appendix. The findings presented in the main analysis remain robust across different choices of the exposure threshold.

After constructing a panel of polling stations over the period of 2004-2018[3], I proceed with an empirical analysis at the disaggregated level of polling stations. It is based on the multiple period difference-in-differences strategy; the framework is presented in Equation 1 below:

$$\text{Y}_{pmt} = \beta_t Year_t \times Exposed_p + \mu_p + \sum_t \alpha_t Z_p \gamma_t + \theta_m \gamma_t + \varepsilon_{pmt} \tag{1}$$

[3]The details are presented in Appendix.

The dependent variable represents the logarithm of votes received by the incumbent presidential candidate in each voting poll p of the municipality m in the election year t. The parameters of interest are β_t: for $t < 0$ they stand for the parallel pre-trends evidence; for $t \geq 0$ they indicate the effect of being exposed to the defense enterprise after the political conflict in 2014. Z_p indicates the number of people attached to the voting poll p fixed at the pre-conflict level (specifically, in 2012); this measure is interacted with year dummies. I add polling stations fixed effects μ_p to the specification in order to capture the unobserved heterogeneity of voting polling stations that is constant over time. γ_t stands for year fixed effects, reflecting fluctuations in electoral outcomes which are common among all the stations each election year. By adding the municipality fixed effects θ_m, interacted with year dummies, I allow the neighborhoods to evolve along different electoral trends. Throughout the analysis, I cluster standard errors based on the level at which the exposure is defined. For instance, in the precinct-level analysis, the standard errors are clustered at the polling station level, while in the municipal-level analysis (further details are presented subsequently), they are clustered at the municipal level.

The identification assumption behind this empirical strategy is such that, absent the political conflict in 2014, voting polling stations that are close to a military production factory and those that are not, would have evolved along parallel electoral trends. Note that focusing only on defense enterprises that remain from the Soviet Union allows me to strengthen the empirical setting, since these factories are not strategically placed by the incumbent at each specific location.

In all the empirical specifications, I am controlling for the total number of eligible voters of each unit, via the variable Z_p. The importance of this step is illustrated in Figure 6: as one can note, when we switch our attention from the lower quantile of the "size" of the voting poll to the upper one, we observe an increase in the number of incumbent party votes. At the same time, the share of votes is decreasing, suggesting that the growth of the incumbent's supporters does not overcome the growth of his non-supporters; it is important to consider this factor in order to capture this relationship. To avoid the problem of adding bad controls to the linear regression, I fix the voters measure at the pre-conflict level of 2012 and incorporate interactions with time dummies.

For the second part of the empirical analysis, to mitigate potential idiosyncratic differences between the polling stations, I am aggregating the electoral data to the municipality

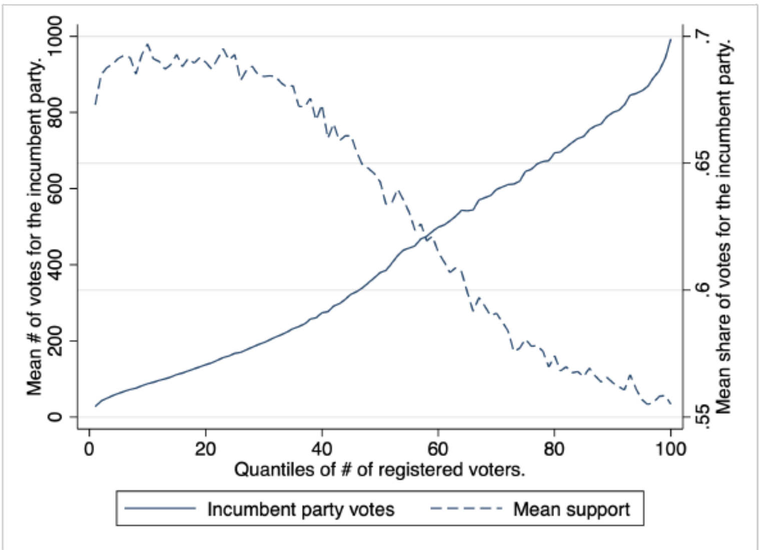


Figure 6: Number of Registered Voters and Electoral Outcomes

Data source: Central Electoral Commission of Russia.
Note: "Incumbent party votes" stands for the aggregate number of votes for the incumbent; "Mean support" refers to the vote share for the incumbent with respect to the total number of eligible voters.

(or neighborhood) level. In order to define exposure to the defense industry enterprises, I am calculating the shares of exposed eligible voters within a municipality in the total number of voters within this municipality (exposure being defined as in the polling station level analysis), and this measure of the "share of affected voters", or the "exposure share", is fixed at the year of 2012:

$$Exposure_m = \frac{\sum_{p \in Exposed} EligibleVoters_{pm}^{2012}}{\sum_q EligibleVoters_{qm}^{2012}}$$

In this context, I am employing a slightly modified specification of a heterogeneous treatment effect, outlined as follows:

$$\text{Y}_{mrt} = \delta_t Year_t \times Exposure_m + \mu_m + \sum_t \alpha_t Z_m \gamma_t + \theta_r \gamma_t + \varepsilon_{mrt} \quad (2)$$

where $Exposure_p$ stands for the fraction of people living in a municipality m who are exposed to the military unit in the close vicinity, in the total number of registered citizens. The dependent variable remains the same as previously mentioned: it represents the logarithm of votes for the incumbent presidential candidate in the municipality m during the year t. δ_t captures the effect of exposure to the industry over time. The variable Z_m includes the number of attached voters in the municipality m in 2012, and as before, it interacts with the year indicators. As in the previous specification, I add municipality fixed effects μ_m to capture time-constant unobserved heterogeneity of the units. θ_r stand for region-specific fixed effects, and they are interacted with year dummies to account for regional-specific differences in voting trend patterns.

With the municipal-level analysis, the identification assumption is slightly modified: absent the conflict in 2014, areas with high versus low levels of exposure to defense enterprises would have evolved along parallel electoral trends.

4 Results

This section is structured as follows. Subsection 4.1 presents the baseline results of the analysis conducted at the polling station level, which represents the most detailed level of granularity. Further, in subsection 4.2, the focus shifts to the aggregated level municipal analysis. Subsection 4.3 delves into empirical results and presents a decomposition analysis. In Subsection 4.4, the main findings are further validated by employing an instrumental variable approach.

4.1 Voting Polling Station Level

In this part of the empirical analysis, I am using the regression specification 1 described earlier in Section 3. The dependent variable is represented by the logarithm of votes received by the incumbent party, and the coefficients of interest are β_t's, which reflect the effect of exposure to a defense enterprise over time.

The results are displayed in Figure 7, with 2012 as the base year. They reveal that prior to 2014, we observe no statistically significant deviations from zero in the β_t coefficients, and this supporting evidence strengthens the parallel trend identification assumption. However, a notable increase is evident in the year 2018, where the coefficient becomes statistically significant and positive. The effect decreases in magnitude in the case of the constitutional referendum in 2020. This pattern can be attributed to a potential distortion of electoral outcomes due to the pension reform, which involved an increase in the retirement age and sparked widespread discontent among citizens. It was implemented in late 2018, being greatly unpopular among the population (BBC, 2018).

The electoral outcomes of other political parties are displayed in Figure A12 in Ap-

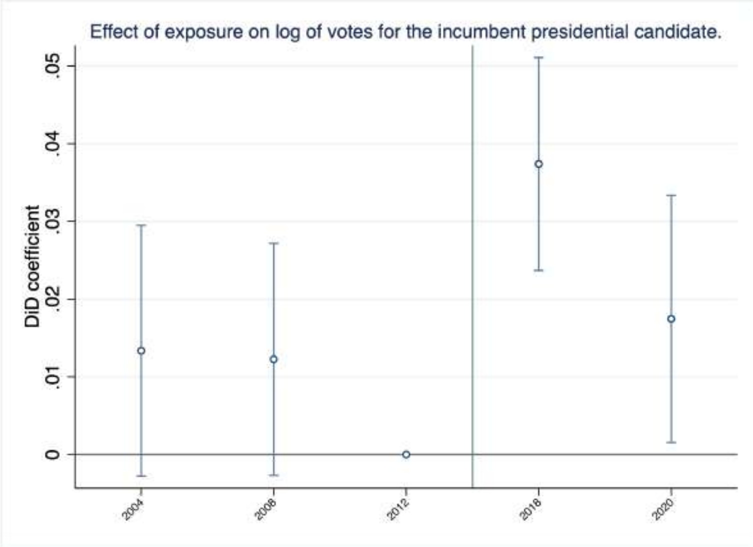


Figure 7: Effect of Exposure on Log of Votes for the Incumbent Presidential Candidate

Note: the graph depicts the evolution of coefficients from the specification 1 over the years. The dependent variable of the equation is the logarithm of aggregate votes for the incumbent presidential candidate. Standard errors are clustered at the voting poll level. N = 116,190 observations.

pendix. The empirical analysis indicates that the votes for the Liberal Democratic Party do not exhibit any significant effects across all periods examined. In contrast, the votes for the Communist Party consistently display an upward trend over the years.

