Choosing Sides: The Price for Battlefield Loyalty under Autocracy

Roya Talibova

Are there long-term personal benefits to military service? This paper examines whether serving in the state's army or explicit loyalty during a civil war might benefit war veterans in the longer term by exempting them from future oppression and violence when revolutionaries gain power. Using original geo-referenced administrative data on World War I, personal records of the White and Red Armies from the Russian Civil War, district-level demographic statistics, and Soviet secret police records, I study whether individuals who fought in interstate and civil wars were treated differently by the Bolshevik regime during the Stalin purges. I show that the motivation to overthrow the old regime often leads to community-level and individual sacrifices that are rarely rewarded in the post-revolutionary setting. In doing so, I address a key question that underscores the utility of military service: the significance of recognized veteran status and protection in exchange for human and material sacrifices that wartime service entails.

August 2023

I would like to thank Christopher Blair, Christopher Fariss, Walter Mebane, James Morrow, Andrea Ruggeri, Kevin Quinn, Austin Wright, and Yuri Zhukov for their valuable feedback. I also thank audiences at the ESOC Annual Conference (2022), Peace Science Annual Meeting (2022), and Columbia University Conference on Political Elites in Comparative and Historical Perspective (2022) for helpful comments. I thank Brendan Chen for his outstanding research assistance. All errors are mine.

1. INTRODUCTION

Serving in the military during wartime requires readiness to sacrifice the most human possession – one's own life. Although it is conventional wisdom to perceive military service members as citizen-soldiers driven by intrinsic motivations – patriotism, sense of duty, commitment to country, material and non-material benefits to service, and expectations of honorable treatment are what motivate the majority of ordinary people to put their lives at risk (Krebs and Ralston, 2022). A growing empirical literature has identified countless factors that affect how individuals with different motivations fight and get treated on the battlefield, both through social and institutional channels (Lyall, 2020; Ager et al., 2021; Huff and Schub, 2021; Rozenas, Talibova and Zhukov, 2022). Yet we know little about the long-term benefits of fighting for the state: whether community and individual level sacrifices are more or less likely to be rewarded by the regime when soldiers lay down their arms.

Understanding the effects of military service and veteran status on the civilian lives of soldiers is crucial for many reasons. Since the French Revolution, the idea of self-sacrifice – dying for one's country – has become the cornerstone of citizenship and citizen-soldier status. Past research has extensively explored the role of citizen-soldiers in democratic states (Levi, 1997; Reiter and Stam III, 1998; Qian and Tabellini, 2021), while the motivational context for wartime self-sacrifice in authoritarian states has evaded scholarly scrutiny. In democratic contexts, scholars argue, "benefits of a war can not possibly exceed the cost of dying," making materialistic private benefits not a dominant motivational factor for a citizen-soldier to enlist (Levi, 1997). Instead, an altruistic reason guides a citizen-soldier, exemplified in the famous saying, "the individual must die so that the nation might live." To the extent that military service and citizenship are cornerstones of the liberal social contract, it is customary to expect military service in democratic states to result in equal treatment of servicemen (Parker, 2009).

In states ruled by authoritarian leaders, who frequently resort to repressive tactics to maintain control and rarely provide public goods, the state-citizen liberal social contract is broken, and soldiers might have a hard time becoming intrinsically motivated to self-sacrifice. Especially in times of mass conscription, when the choice set involves punishment for draft evasion or enlisting to fight, most soldiers will likely be motivated exclusively by extrinsic factors, such as monetary rewards, social status, investment in human capital, and expectations of preferential treatment by the state after the war. Some of these rewards are unintended products of wartime military service that the state has no direct control over. Economists and sociologists agree that there are significant gains in human capital from military service and combat exposure, such as increased organizational and leadership skills and advanced literacy (Sampson and Laub, 1996; Avrahami and Lerner, 2003; Angrist, Chen and Song, 2011; Jha and Wilkinson, 2012; Eynde, 2016; Leal and Teigen, 2018; Bingley, Lyk-Jensen and Rosdahl, 2022).

While decades of scholarship on military service have demonstrated that it has long-lasting positive effects on human capital accumulation and other tangible benefits directly extracted from the service, there has been little effort to systematically study the materialization of rewards that are at the discretion of the state. Do authoritarian states reward wartime loyalty and veteran status in the long term? Building on and extending an emerging body of literature on the long-term impact of military service, this paper is the first to directly investigate the link between wartime sacrifices and exposure to political repression. Political violence is an authoritarian leader's primary tool of societal control since the needs of the state are always considered superior to the needs of the citizens. Therefore, a tyrannical state rarely exercises moderation in wielding repressive power over those it considers a threat to its survival. But we also know that autocrats occasionally reward certain citizens for their loyalty to the regime. Do autocrats forego their most powerful tool of control to recognize the sacrifices of their loyal supporters?