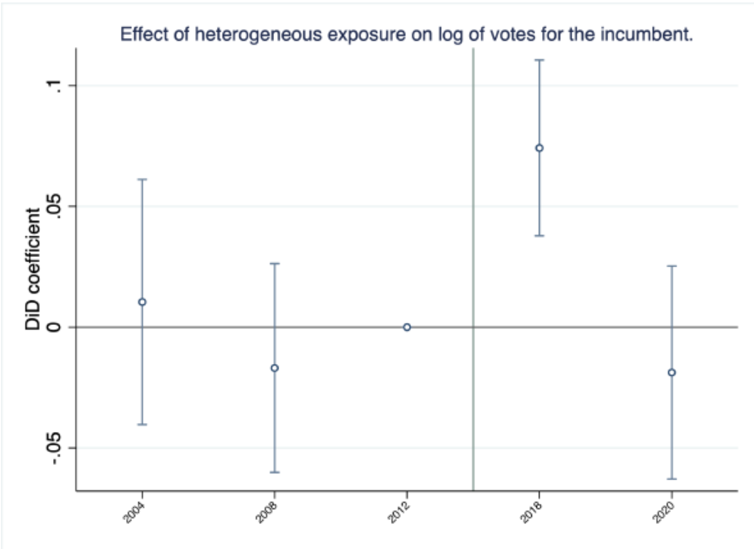
4.2 Municipal Level

A challenge with conducting a polling station level analysis is that merging these units with time and constructing a large panel dataset can incorporate statistical idiosyncratic errors, i.e. if voters switch to different precincts which are located adjacently. To address this concern, in the remaining part of the analysis, I aggregate the data into larger units known as "territorial electoral commissions", and map them into the municipalities of Russia. There are around 2,000 aggregated municipalities. The median number of polling stations within a single municipality is 324, while the mean stands at 565 precincts.[4]

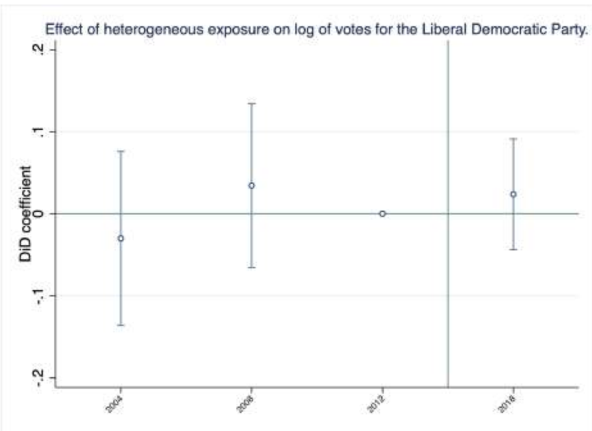
For the aggregated-level analysis, exposure to defense factories is defined as the fraction of exposed voters within a municipality in the total number of voters attached to these neighborhoods in 2012. In the resulting sample, 54% of the data sample has zero exposure share. For the remaining 46%, the exposure measure is greatly heterogeneous, with values

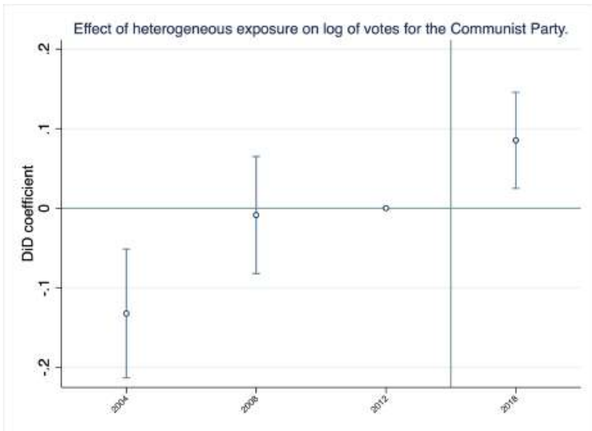
[4]To construct a valid sample for further analysis, I omit outliers, as described in Appendix. For this part of the analysis, I omit cases with complete exposure since, by construction, they tend to represent rather small neighborhoods.

varying from very low to very high numbers: the histogram is presented in Figure A7 in Appendix, and Figure A8 illustrates the spatial representation of this measure on a map of Russia, which highlights its variation across different areas. This spatial heterogeneity suggests that the obtained result is not solely driven by a specific geographical region.



Panel A: Incumbent Outcome





Panel B: Liberal Democratic Outcome *Panel C: Communist Outcome*

Figure 8: Effect of Heterogeneous Exposure on Log of Votes

Note: the graphs depict the evolution of coefficients from the specification 2 over the years. Panel A incorporates the dependent variable of the logarithm of aggregate votes for the incumbent; panel B refers to the logarithm of votes for Liberal Democratic candidate; panel C involves the Communist logarithm votes outcome. Standard errors are clustered at the municipality level. N = 8,031 (panel A) and 6,412 (panels B and C) observations.

In the empirical analysis, I proceed with the specification 2 of heterogeneous treatment effect. The key distinction from the polling station level analysis is that the exposure variable is no longer binary but continuous. Similar to previous cases, the dependent variable represents the logarithm of votes in favor of the incumbent candidate. The results from Figure 8, panel A (and Table A3 in Appendix, accordingly) indicate a positive effect in the year 2018, which is consistent with the previous findings. Insignificant effects prior to 2014 provide supporting evidence in favor of the parallel trend identification assumption. The results indicate that one standard deviation of exposure to Soviet military production enterprises is associated with a two percent increase in the number of votes for the incumbent presidential candidate in 2018.

Further, to understand if the effect shifts an electoral result of one specific party, or if it has polarizing patterns, in the empirical specification of heterogeneous treatment effects (see Equation 2), I am shifting the focus to the logarithm of votes for other presidential candidates as dependent variables. My specific objective is to examine whether there is an impact on the votes for the Liberal Democratic Party and the Communist Party of Russia, which were the only parties consistently listed on the ballot (see Table A2 in Appendix).[5] The results are depicted in Figure 8, panels B and C. For the Liberal Democratic Party, the effects are not statistically different from zero for all the analyzed periods. However, for the Communist Party, there is a growing trend of votes over the years, which is consistent with the results presented at the polling station level. Notably, the 2018 presidential campaign of the Communist Party encompassed such statements as ensuring the defense capability and security of the country, as well as establishing regulated prices for basic food items, commodities, and even housing (Communist Party of the Russian Federation, 2018). Over the observed periods, the party's platform continued to advocate for socialist policies and critiqued the direction of Russia's market-oriented reforms (Forbes, 2011). These patterns potentially offer some insights into the observed effects.

4.3 Decomposition Analysis

In the preceding analysis, I am considering the logarithm of votes for the incumbent presidential candidate as an outcome of interest. However, what lies beneath this measure of electoral approval? To further explore this measure and understand factors contributing to the observed effect, I start with examining a basic identity and then proceed by decom-

[5]For the 2020 constitutional referendum, I can only construct the measure for the incumbent's approval.

posing the logarithm vote gap. By construction, the number of votes for the incumbent equals the following product:

$$\text{Votes}^{\text{I}} = \frac{\text{Votes}^{\text{I}}}{\text{Voted}} \times \frac{\text{Voted}}{\text{Voters}} \times \text{Voters}$$

Taking logarithms on both sides,

$$\text{Log}(\text{Votes}^{\text{I}}) = \text{Log}\frac{\text{Votes}^{\text{I}}}{\text{Voted}} + \text{Log}\frac{\text{Voted}}{\text{Voters}} + \text{Log}(\text{Voters})$$

If we take the difference between the “exposed” group and the “control” group (i.e., the logarithm vote gap), this measure can be decomposed into three components:

$$\overbrace{\Delta\text{Log}(\text{Votes}^{\text{I}})}^{\text{Logarithm Vote Gap}} = \underbrace{\Delta\text{Log}\frac{\text{Votes}^{\text{I}}}{\text{Voted}}}_{\text{Political Support}} + \underbrace{\Delta\text{Log}\frac{\text{Voted}}{\text{Voters}}}_{\text{Political Participation}} + \underbrace{\Delta\text{Log}(\text{Voters})}_{\text{Relocation}}$$

Thus, the effect on the logarithm of votes for the incumbent candidate observed in 2018 can be driven by three separate sources: change in electoral approval (shift in the incumbent vote share), change in political participation (shift in turnout), and change in the number of people registered to vote (shift in the composition of municipalities). To further understand the effect from the first panel of Figure 8, I am using the “support” measure as the dependent variable (calculated as the fraction of the overall municipal votes for the incumbent in the aggregated municipal turnout) and weigh the regression from the specification 2 by the size of each municipality. The results are presented in Figure 9, and Table A4 in Appendix, respectively. The dependent variable now represents the measure of governmental support described above, while the treatment variable remains heterogeneous, defined as the proportion of exposed voters among the total number of registered citizens within a municipality. The patterns remain similar if the outcome is taken in logarithm (see Figure A13 in Appendix).

Figure 9 displays a slightly declining trend leading up to the “treatment” period of 2014. This observation suggests that the level of government support may have been gradually decreasing over time in more exposed areas. However, following the conflict in 2018, there is a slight positive effect on the vote share for the incumbent party in municipalities where a higher proportion of eligible voters are exposed to defense enterprises. The existence of a pre-trend poses challenges in interpreting the post-conflict effect in the difference-in-differences framework, suggesting a possible violation of the parallel trends identification assumption. Hence, to obtain a more accurate interpretation of the effect, I employ the synthetic difference-in-differences strategy in the subsequent analysis.

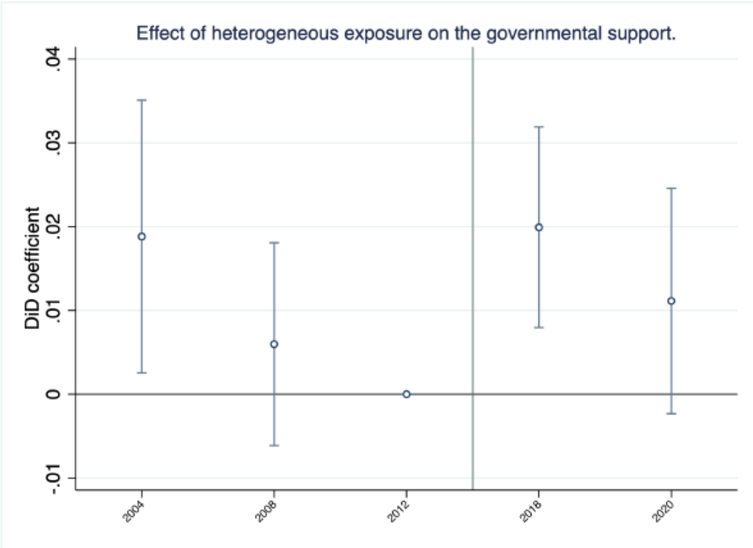


Figure 9: Effect of Heterogeneous Exposure on Governmental Support

Note: the graph depicts the evolution of coefficients from the specification 2 over the years. The dependent variable of the equation is the vote share (with respect to turnout) for the incumbent candidate. Standard errors are clustered at the municipality level. N = 8,031 observations.