This paper empirically examines the effect of wartime participation on subsequent treatment by the newly-established revolutionary regime in the context of the Russian Empire and its successor, the Soviet Union. Between 1914 and 1922, the citizens of the Russian Empire were caught in a conflict cycle: they first had to fight major European powers on the battlegrounds of World War I. Then, before the war was over, a wave of domestic protests grew to become the most significant revolution in the history of Russia, which paved the way for a bloody civil war. Almost all the male population of the Russian Empire fought in World War I due to mass conscription. Thousands later turned against each other to fight as divided armies in the emerging civil war. Decades later, during Stalin's reign between 1922-1953, Russian authorities sent millions of ordinary citizens to labor camps.

To explore whether and how WWI and civil war veteran status interacted with the Soviet authorities' decision to persecute individuals, I focus on three separate armies: the Russian Imperial Army of World War I, the Imperial White Guard, and the Revolutionary Red Army. Service in these armies represented multiple cross-cutting loyalties. Fighting as part of the Russian Imperial Army during WWI meant making the ultimate sacrifice to the empire: nearly 3% of the entire male population died in battle, while an additional 8% were disabled for a lifetime.[1] Of all the mobilized citizens, only 40% (regular soldiers and reserves) had any idea of what they would face on the battlefield, as the remaining had no previous army training or any kind of preparation for war (Gatrell, 2014). The revolution and civil war that followed divided these loyalties. Most veterans were forced to join one of the two warring sides. Some remained loyal to the state by fighting to suppress the revolutionary movement, while others turned their weapons against the state to join the revolution. Although divided, their sacrifices nonetheless demonstrated loyalties: to the crown or the Bolsheviks. This paper analyzes variations in levels of fighting, resistance, and loyalty in Imperial Russia across various geographic units and looks into patterns of arrests across the Soviet Union: Were the veterans of World War I and the Russian Civil

[1] This number does not include half a million missing soldiers.

War, and their families, treated differently during Stalin's purges – especially those who received official recognition for their bravery?

Imperial Russia's war veterans and Stalin's purges provide an interesting case for unpacking the relationship between military service and post-service treatment. Russia's entry into World War I and its fall into a civil war happened before the Soviet Union was created. Yet comprehending the political landscape and the state-society relations in the Soviet Union without studying the revolution that brought the Bolsheviks to power is impossible. The prolonged period of revolutionary warfare and the accompanying societal devastation defined the nature of the Soviet state. Unlike its predecessor, and perhaps based on the lessons of its demise, the Soviet state became a ruthless, tyrannical state that oppressed not only ethnic minority people but also its core ethnic constituents. The state proceeded to punish any citizen for the slightest suspicion of anti-regime political views, no matter the demographic background. As a revolutionary state, the regime came to power thanks to two distinct sacrifices of ordinary citizens: when millions fought in World War I to defend the territorial integrity of the country and when many of the same veterans joined the revolutionary movement and civil war to reverse the tide in favor of the Bolshevik victory.

Using archival administrative data from the Russian Civil War and Soviet Secret Police records, I construct district-level, grid-cell level, and individual-level measures of repression and link these with World War I and Russian Civil War enlistment records to study the impact of personal and community-level sacrifices in wartime on subsequent well-being of veterans and their families. To measure repression, I use both direct exposure of the person and inter-generational exposure through family members. To do so, I focus on last-name matches between veterans and arrestees around their birthplaces. The granularity of individual data across all datasets allows me to directly trace individuals across time and space and control for individual, temporal, and geographic characteristics that might confound the results.

I find that the Bolsheviks repressed heavily in areas with the highest concentration of WWI and Russian Civil War veterans, disregarding the personal sacrifices made by soldiers either to the previous regime or to the Bolsheviks themselves. The remuneration for the support of the revolution was continued repression, only more intense and targeted. I address alternative explanations, account for possible measurement errors, and perform additional robustness checks. The results shed light on the critical question that underscores the utility of military service: the significance of recognized veteran status and protection in exchange for human and material sacrifices that wartime service entails.

These findings contribute to the literature on political violence, revolutions and civil wars, military service, and historical legacies. The political violence scholarship has thus far focused on the effects of state repressions on a range of short and long-term political and economic outcomes (Balcells, 2012; Lupu and Peisakhin, 2017; Rozenas, Schutte and Zhukov, 2017; Zhukov and Talibova, 2018; Rozenas and Zhukov, 2019; Young, 2019). A few studies that treat state repression as a dependent variable emphasize factors influencing whether, when, and to what end the states repress their citizens. Neglected in the literature, however, is the empirical evaluation of the determinants of the targets of repression. What individual characteristics the state takes into account when choosing its targets is a crucial question for our understanding of state-citizen relations in information-rich authoritarian states and should therefore be of interest to scholars of political violence.

Similarly, military historians, economists, and sociologists have analyzed the effects of wartime participation and veteran status on a myriad of socio-economic, behavioral, and health outcomes (Berger and Hirsch, 1983; Richard and Wilhite, 1990; Angrist and Krueger, 1994; Bedard and Deschênes, 2006; Lee, 2012; Eynde, 2016; Leal and Teigen, 2018). However, these studies tend to focus on tangible effects, ignoring "silent" outcomes that are difficult to observe directly. Finally, a widespread body of scholarly literature on civil wars and revolutions identifies when revolutions occur and become successful (Gurr, 1970; Tilly, 1978, 1992; Skocpol, 1994), how they affect state-building and state capacity in general (Besley and Persson, 2008; Boix, 2008; Arjona, 2016; Cárdenas, Eslava and Ramírez, 2016), and how they attract civilian support (Weinstein, 2007; Mampilly, 2012; Huang, 2016; Stewart, 2021). Yet the effect of support and loyalty of civilians on their post-war lives is more ambiguous. I aim to advance these separate strands of scholarship by providing empirical evidence for the effect of military service and political loyalty on a type of remuneration that the previous empirical literature has not yet examined: personal and family safety and security.

This paper is organized as follows. Section 2 explores the theoretical links between wartime enlistment and post-war rewards. Section 3 discusses the historical background of the two wars and Stalin's repressions. Section 4 describes the data and units of analysis. Sections 5 and 6 outline the empirical strategy and present the main results. Section 7 addresses alternative explanations and Section 8 concludes.

2. Theoretical Framework

Military service in wartime is the litmus test of the strength of the social contract between the state and its citizens in any regime context. The ability of any state to wage war against a formidable enemy hinges on the motivation of its citizens to enlist in the army (Levi, 1997). Studies show that citizens of democratic countries with inclusive institutions during wartime are more likely to be motivated to volunteer for the military or submit to conscription, while the opposite may reduce motivations to fight (Alesina and Ferrara, 2005; Alesina, Reich and Riboni, 2020). This reasoning helps us distinguish between two motivational sources for fighting, contingent on regime types: citizen-soldiers in democratic countries are usually guided by intrinsic motivations, whereas soldiers' loyalty to the state under authoritarian regimes is based on calculations of extrinsic rewards.

In the context of military service, an authoritarian state can reward veterans according to two considerations: previous wartime sacrifices of soldiers that lead to the successful defense of the national state and its territory, regardless of the political regime in power, and sacrifices of the loyalists that dislodge the incumbents and bring the regime in question to power as a result of an internal conflict. It would be naive to assume that the state is unaware of the incentive structures driving individual behavior during wartime. As long as the state needs citizen support for war-making efforts, it will continue to induct soldiers with extrinsic motivations into the military to wage a successful war, despite knowing citizens' true intentions. Since the state is usually aware that military service may help overcome certain dynamics that impede political participation and lead to a greater likelihood of citizen activism (Brooks, 2004; Leal and Teigen, 2018), it will only keep its end of the contract until the threat of war is over. An authoritarian ruler will always treat military-trained citizens (or war veterans) more suspiciously and attempt to punish them selectively in their civilian lives.

Not everyone who enlists in the military acquires the same level of training or becomes equally skilled. A more refined targeting by the state could identify soldiers who have distinguished themselves in battles and, thus, might pose a greater threat to the state as civilians. The state usually has direct access to information about military decorations and awards individuals receive for their wartime bravery, which indicate their high potential for combat success. Therefore, war veterans with military distinctions might be more likely to be targeted by the state.

Based on these considerations, I propose the following hypotheses relating wartime participation to post-war repression:

H1. Military training, in general, reduce the costs of political participation and advance individual skills, thereby increasing the likelihood of the state's selective targeting of individuals with such skills.

H2. An increased presence of high-skilled, distinguished, and decorated veterans is more likely to increase the likelihood of state repression.

This line of reasoning ignores sacrifices made based on loyalty to a specific political entity. After all, wartime military service, whatever the motivational drivers for enlistment, is rarely avoidable and usually carries high costs for evasion. Moreover, wartime enlistment in the military does not signal any political loyalty directly. In certain contexts, it might indicate allegiance to the nation-state – to a higher cause than the survival of the existing political regime. It certainly does not require a conscious and observable choice between loyalties to different political actors or entities.