The synthetic difference-in-differences technique was first introduced in Arkhangelsky et al. (2021): it aims to overcome the limitations associated with the traditional difference-in-differences approach when estimating treatment effects. This procedure addresses the parallel trends assumption by constructing a "synthetic" control group that approximates the counterfactual scenario of what would have happened to the treatment group if they had not been exposed to the policy. In this framework, the synthetic control is constructed by combining different characteristics of existing control units and weighting them to best match the pre-treatment outcome trends of the treatment group. Thus, by construction, the synthetic control closely matches pre-trends of the treated, or exposed in the context of this study, group. By employing this strategy, we are able to construct a well-grounded counterfactual scenario for highly exposed municipalities (i.e., above the 75th percentile of the exposure share distribution).

Given the existence of pre-trends in Figure 9, I proceed with the synthetic difference-in-differences estimation approach. This methodology does not allow for using the heterogeneous treatment variable, so I construct a binary variable that takes the value of one if this measure is above the 75th percentile of the exposure variable distribution.[6]

In this part of the empirical analysis, I am focusing solely on the periods corresponding to the presidential elections of 2004, 2008, 2012, and 2018. This selection is made because previous specifications have not yielded significant effects for the constitutional referendum in 2020. The synthetic difference-in-differences analysis is conducted on the balanced panel of municipalities, suggesting that the effects are not driven by the change in sample composition over time. From the decomposition analysis in the previous subsection, we know that the difference in the logarithm of votes stems from three separate components: support, turnout, and number of voters. I proceed with the synthetic difference-in-differences strategy, focusing on the logarithms of each component separately. I keep other terms in covariates, taking pre-treatment values, to keep them constant in evaluating the effect in 2018.

Table 1: Synthetic DiD Estimator, Presidential Elections

	(1)	(2)	(3)	(4)
Dependent Variable (Logs):	Incumbent Votes	Support	Turnout	Eligible Voters
ATT	0.037***	0.007***	0.001	0.027***
	(0.007)	(0.002)	(0.003)	(0.007)
# obs.	5,732	5,732	5,732	5,732
Years	4	4	4	4
Municipalities per year	1,433	1,433	1,433	1,433
Support as a covariate	Yes	No	Yes	Yes
Turnout as a covariate	Yes	Yes	No	Yes
Eligible voters as a covariate	Yes	Yes	Yes	No

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: inference is based on 1,000 bootstrap replications.

Treatment is defined as above the 75th percentile of exposure share distribution.

The results are presented in Table 1: they are robust to including demographic controls as covariates.[7] As can be seen from column 1 of Table 1, the effect on the logarithm of incumbent votes in 2018 remains statistically significant and positive with this estimation procedure. This finding aligns with the results obtained from alternative specifications discussed in earlier subsections. For the logarithm of the support component, we observe

[6]Figure A9 in Appendix plots the distribution of the exposure variable. This treatment group definition is robust to using the median or zero value as thresholds (see Tables A5 and A6 in Appendix).

[7]Share of elderly citizens, female share, and local average wages, see Table A7 in Appendix.

a positive effect (Table 1, column 2). At the same time, the logarithm of turnout (column 3) does not exhibit a statistically significant effect, whereas the logarithm of attached voters demonstrates a positive and statistically significant effect (Table 1, column 4).

These findings suggest that the logarithm vote gap revealed in the first part of the analysis is driven by two separate components. The first one is a change in the number of eligible voters, indicating the shift in the composition of the municipalities. The observed result could be attributed to the relocation of voters, if defense enterprises started to "attract" citizens with higher salaries and better living conditions, or higher expected job opportunities. During that period, the government implemented various policies to support the defense industry, including enhancing vocational education and training programs to develop a skilled workforce. According to official governmental reports in 2018, a particular emphasis was placed on the employee policy within the defense industry; the standards of living were on the rise, and specific measures were implemented to address the housing concerns of the defense industry workers (The Government of Russia, 2018). Moreover, according to the official parliamentary report in 2018, the share of young people under the age of 35 among defense industry employees had increased from 20% to more than 30% and continued to grow; at the same time, the level of wages of workers in the military-industrial complex exceeded the level of wages in the industry as a whole (The Government of Russia, 2018). This could be one potential explanation for the positive effect observed in column 4 of Table 1.

The support component presents a particularly interesting outcome (Table 1, column 2). We observe a positive and statistically significant effect for the measure of governmental approval after the beginning of the political conflict between Russia and Ukraine, specifically for municipalities above the 75th percentile of exposure distribution. As a result, the incumbent government gained relatively more electoral approval from these highly exposed neighborhoods in 2018.

4.4 Instrumental Variables

The nowadays geographical distribution of economic industries in Russia takes its roots in the Soviet era. The country's primary industrial facilities tend to be inherited from institutional formations back then. For instance, the region of Lipetskaya Oblast vastly relies on steel production due to the presence of Novolipetsk Steel, the third largest steel plant in Russia that was established in 1934 (Ananyev and Guriev, 2019). This inheritance of economic activity over the years is called the "path dependence" of economic activity: it is common in various countries over the world. For instance, Krugman (1991) argued that the geographical distribution of manufacturing in the United States dated back to the agricultural settlements established during the early colonial period in the Northeastern region. As for the Soviet rhetoric, Mikhailova (2012) indicated that the development of Russian geographical areas was significantly impacted by Stalin's industrial policy, leading to long-run effects. The historical data used in this paper includes defense enterprises that have been in operation since the year 1920 (see Appendix, Figure A6).

Exposure to the defense industry can be correlated with other characteristics that might affect political attitudes and, at the same time, vary with time. This suggests that the fixed effects of the difference-in-differences specifications may not fully account for these peculiarities. For example, in the main analysis, the calculated exposure shares are considering the composition of geographical areas in 2012, specifically, the population residing within municipalities at that time. However, citizens could migrate and relocate over time, leading to instability of this measure across different periods.

To account for this issue, I am implementing an instrumental variable approach and proceeding with a two-steps-least-squares estimation strategy. In their paper, Ananyev and Guriev (2019) used the survey of industrial enterprises of 1989 and derived the Soviet capital goods employment structure as the shares of employment for each Russian region back in 1898. I am using these data and focusing on the industries with Standard Industrial Classification (SIC) indices of 35 and 13, standing for the "Industrial Machinery and Equipment" and the "Oil and Gas Industry", respectively.

As can be inferred from Figure 10, exposure shares that I use in this study tend to be strongly correlated with both the Industrial Machinery and Equipment 1989 Soviet employment share, and the Oil and Gas Industry 1989 Soviet employment share. From the first column of Table 2, the F-statistics of the 1^{st} stage regression equation constitutes 150.99, indicating the relevance of the instruments employed in the analysis, and suggesting that the inclusion restriction of the instruments is satisfied. This result indicates that the measure of exposure to the defense industry calculated in the municipal level analysis is indeed relevant, reflecting local institutional and industrial peculiarities traced back to the Soviet-time plants' location.

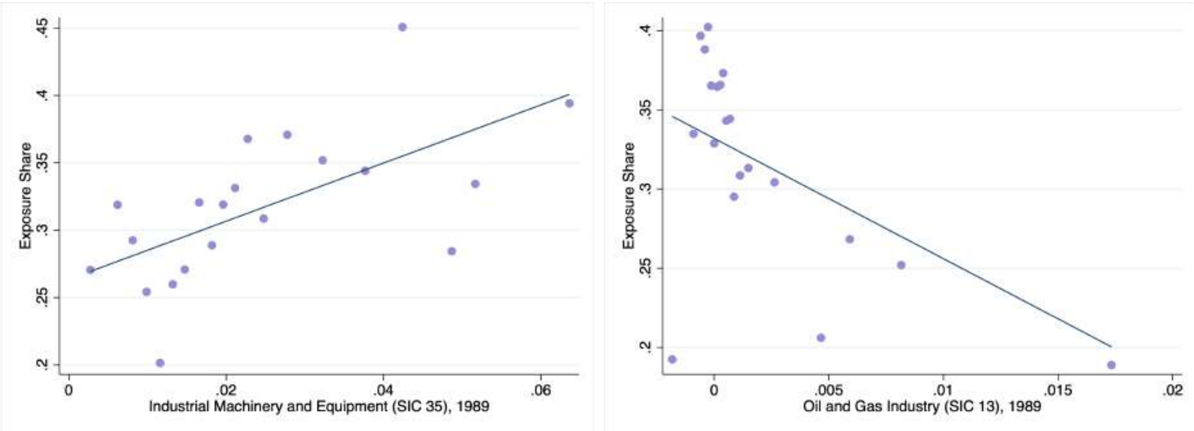


Figure 10: Heterogeneous Exposure and 1989 Soviet Employment Structure

Note: the left panel plots the relationship between the constructed exposure share and the Industrial Machinery and 1989 Equipment Soviet employment share; the right panel depicts the correlation between the constructed exposure to military production and the Oil and Gas Industry 1989 Soviet employment share.

Secondly, in order to ensure the validity of instrumental variables, they must meet the exclusion restriction condition. Since the Soviet regional employment structure in this framework dates back to the year 1989, it is reasonable to assume that these measures are exogenous to electoral outcomes in the 2000s and affect political attitudes only via the presence of existing industrial facilities. Finally, the last one is the monotonicity condition, suggesting that the instruments should affect all municipalities in the same direction (Mogstad et al., 2021).

The results of the estimation are presented in Table 2, columns 2-7. In all the regressions, I am controlling for such demographic variables as the logarithm of local wages, the share of the elderly local population, and the share of females. Additionally, I am controlling for the number of attached voters in 2012, to keep the size of each municipality constant when estimating the electoral effect. For columns 2-3, the dependent variable represents the growth rate of aggregate votes for the incumbent presidential candidate in 2018. We observe that while the OLS estimation does not yield statistically significant results for this outcome, the coefficient for the 2SLS estimation procedure is statistically significant at 10% level and positive. For the growth in support outcome (Table 2, columns 4-5), the OLS estimate is not statistically significant, while the 2SLS estimate demonstrates a positive coefficient with significance at 1% level. For turnout, (Table 2, columns 6-7), the coefficients are not statistically significant either for OLS or

2SLS estimation procedures.

Table 2: OLS and 2SLS Approaches

Dependent Variable:	Exposure	2012-2018 Growth in Incumbent Votes		2012-2018 Growth in Support		2012-2018 Growth in Turnout	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	1^{st} stage	OLS	2SLS	OLS	2SLS	OLS	2SLS
1989 Industrial Machinery and Equipment Employment Share	1.801**						
	(0.823)						
1989 Oil and Gas Industry Employment Share	-6.397**						
	(2.552)						
Exposure		0.064*	0.696*	0.053***	0.615*	-0.021	0.311
		(0.033)	(0.372)	(0.019)	(0.318)	(0.016)	(0.199)
# obs.	1,896	1,896	1,896	1,896	1,896	1,896	1,896
Eligible voters control	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Demographic controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F-stat., 1^{st} stage	150.99						

Standard errors in parentheses, clustered at the regional level (the level of instruments' variation).
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Overall, the IV approach validates the direction of the effect observed in the main analysis. The results indicate that the effects on the votes for the incumbent, as well as the vote share, are persistent when I use a "cleaner" variation, which is explained solely by the employed instrumental variables, namely, factories' location coming from the differences in the local Soviet-time employment structure.

5 Discussion of the Mechanisms

Based on the empirical findings, there is a notable relationship between exposure to a Soviet military production plant and a significant increase in support for the regime, particularly following the onset of the political conflict in 2014. These results can be attributed to various possible explanations. The first one revolves around the institutional channel, which suggests that individuals residing in close proximity to these enterprises might hold more militaristic attitudes toward other countries (e.g., see Figure A5 in Appendix) and place a greater emphasis on the military sector's significance within the economy. This could lead to intensive rally-around-the-flag effects in close areas. The existence of this channel could be tested by examining the geographical distribution of political attitudes in Russia. Theoretically, these data could be obtained from the public opinion poll "Levada-Center", the only independent polling research organization in Russia. However, the geographical distribution of responses to political questions is not publicly available. This empirical question and a test of this possible institutional mechanism of the electoral effects are subject to further research, with comprehensive data on political attitudes and geographical components.

The phenomenon of electoral fraud is a prevalent occurrence, particularly in areas with non-democratic institutions (Egorov and Sonin, 2021). Specifically, there is a piece of empirical evidence suggesting that there is a certain extent of electoral manipulation in Russia. In the paper of Enikolopov et al. (2013), by focusing on the Russian parliamentary elections in the city of Moscow, the authors indicated that the magnitude of the fraudulent activities was significant enough to greatly influence electoral outcomes. If the degree of this manipulation varies geographically and is correlated with the presence of the defense enterprises, this could inflate the estimated effect of the exposure to a military enterprise, and be a potentially relevant mechanism driving the findings from this study (Hong and Park, 2016). To test this channel empirically, I refer to the article of Klimek et al. (2012) and construct the measure of statistical electoral manipulation. Authors argue that extreme fraud is characterized by reporting full voter turnout and a majority of votes in favor of a single party. For instance, this phenomenon can be observed in the data that I use in this study (see Figure 11, left panel).

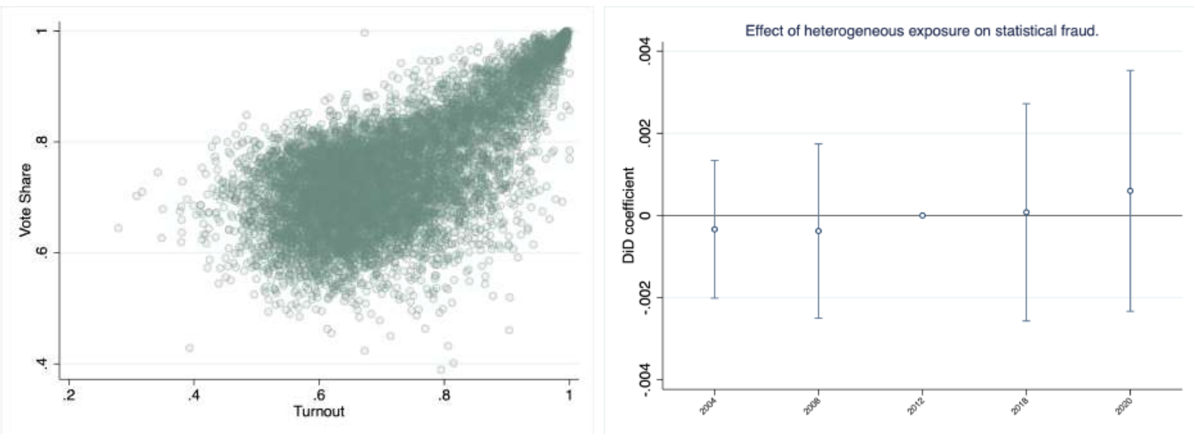


Figure 11: Effect of Exposure on Statistical Manipulation

Note: the left panel plots correlation between turnout and the incumbent vote share; the right panel illustrates the evolution of estimates from 2 over the years, where the dependent variable is the dynamic measure of statistical manipulation, constructed as in Klimek et al. (2012). Standard errors are clustered at the municipality level. $N = 8{,}031$ observations.

Units usually cluster around a given turnout and vote percentage level, for instance, in such countries as France, Austria, or Switzerland (Klimek et al., 2012). The two-dimensional scatterplot (Figure 11, left graph) reveals that these clusters are spread out towards the upper right section, reaching a peak at a 100% turnout and 100% of vote share. The observed statistical pattern suggests the potential existence of electoral fraud in the data (Klimek et al., 2012). To investigate if this could speak to the empirical findings of this study, I proceed with the same multiple periods difference-in-differences framework, focusing on the fraction of suspicious occurrences in the data over time. In particular, I am calculating the share of voting polls within each municipality with both the turnout and the vote share of 70% and higher. The results are presented in the right graph of Figure 11. These findings are robust to choosing different thresholds of statistical manipulation (see Appendix, Figure A14). We observe no statistically significant differences in the extent of electoral fraud between territories with low versus high exposure to military production over time. This finding supports the conclusion that electoral fraud does not explain the effects on voting behavior observed in the main analysis.

The effects of exposure to the Soviet-time defense industry on electoral results could be driven by the local labor market channel. If the factories still functioned and the local employment structure persisted, with high shares of defense industry employment within higher exposed areas, these enterprises could affect the local economic environment and indirectly influence electoral outcomes after the beginning of the political conflict. This could happen through the channel of increased demand for military goods or higher salaries of employees of defense organizations (The Government of Russia, 2018). Due to data limitations, I cannot test this mechanism with causal interpretation. However, I can present some descriptive evidence speaking to this channel.

In Figure 12, I plot the relationship between the constructed share of exposure to Soviet defense enterprises and the average monthly wages in rubles in 2018. The municipal statistics on wages are coming from the Rosstat database (Federal State Statistics Service of Russian Federation, 2022). The left graph shows the raw relationship, while the right graph depicts the relationship controlling for the size of the municipalities in terms of the number of registered citizens eligible to vote. The strongly positive correlation is evident from the observed data, with a higher share of exposure to defense enterprises associated with higher average monthly wages in 2018.[8] While this empirical evidence does not allow us to make a causal interpretation, it gives us some important descriptive evidence. This mechanism relates to the paper of Finan and Schechter (2012) who showed that receiving money from the government may engender feelings of obligation within the electorate, this, in turn, influence politicians target reciprocal individuals. As a result, governments may prioritize the allocation of funding to regions or areas that have a stronger economic significance or potential.

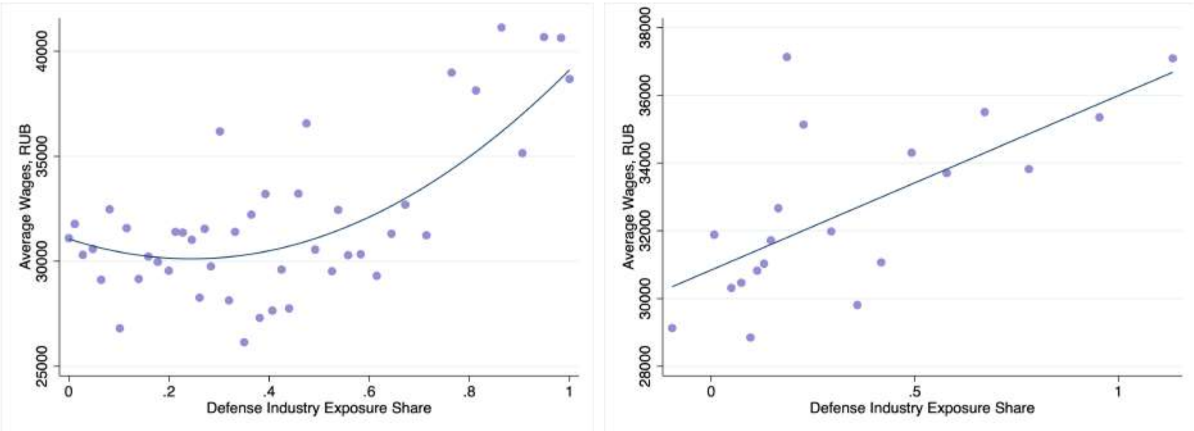


Figure 12: Exposure Share and Average Monthly Wages in 2018

Note: the left panel plots the relationship between the constructed share of exposure to the defense industry and average wages in rubles in 2018 at the municipal level; the right panel illustrates the same relationship but controlling for the municipality size.