Choosing to fight for different warring sides of a revolution or civil war is qualitatively different. Deciding to resist by fighting for the challenger or remaining loyal to the regime on the battlefield are both risky acts. Though not always, citizens usually have a choice not to openly show their loyalties and/or put their lives at risk by joining a civil war. And when they do, their choice signals their political loyalty openly, and carries significant risks for their future lives, contingent upon the outcome of the domestic conflict.

In an authoritarian state, enlistment during an interstate conflict only carries direct risks for one's own life on the battlefield, whereas the consequences of fighting in a civil war might extend to family members and entire communities. Because the cost of participation is higher in a domestic war context and the signal of political loyalty more distinct, the state might reward citizens and certain communities for their sacrifices in bringing them to power and punish those who opposed them.

Alternatively, individual loyalties or preferences might be irrelevant for an authoritarian ruler when regime survival is under consideration. Further, the state might consider soldiers who have demonstrated political loyalty by fighting on their side as untrustworthy citizens, ready to subvert the regime that mistreats them. As such, the state may treat them as potentially seditious individuals who might threaten the leader's long-term power. In this case, we should expect the state not to treat revolutionary loyalists more favorably in the long run.

These arguments suggest the following predictions linking political loyalty to post-war repression:

H3. Authoritarian rulers, who come to power through revolutions, will treat veterans of the revolutionary movement and their families preferentially in the long term and punish counter-revolutionaries who opposed their cause.

H4. Authoritarian rulers, who come to power through revolutions, will not distinguish between their loyalists and counter-revolutionaries when employing coercive tools to control the society.

3. Historical Background

To test my theoretical expectations, I turn to the Soviet Union and explore the empirical relationship between service in the revolutionary and counter-revolutionary army during the Russian Civil War and exposure to state repression in a post-revolutionary setting in Stalin's Russia.

3.1. Imperial Demise in Two Wars

The Russian Empire entered World War I in the summer of 1914 with the largest standing army in the world, comprised of 1.5 million soldiers, almost all of whom died in the first year of the war. Facing a shortage of manpower, the Tsar was forced to reverse the long-standing imperial policy of recruiting only "native-born Russians" to the Russian Imperial Army. As a result, millions of non-Russians of military age were conscripted to serve on the front in a few months. Countless imperial citizens, who their own government often mistreated, fought and fell in the trenches of WWI. One of the few Jewish members of the imperial parliament, Naftali Fridman described the Jewish efforts in WWI (Hofmeister, 2016):

> The Jewish youth, which, as a result of the restrictions as to admission to the high schools of the country, had been forced to study abroad, returned home

> when war was declared, or entered the armies of the allied nations. A large number of Jewish students fell at the defense of Liege and also at other points of the western front... The Jews built hospitals, contributed money, and participated in the war in every respect just as did the other citizens. Many Jews received marks of distinction for their conduct at the front.

The political atmosphere across the empire in the period leading to WWI was repressive and divisive. Many marginalized citizens saw the chance to serve the empire within the ranks of its most elite security institution as both an opportunity to stand out in the eyes of the state and hope for a better future if they survived the war. There was almost no recorded case of draft dodging; on the contrary, thousands of rural peasant and minority citizens volunteered to serve in the front. However, most conscripted soldiers, being of overwhelming peasant and ethnic minority origin, did not have previous military experience and lacked proper training to face modern, well-equipped, and adequately trained European armies. As a result, Russia suffered one of the heaviest human tolls of the Great War. A letter written by an imperial soldier describes the grave conditions of the battlefield (Postnikov, 2014):

> Literally like ants, people began to jump out of the trenches, with eyes to the right, marching together, looking death right in the face... The battle took place under terrible conditions. We were advancing. There was heavy fog, nothing could be seen ahead. The offensive had to be carried out through a continuous swamp, and in some places completely in knee-deep water. The double ice collapsed, which made our movement even more difficult. Finally, we approached the enemy by 600 - 700 feet. Up to this point, they hadn't fired a single bullet. We couldn't see the enemy because of the fog. When we approached further, the enemy opened a terrible rifle, machine-gun and artillery fire at us. We had nowhere to hide. Since it was difficult to dig trenches in the swamp, we hid behind the bushes, hoping not to die.