Several conclusions can be drawn from the findings. First, electoral fraud is unlikely to drive the effect of exposure to Soviet-time military enterprises. The hypothesis that the rise of electoral support is explained by increased electoral manipulation within municipalities of higher exposure to the defense industry is rejected. Secondly, the local labor market emerges as one potential explanation for the impact on electoral outcomes observed in the main empirical analysis. Since defense industry exposure is associated with higher levels of local wages after the conflict, it is plausible that this economic variable may serve as a mediator for the rise in governmental approval within these highly exposed neighborhoods. Finally, an alternative explanation posits a cultural, or institutional, mechanism. The revealed effects could be driven by shifts in rally-around-the-flag

[8]At the same time, this relationship is not driven by the fact that neighborhoods with higher salaries exhibit greater levels of governmental approval.

effects in the exposed areas, leading to more militaristic attitudes and stronger approval of the incumbent government. Unfortunately, measuring political attitudes, cultural features, and institutional aspects at a very granular level presents certain challenges, and it constitutes an important and interesting question for future research.

Conclusion

This study aims to investigate the role of the military-industrial complex of Russia in the significant surge of governmental approval following the beginning of the Russia-Ukraine conflict in 2014. To explore this relationship, I utilized a historical dataset with the geocoded coordinates of Soviet-time defense enterprises located in Russia. This dataset was combined with highly precise electoral data at the local level of voting polling stations. To examine the relationship between military production plants and electoral outcomes empirically, I employed a difference-in-differences framework, comparing polling stations in the vicinity of an old military enterprise with those located elsewhere, both before and after the armed conflict in 2014. The underlying assumption behind this strategy is that, in the absence of the conflict, polling stations without nearby defense factories and those exposed to such facilities, would exhibit similar electoral trends.

The second part of the empirical analysis was conducted with the aggregated data of municipalities. I constructed a measure of municipal exposure to Soviet military production and employed a multiple periods difference-in-differences strategy with the continuous treatment variable. The main findings indicate that, following 2014, the higher degree of exposure to military plants was associated with a significantly higher level of support for the current regime. In particular, one standard deviation in the share of exposure to the defense industry was associated with a two percent increase in the number of votes for the incumbent candidate during the 2018 presidential elections.

Along with the standard difference-in-difference estimation, I employed an instrumental variable approach, leveraging the more precise variation of exposure to the defense industry. Following Ananyev and Guriev (2019), I use data on Soviet-time employment structure, specifically, the employment shares of the "industrial machinery and equipment" and the "oil and gas" industries of 1989. I use these variables as instruments for the constructed exposure shares: my novel measures turn out to be strongly correlated with the instrumental variables, which supports the "path dependence" hypothesis. I claim that the employed instruments satisfy the exclusion restriction: most likely, the Soviet-time employment structure affects post-conflict electoral outcomes only via exposure to preserved defense factories. The 2SLS estimation procedure confirms the direction of the effect observed in the main analysis.

Additionally, I decompose the logarithm vote gap observed in the findings into three separate components: a shift in governmental support, a shift in political participation, and a shift in municipal composition. I employ the synthetic difference-in-differences framework, and the results suggest that two components are contributing to the vote gap: an increase in support for the incumbent government, and a compositional change. This might suggest that the enterprises started to attract people during that period, perhaps due to increased wages (e.g., see Figure 12) or associated social policies such as housing subsidies for defense industry employees (The Government of Russia, 2018), and at the same time shift local levels of governmental approval.

Importantly, the discussion of potential mechanisms reveals that the observed effect is unlikely to be attributed to the electoral fraud channel. The data did not provide any evidence indicating that the degree of statistical electoral manipulation varies over time within low versus highly exposed municipalities. One potential channel explaining the effect relates to labor market features. The continued operation of these defense factories could impact the local economic environment, which, in turn, indirectly could shape electoral outcomes in the aftermath of the conflict. For example, this relationship could manifest through the surge in average wages within the sector (The Government of Russia, 2018) or increased demand for military goods after the beginning of the political conflict (The Moscow Times, 2014). These factors might contribute to a favorable perception of the regime among individuals who benefit from employment opportunities or economic growth generated by the military-industrial complex. Simultaneously, the augmented production within this sector could serve as an informative signal regarding the government's objectives, including the potential implications of further military conflicts.

The proximity to the Soviet-time military production and the degree of exposure to these defense enterprises was indeed related to the formation of electoral approval of the government within the population, particularly in times of political tension.

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Appendix

List of Figures in Appendix

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Sample Construction

Construction of the electoral panel at the most disaggregated level involves several technical steps and granular work with the data. For the years after 2012, I merge voting polls by geography, using the time-specific coordinates of the precincts. For every voting poll in year t, I attach the closest voting poll in year $t+1$ using geographical coordinates. I exclude merged pairs in cases where the closest pair in another period exceeds a distance of 5 km, indicating a potential erroneous match. Due to limitations in the available data, we are unable to employ the same strategy of merging polls prior to the year 2012. To construct the panel for the earlier years, I merge voting polls based on the region and precinct identifier. To proceed with the panel construction for years prior to 2012, it is necessary to assume that the pairs "region-identifier", which serve as unique identifiers for voting polls, remain stable over time. As a result of this process, I obtained a balanced panel of presidential elections of a total of 49,278 observations each year.

Further, I proceed with cleaning the merged observations. For the following empirical analysis, from the resulting sample, I eliminate outliers that display variations of more than 50% in the number of registered attached individuals who are eligible to vote at a specific location. I incorporate this step as a precautionary measure to verify the accuracy of the merge over the years. Additionally, I omit outliers in terms of the number of voting polls higher than 5,000 units within a municipality. Figure A1 illustrates the resulting histogram, displaying the growth rate in attached eligible voters over all the available periods. As evident from the graph, the growth in the number of voters at the aggregated municipal level appears to be more stable, with a mass concentrated closer to zero. This indicates that the process of aggregation helps mitigate idiosyncratic precinct changes and potential erroneous matches. Consequently, a significant portion of the subsequent empirical analysis is conducted using aggregated data at the municipality level, rather than at the level of individual voting polls.

Finally, I constrain the data and remove outliers in terms of the unit size. For the analysis conducted at the polling station level, the focus is limited to the polling stations with up to 2,000 attached voters (Figure A2, left panel), and for the aggregated analysis, municipalities with a population of 80,000 people or fewer are retained for the analysis (Figure A2, right panel).

The presence of Soviet military enterprises is determined using a binary variable that equals one if a voting poll is located within a 6-kilometer radius of an enterprise (the results obtained from alternative threshold definitions are provided in Appendix for reference). When conducting the analysis at the voting poll level, approximately 25.55% of the precinct units included in the panel were identified as being exposed to these military enterprises.

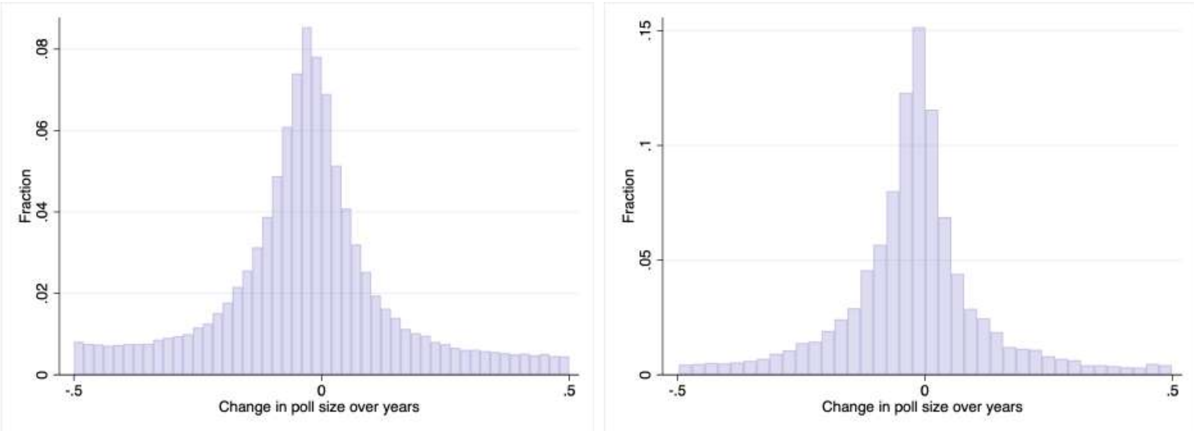

Figure A1: Histogram of Growth Rate of Eligible Voters

Note: polling station level and aggregated level, respectively.

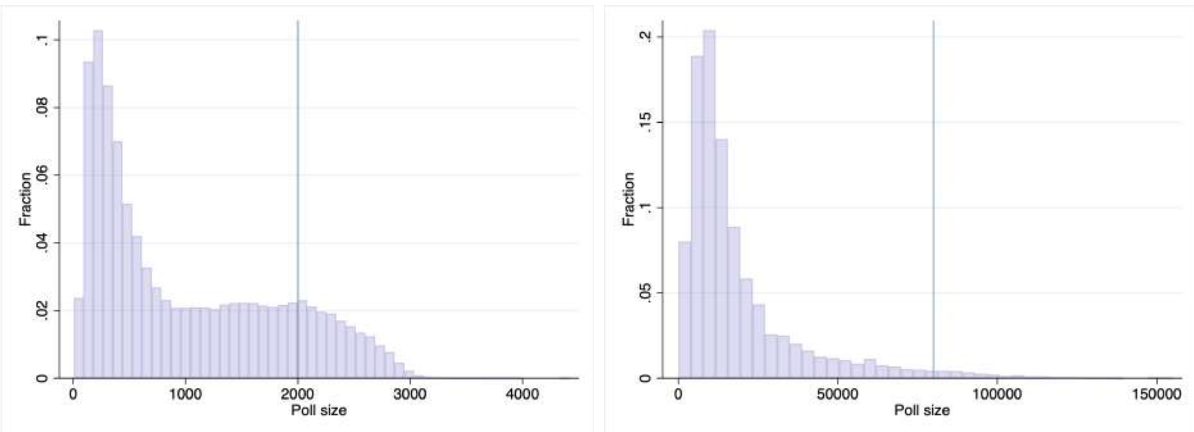

Figure A2: Histogram of the Number of Eligible Voters

Note: polling station level and aggregated level, respectively.