Every enlisted soldier, whether conscripted or volunteer, faced similar conditions on the battlefield as the pace of wartime developments and the lack of proper preparation for war prevented the imperial state and military authorities from assigning individuals to combat vs. non-combat positions based on pre-war characteristics or discriminate against specific groups when assigning troops to the front or the rear (Talibova, 2022). Therefore, no lower or higher risk was associated with individual background characteristics or past experiences. Despite the initial opposition to the induction of certain minorities into the imperial army, the state embraced the potential of a mass draft as its only choice for surviving the war. Even with the mass draft, because of poor preparation and looming domestic instability, Russia withdrew from WWI, having lost several territories and more than three fourth of its forces.

The Russian Civil War of 1918-1922 was a transformative event in Russian and global history that led to the Bolshevik's rise to power and the formation of the Soviet Union. It unfolded with the February uprising in 1917, during which Tsar Nicholas II abdicated his throne, and the country was proclaimed a republic. This was followed by the October Revolution of 1917 and the overthrow of the Provisional Government by the Bolsheviks. With the renewed attempts to overturn the October revolution, a civil war ensued between the Imperial White Army and the Revolutionary Red Army.[2] The soldiers of WWI, upon returning home, faced additional challenges. Having only recently fought for the survival of the empire, they were now confronted with a fundamental choice: should they use the ongoing political crisis as an opportunity to depose the repressive regime or continue to defend the state, this time against internal enemies?

Empirical evidence shows that many chose the former and joined the ranks of the Bolshevik army to topple the empire. Many were recognized for their bravery in supporting the revolutionary movement and support for the creation of a new socialist state. During the revolution and in the years immediately following it, there was a general feeling of

[2] There were additional notable factions, such as the Green Army – local militias, comprised of politically neutral armed peasants who opposed and fought against all other factions between 1917-1922.

celebration among the veterans who joined the revolution – hope for a better and brighter future, in which their personal and their community's sacrifices would be acknowledged and rewarded.

3.2. Soviet Repression

Stalin's Terror – overt and covert forms of Soviet repression – raging between 1929 and 1953 resulted in the arrest, imprisonment, deportation, and exile to "death colonies" of an estimated 15 million Soviet men, women, and children (Conquest, 1997).[3] This period is considered one of the largest recorded coordinated state-led violence in history. In the most intense period of the purges in the late 1930s, more than 800,000 citizens were shot in a single year on charges of treason against the state. A particular place among these repressive measures held a class of activities deemed as "counter-revolutionary" crimes under Article 58 of the RSFSR Penal Code 1927, some of which were punishable by death.[4]

Repression was the primary manner with which Stalin's regime imposed public order and reshaped the society to "get rid of alien and hostile segments of the Soviet population" (Shearer, 2014).[5] A typical scenario of an arrest would involve a sudden show of NKVD police officers at a victim's door in the most unexpected hours of the day. After a thorough search of the victim's personal belongings for incriminating evidence, the officers would imprison the individual under trumped-up charges of political opposition, spying for the interest of foreign states, or anti-Soviet conspiracy. The most severe punishment was reserved for individuals suspected of "threatening the Soviet order" (Gregory, 2009). Victims would have to endure endless weeks of interrogation, torture, and isolation in prison before being hastily sentenced and delivered to the nearest train station to

[3] The most conservative estimates of the overall death toll of Stalin's repressions indicate figures as high as 20-30 million people (Dyadkin, 1983). This figure excludes around 1 million executions.

[4] These included treason, terrorism, espionage, insurrection, anti-Soviet propaganda and agitation, and working for a foreign state.

[5] Victims were dubbed with a specific term – "*chuzhdye elementy*", which in translation meant alien elements of society.

be exiled to GULAG camps or executed.[6] At GULAG camps, they would be given the bare minimum to settle and start a new life as forced laborers employed to extract raw materials in inhuman conditions to aid the country's industrialization effort. According to estimates, at its peak, the GULAG complex included more than 475 separate filtration, POW, and corrective labor camps and prisons across the Soviet Union (Viola, 2007). Most of the exiled died in the forced labor camps before having a chance for rehabilitation or amnesty.

Stalin's first repression campaign started with the wave of arrests and sentences in 1930-1933 in accordance with the policies of forced industrialization and collectivization of agriculture and dekulakization of the society, adopted by the Central Committee of the Communist Party Plenum in November 1929. The latter term referred to the elimination of rural peasants who opposed forced collectivization. Soviet authorities set special arrest quotas based on distinct categories of kulaks.[7] In addition to stifling opposition to forced collectivization, the new policy was aimed at quickly inhabiting vastly inhospitable (but resource-rich) regions of Siberia and Central Asia in order to achieve the first Soviet Five Year Plan of economic development. Only in the first two years of the dekulakization efforts, the Soviet authorities arrested and tried more than half a million citizens, of whom more than half were convicted, one-third were sentenced to the GULAG, and the remaining deported to remote regions of the country or executed immediately (Gregory, 2009).

The second episode of mass repressions – "Yezhovschina," culminated in the operations of 1936-1938 that targeted the potential political rivals of Stalin among Communist party members.[8] Leon Trotsky, the famous leader of the Russian Revolution himself, was

[6] GULAG is an acronym for *"Glavnoe Upravlenie Ispravitelno-Trudovykh Lagerei" – the Main Administration of Corrective-Labor Camps officially founded in 1930.*

[7] First category included the most active kulaks, engaged in counter-revolutionary activities, who were estimated at around 60,000 heads of household. Despite the original estimations, more than 280,000 kulaks were arrested under this category. The second category was defined as wealthy but less active kulaks and included 154,000 families (more than half a million people).

[8] This episode was named after Nikolay Yezhov, Chief of the Soviet secret police and supervisor of the most brutal stage of great purges, who later himself became a victim of the purges and was executed in 1940.

assassinated by an agent of the Soviet secret police on the orders of Stalin in this period. More than half a million Soviet citizens were executed, and another half a million were sentenced to the GULAG and deported. Among these were military veterans, as the People's Commissariat of Internal Affairs arrested and executed thousands of officers with combat experience (Murphy, 2006).

In the final stages of Stalin's terror between 1940-1945, thousands of ethnic minority citizens were arrested and executed as agents and collaborators of hostile states. More than 3.5 million citizens belonging to ethnic minorities were accused and forcibly deported to the uninhabitable remote regions of the country in the north and northeast between 1940-1950. Stalin's authoritarian rule and his repressive machine reshaped Russian society, transformed the country's economy, and in many ways, defined its political trajectory.

4. Data

I combine several original and published archival sources to construct four data sets: administrative data for soldiers of WWI, administrative data for veterans of WWI who later participated in the Russian Civil War, administrative data for individuals arrested for political views during Stalin's reign, and the Imperial Russian census data, available at the district level and representing pre-war population demographics of the empire. As some of the community-level analyses are carried out at the level of 775 districts (*"uezds"*) and others at the level of grid-cells, I aggregate the number of veterans and arrestees for districts and grid-cells separately.[9]

[9] In the territorial-administrative division of the Russian Empire before the start of WWI, districts were the second tier of administrative division. Overall, there were 101 unique provinces (*gubernia or oblast*), 824 unique districts including the Grand Dutchy of Finland (*uezd*), and thousands of localities (*volost*) and villages (*derevnya or selo*).

4.1. World War I Records

The information on WWI participation comes from an administrative dataset contained in the "In Memory of the Heroes of the Great War 1914-1918 *(Pamyati Geroev Velikoy Voyni)*" archival portal (Pamyati Geroev, 2020) and created by the Russian Ministry of Defense with the support of the Federal Archival Agency and the Russian Historical Society. The database includes biographical information, combat details, and the fate of those who served in the Imperial Russian army during World War I. There are multiple documents for each soldier in the data, retrieved from 6.6 million registration records of losses on the battlefronts, 5.6 million records of casualties of soldiers and officers, 3.4 million records on prisoners of war, 476 burial area records of 8133 known and 38,940 unknown soldiers, and 845,168 award records.

I restrict the sample to those participants for whom accurate geocoding was possible based on the geographic coordinates of the provided residential address field. The reason for this is that several addresses were impossible to locate due to imprecision and inconsistency in address reporting and irregular spelling, as well as some of the untraceable administrative changes to the boundaries of villages and localities.[10] I retain data on 42,660 soldiers confirmed as killed in action during WWI and 4,196 soldiers whose bodies were left on the battlefield, as I am interested in whether their family members were exposed to repression even after the soldier's death on the battlefield.

4.2. Russian Civil War Records

The database of Russian Civil War soldiers draws on two principal data sources: a) data on soldiers of the Workers' and Peasants' Red Army, collected from multiple archival books, casualty lists, and award orders, and b) data on soldiers of the White Guard, assembled from the digitized "Participants of the White movement in Russia *(Uchastniki Belogo dvijeniya v Rossii)*" archival record-book (Volkov, 2016).

[10] 297,925 records have missing birth location field.

The primary source for the first data is an archival record book published in 1926 by the Office of the Creation and Service of Troops of the Main Directorate of the Workers' and Peasants' Red Army (RKKA) (G.U.R.K.K.A., 1926). The database includes biographical information, enlistment logs, address records, and casualty reasons for more than 50,000 Red Army soldiers who died during the Russian Civil War. The secondary source for the first data is the list of awardees for the "Cavaliers of the Order of the Red Banner" and the "Honorary Revolutionary Weapon Award" given for battlefield performance in the Russian Civil War.