Propensity Score Matching

As a robustness check, to compare the electoral outcomes of similar municipalities, I am employing the propensity score matching estimation approach. In particular, I am using the nearest-neighbor matching procedure: for each treated unit, I find the control unit with the closest probability of being exposed based on various observable characteristics (with replacement), and I omit unmatched control units.[9] This methodology allows for a more rigorous comparison of electoral outcomes between comparable municipalities. For this purpose, I am using municipal demographic and economic characteristics, as well as electoral turnout before the conflict, measured in the year 2012. The results of the matching procedure are presented in Figure A3.

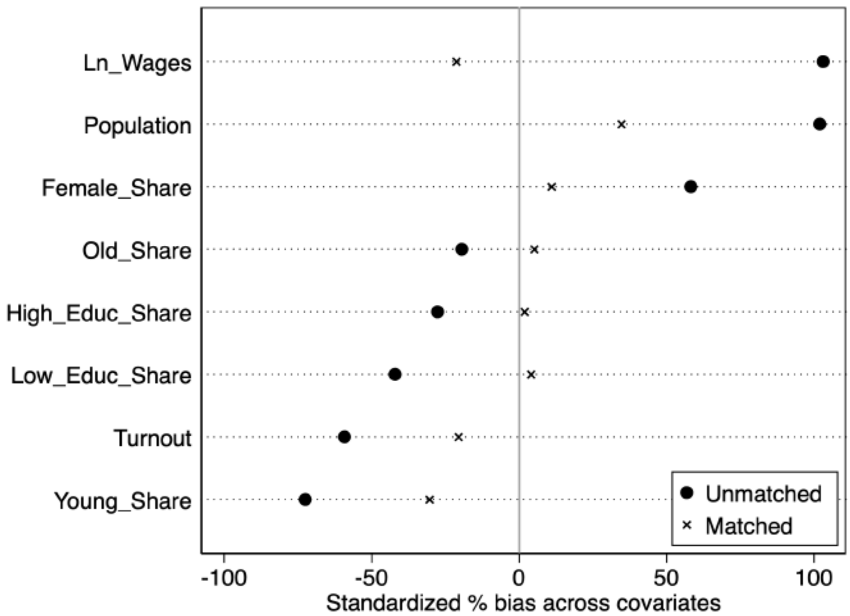

Figure A3: Balance of Pre-Treatment Characteristics (2012)

Note: treatment is defined as above the 75th percentile of exposure distribution.

From the graph above, it is evident that the matching procedure has substantially increased the comparability of municipalities: the median bias reduced from 58.7% to 15.8%. Further, the results for the vote share as the dependent variable are presented in Table A1. As can be seen, the positive effect on the measure of support of the government is preserved in matched samples and becomes marginally significant while controlling for the pre-treatment measure of political participation (turnout) in 2012.

[9] As before, I define the binary treatment as being above the 75th percentile of the exposure share distribution.

Table A1: Propensity Score Matching Estimation

Dependent Variable:	2018-12 Growth in Support				
Sample:	Unmatched	Matched		Matched	
P-Score Est.:		Probit	Logit	Probit	Logit
Exposed	0.225	0.225	0.225	0.225	0.225
Control	0.157	0.109	0.110	0.172	0.175
Difference	0.068***	0.116***	0.115***	0.053*	0.050
	(0.006)	(0.028)	(0.029)	(0.031)	(0.032)
Demographic covariates of 2012	Yes	Yes	Yes	Yes	Yes
Turnout covariate of 2012	No	No	No	Yes	Yes
# obs.	1,763	1,763	1,763	1,763	1,763
t-stat.	10.53	4.12	3.99	1.71	1.58

Standard errors in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Additional Figures and Tables

In this section, I present additional tables and figures supporting the findings from the paper.

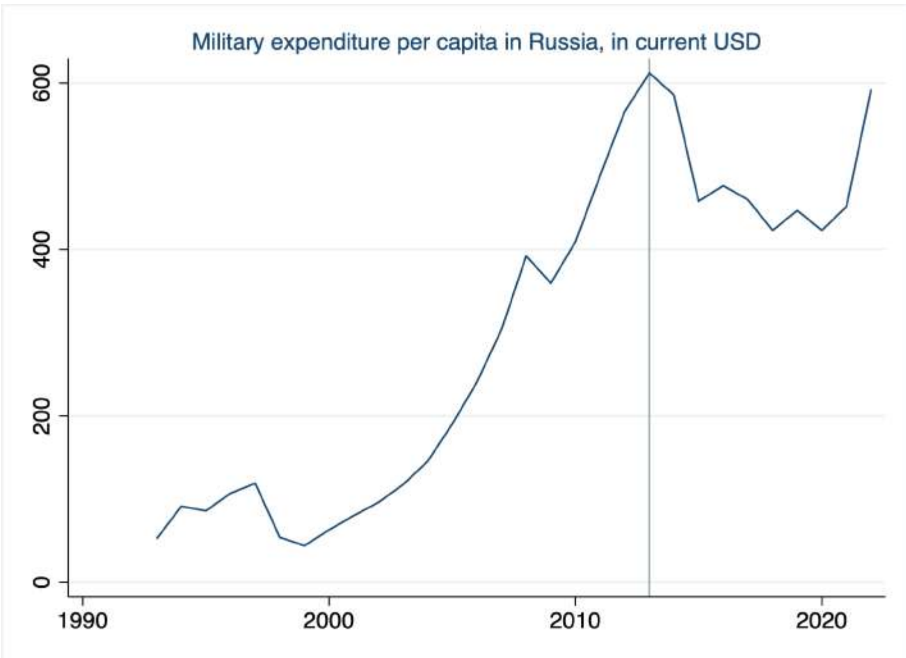

Figure A4: Military Expenditure per Capita

Data source: Stockholm International Peace Research Institute.

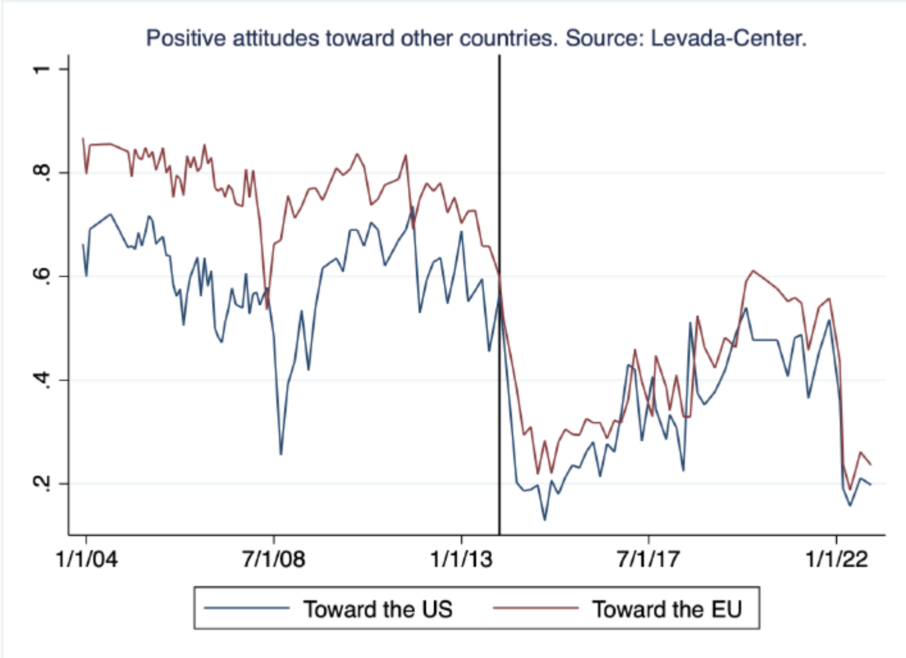

Figure A5: Attitudes of Russian Citizens Toward Western Countries

Data source: Levada Analytical Center, Russian non-governmental research organization.

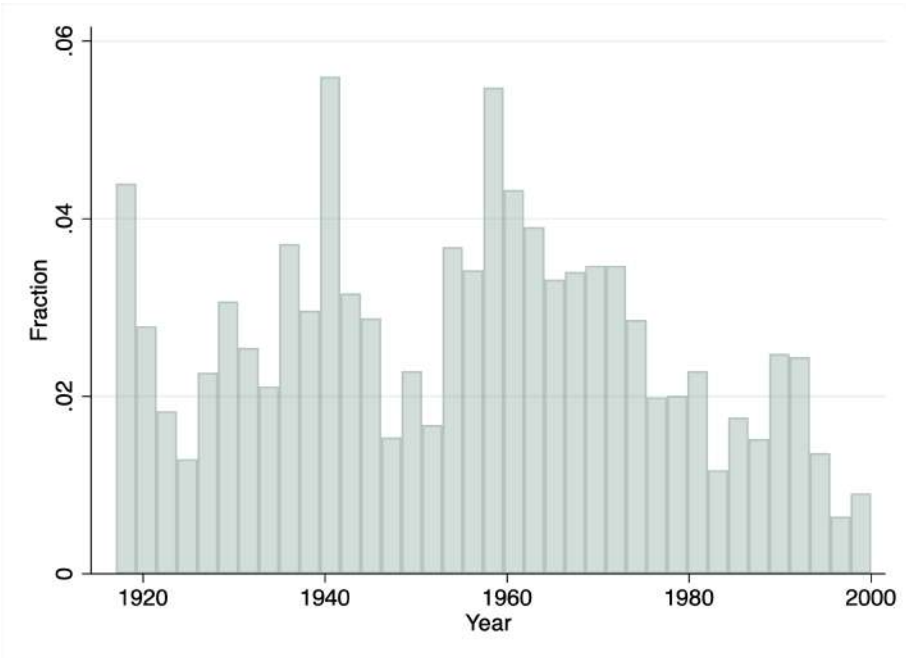

Figure A6: Dates of Soviet Defense Plants' Establishment

Data source: Dexter and Rodionov (2022).