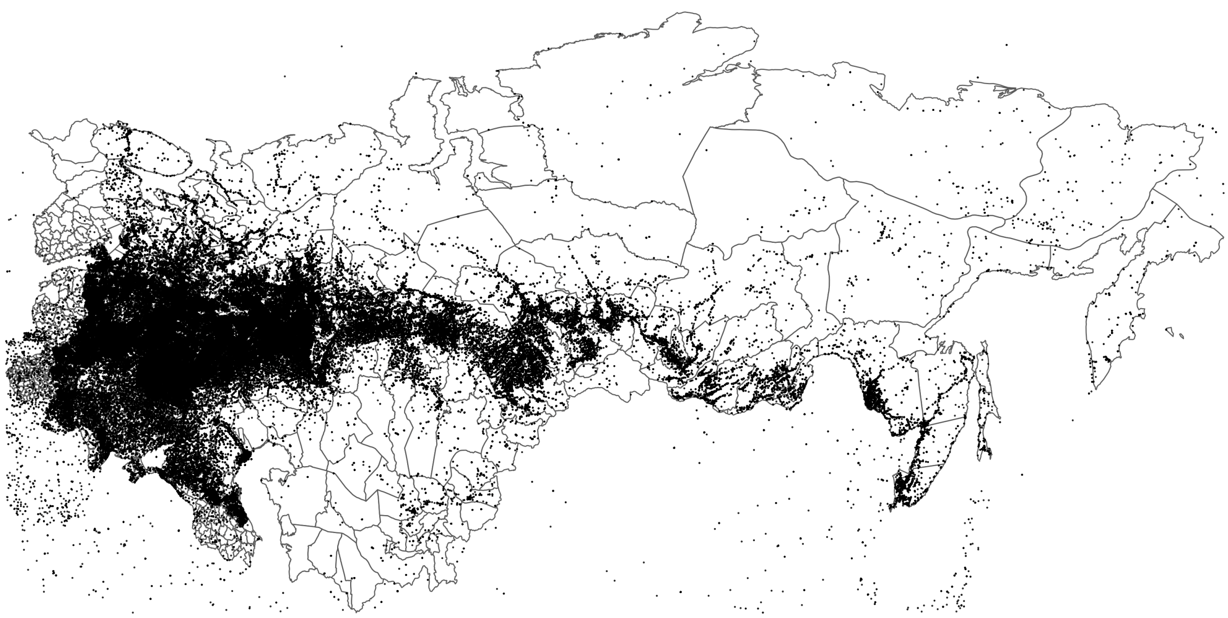
The second data includes details for soldiers who participated in the anti-Bolshevik struggle in 1917-1922 within the ranks of the White Guard, including rank and file soldiers, officers, volunteers, and Cossacks. The data draw on 1.5 million entries compiled from a variety of sources, including official archives, personal memoirs, emigrant records, obituaries and mourning announcements in the Russian foreign press, published and unpublished necropolises of Russian cemeteries abroad, award orders, wartime issues of newspapers, and information provided by surviving family members. Figure 2 shows the geospatial distribution of the birth locations of the veterans who fought in the Russian Civil War.

4.3. Memorial Records

The data on Stalin-era repressions come from the "Victims of Political Terror in the USSR *(Zhertvy Politicheskogo Terrora v SSSR)*" archival portal (Zhukov and Talibova, 2018), created and maintained by the Russian human rights organization Memorial since 2001 (Memorial, 2014). The Memorial's database is considered one of the most comprehensive open-source information on victims of Stalin's terror. The final data include 2.65 million records of individuals arrested by the Soviet Secret Police and convicted for political crimes under Article 58 of the Soviet Penal Code between 1921-1959.

The database was assembled from Soviet Interior Ministry documents, 120 regional books of remembrance published since the dissolution of the Soviet Union, records of the Commission for the Rehabilitation of Victims of Political Repression, the materials of other state archives, and individual collections from victims' families. In addition to basic biographical information, the data include the year of arrest and rehabilitation, nationality, and level of education. The data do not cover other forms of repression prevalent across the USSR, such as deportations on ethnic grounds and victims of counterinsurgency operations and famines. Figure 1 shows the geospatial distribution of the birth locations of individuals arrested under Article 58.[11]