Table A2: Electoral Candidates and Electoral Outcomes

<table>
<tr><th>Year</th><th>Type</th><th>Candidates</th></tr>
<tr><td>2004</td><td>President</td><td>United Russia (71.31%)
Communist Party (13.69%)
Rodina (4.10%)
Union of Right Forces (3.84%)
Liberal Democratic Party (2.02%)
Russian Party of Life (0.75%)</td></tr>
<tr><td>2008</td><td>President</td><td>United Russia (70.28%)
Communist Party (17.72%)
Liberal Democratic Party (9.35%)</td></tr>
<tr><td>2012</td><td>President</td><td>United Russia (63.60%)
Communist Party (17.18%)
Mikhail Prokhorov (7.98%)
Liberal Democratic Party (6.22%)
A Just Russia - For Truth (3.85%)</td></tr>
<tr><td>2018</td><td>President</td><td>United Russia (76.69%)
Communist Party (11.77%)
Liberal Democratic Party (5.65%)
Civic Initiative (1.68%)
Yabloko (1.05%)
Party of Growth (0.76%)
Communists of Russia (0.68%)
Russian All-People's Union (0.65%)</td></tr>
<tr><td>2020</td><td>Constitutional referendum</td><td>Support (78.45%)
No (21.44%)</td></tr>
</table>

Source: Central Electoral Commission of Russian Federation (2021).

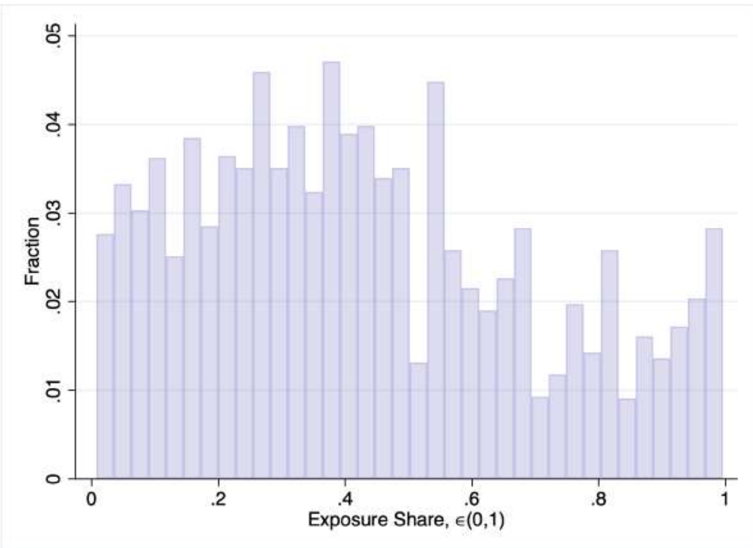

Figure A7: Municipal Level: Histogram of the Exposure Share

Note: this histogram is not considering the values of zero and one. N = 8,031 observations.

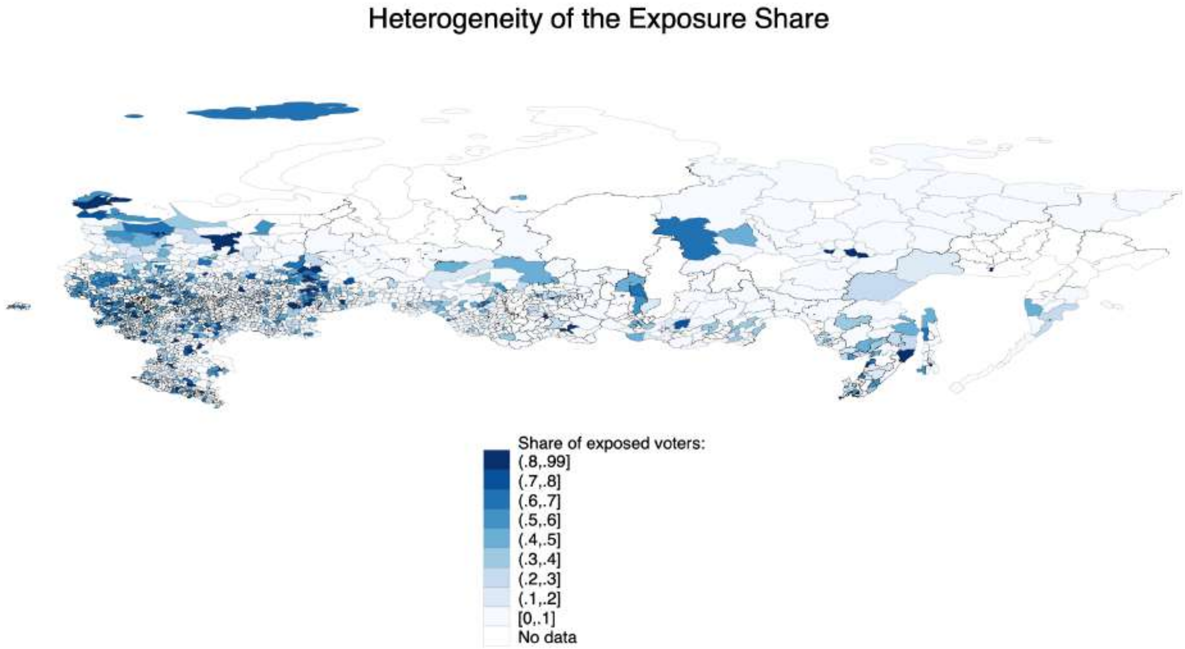

Figure A8: Spatial Municipal Distribution of the Exposure Share

Note: exposure is defined as the fraction of eligible voters exposed to military production plants in close vicinity to the total number of voters within this neighborhood.

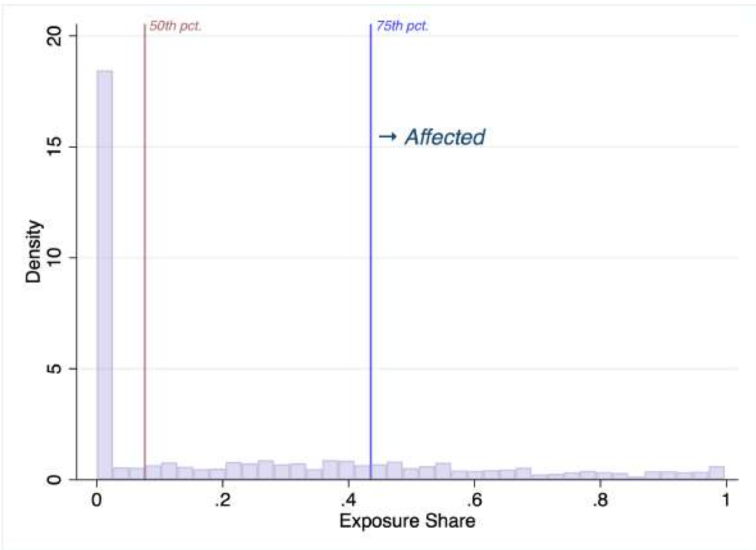

Figure A9: Histogram of the Exposure Share

Note: this graph illustrates the construction of the "exposure" binary variable that takes the value of one if the measure of exposure variable is above the 75th percentile of its distribution.

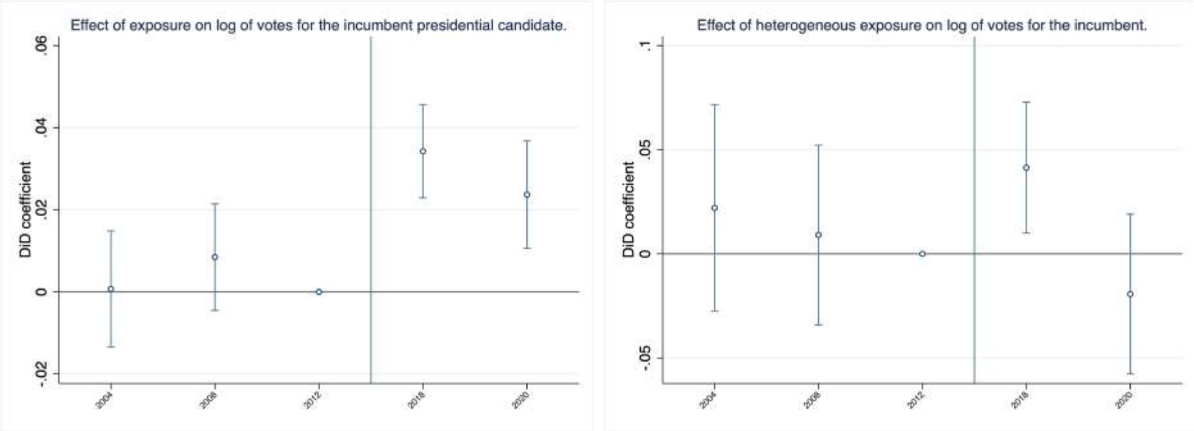

Figure A10: Robustness Check: 10 km Threshold

Note: polling station and municipality level (estimated regression coefficients from 1 and 2), respectively.

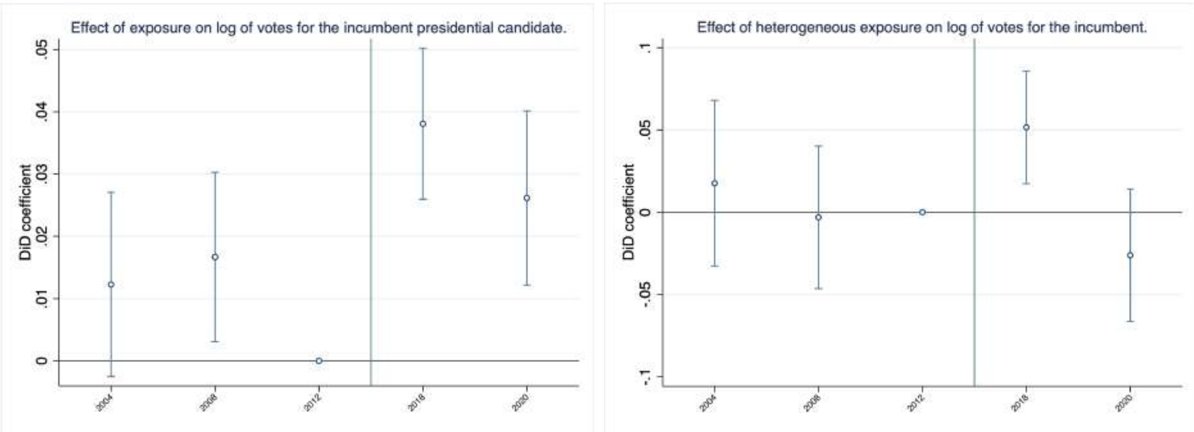

Figure A11: Robustness Check: 8 km Threshold

Note: polling station and municipality level (estimated regression coefficients from 1 and 2), respectively.

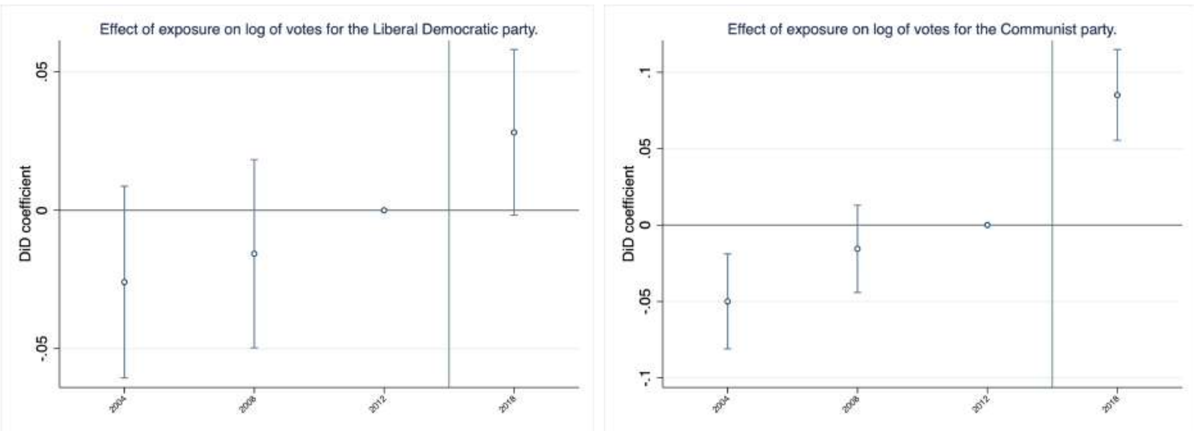

Figure A12: Polling Station Level: Effect of Exposure on Log of Votes for Other Candidates

Note: the graphs present estimates from the equation 1: the left panel uses the votes logarithm for the Liberal Democratic candidate as the dependent variable, while the right panel uses the votes logarithm for the Communist candidate. Standard errors are clustered at the voting poll level. $N = 90{,}815$ observations.

Table A3: Effect of Heterogeneous Exposure on Log of Incumbent Votes

Dependent Variable:	Log(Incumbent Votes)
Exposure × Year = 2004	0.010
	(0.026)
Exposure × Year = 2008	-0.017
	(0.022)
Exposure × Year = 2018	0.074***
	(0.019)
Exposure × Year = 2020	-0.019
	(0.022)
# observations	8,031
Adj. R-squared	0.961
Municipality FE	Yes
Year FE	Yes
Region-year FE	Yes
Eligible voters control	Yes

Standard errors in parentheses, clustered at the municipal level.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A4: Effect of Heterogeneous Exposure on Support for the Government

Dependent Variable:	Support
Exposure × Year = 2004	0.019**
	(0.008)
Exposure × Year = 2008	0.006
	(0.006)
Exposure × Year = 2018	0.020***
	(0.006)
Exposure × Year = 2020	0.011
	(0.007)
# observations	8,031
Adj. R-squared	0.865
Municipality FE	Yes
Year FE	Yes
Region-year FE	Yes
Eligible voters control	Yes

Standard errors in parentheses, clustered at the municipal level.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A5: Robustness Check I: Synthetic DiD Estimator

Dependent Variable (Logs):	(1) Incumbent Votes	(2) Support	(3) Turnout	(4) Eligible Voters
ATT	0.034***	0.007***	0.000***	0.030***
	(0.006)	(0.002)	(0.000)	(0.006)
# obs.	5,732	5,732	5,732	5,732
Years	4	4	4	4
Municipalities per year	1,433	1,433	1,433	1,433
Support as a covariate	Yes	No	Yes	Yes
Turnout as a covariate	Yes	Yes	No	Yes
Eligible voters as a covariate	Yes	Yes	Yes	No

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: inference is based on 1,000 bootstrap replications.

Treatment is defined as above the median of exposure share distribution.

Table A6: Robustness Check II: Synthetic DiD Estimator

Dependent Variable (Logs):	(1) Incumbent Votes	(2) Support	(3) Turnout	(4) Eligible Voters
ATT	0.035***	0.006***	-0.001	0.031***
	(0.007)	(0.002)	(0.002)	(0.006)
# obs.	5,732	5,732	5,732	5,732
Years	4	4	4	4
Municipalities per year	1,433	1,433	1,433	1,433
Support as a covariate	Yes	No	Yes	Yes
Turnout as a covariate	Yes	Yes	No	Yes
Eligible voters as a covariate	Yes	Yes	Yes	No

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: inference is based on 1,000 bootstrap replications.

Treatment is defined as having a positive exposure share.

Table A7: Robustness Check III: Synthetic DiD Estimator

Dependent Variable (Logs):	Incumbent votes	Support	Turnout	Eligible voters
ATT	0.038***	0.008***	0.003	0.028***
	(0.008)	(0.002)	(0.003)	(0.008)
# obs.	4,972	4,972	4,972	4,972
Years	4	4	4	4
Municipalities per year	1,243	1,243	1,243	1,243
Support as a covariate	Yes	No	Yes	Yes
Turnout as a covariate	Yes	Yes	No	Yes
Eligible voters as a covariate	Yes	Yes	Yes	No
Demographic controls	Yes	Yes	Yes	Yes

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: inference is based on 1,000 bootstrap replications.

Treatment is defined as above the 75th percentile of exposure distribution (see Figure A9).

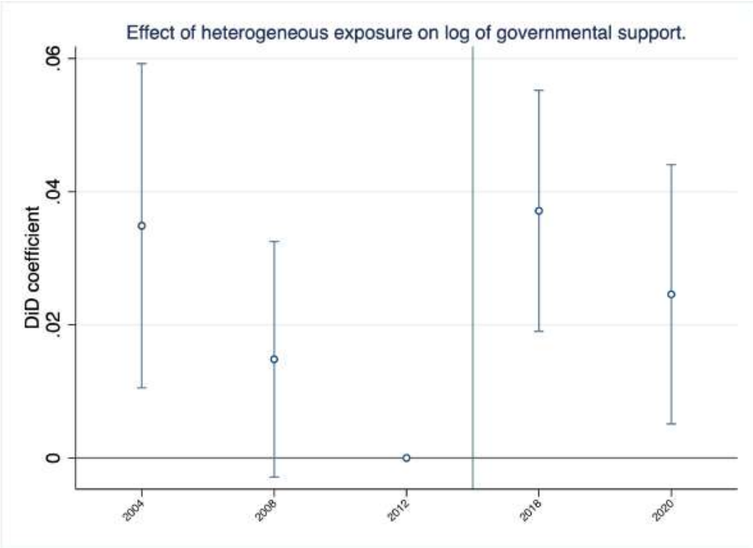

Figure A13: Effect of Heterogeneous Exposure on Log of Governmental Support

Note: the graph depicts the evolution of coefficients from the specification 2 over the years. The dependent variable of the equation is the logarithm of the vote share for the incumbent candidate (with respect to aggregate turnout). Standard errors are clustered at the municipality level. N = 8,031 observations.

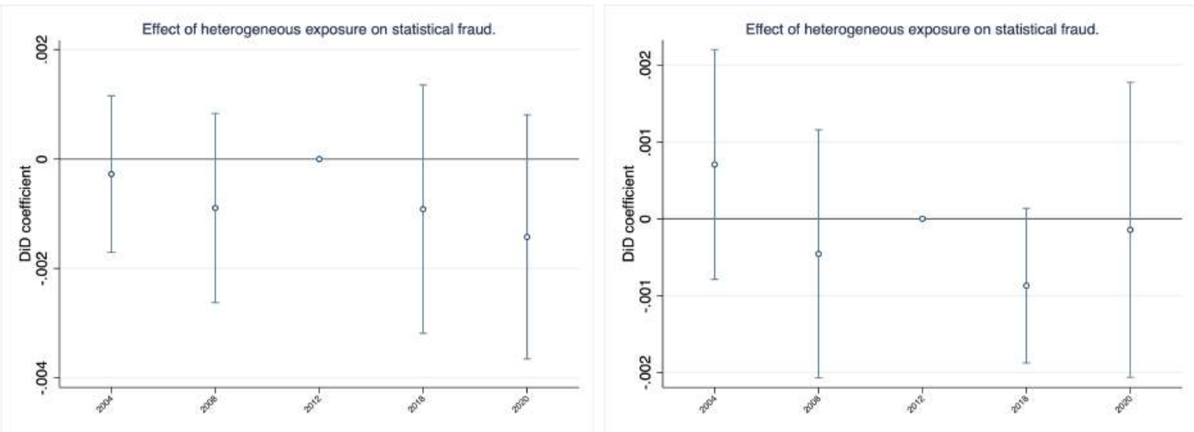

Figure A14: Robustness Check: Thresholds of Statistical Manipulation

Note: the graphs illustrate the evolution of estimates from 2 over the years, where the dependent variable is the dynamic measure of statistical manipulation, constructed as in Klimek et al. (2012), with 80% and 90% thresholds, respectively. Standard errors are clustered at the municipality level. N = 8,031 observations.