Figure 1: Map of Stalin's repression

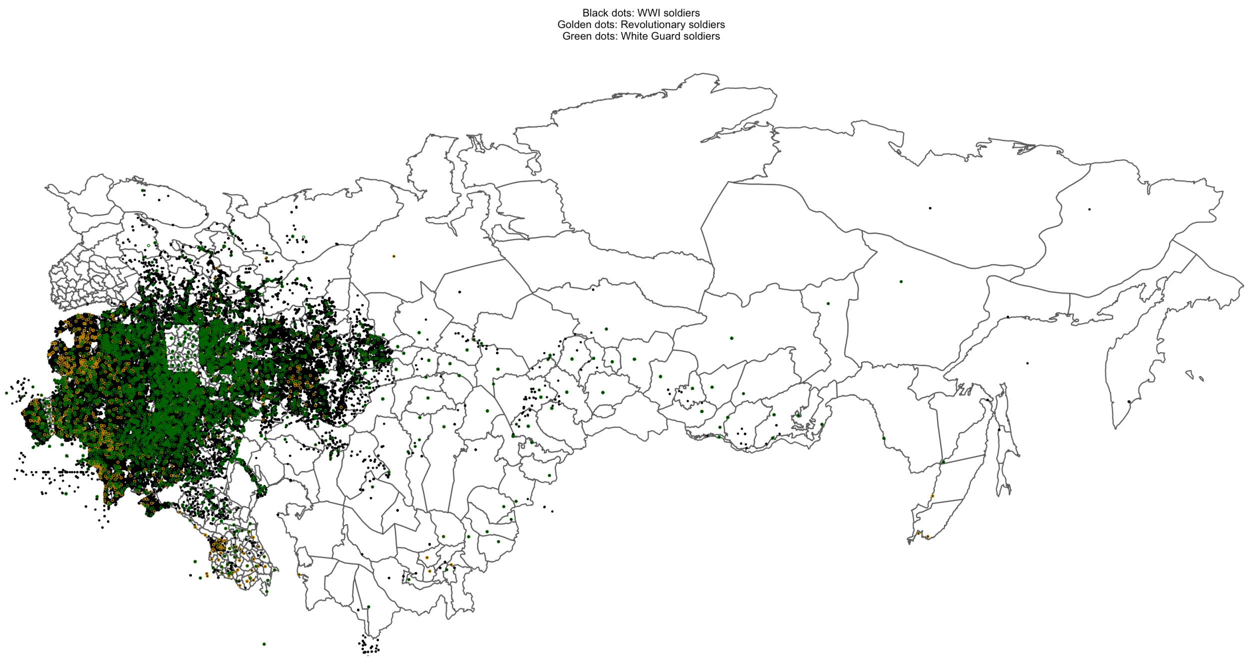


4.4. 1897 Census Data

For socio-demographic variables, my primary source is the census data from the first and only Russian Imperial Census of 1897 (Troynitsky, 1899). The census data for each of the 775 districts contain detailed information on Russian society's socio-economic, cultural,

[11] Vicinity to the train stations affected levels of repression in certain areas, as the transportation department of the secret police was the main source of support for deportations (Kotkin, 2017).

Figure 2: Map of WWI and Russian Civil War Veterans



and demographic statistics.[12] In particular, I use the following sociodemographic controls from the imperial census: population, the share of the military-age male population, the share of the literate male population, the share of the urban population, and overall population density.[13] In addition, to account for exogenous geographic factors, I control for the altitude for each district using the geographic coordinates of the central locality. In individual-level analysis, I additionally control each soldier's ethnicity using a binary indicator for whether the individual is an ethnic Russian or a minority.

4.5. 1926 Census Data

In alternative specifications, I run district-level analyses using administrative units based on Soviet Russia's district borders. To maintain consistency and accuracy in calculating socio-demographic statistics across these administrative units, I use the 1926 Soviet Cen-

[12]In the official imperial census publications, the district is the lowest administrative unit for which information is available.

[13]Originally, density was measured in historical Russian units (*in square versts*). I convert historical units into square kilometers.

sus Data, which provides official population and urbanization measures for the Russian society at the height of the repressive waves. The problem with this approach is that the covariates taken from the 1926 Census will be post-treatment covariates and will likely introduce bias to the estimates.

4.6. Maps

The district boundaries of the Russian Empire are obtained from the map of pre-war imperial administrative borders (Kessler, 2017). However, the district-level (and lower) administrative boundaries of the Russian Empire do not align perfectly, as the Soviet authorities attempted to make boundary changes following the loss of western European districts after WWI. Additionally, the lower-level administrative boundaries of the Russian Empire changed significantly between 1897-1914, long before the revolution. To address the challenges associated with providing accurate geolocations against the backdrop of inconsistent boundaries, I performed several spatial adjustments, using historical atlases of the Russian Empire and the Soviet Union and archival records of territorial and administrative boundary shifts as a point of reference.

4.7. Descriptives

Table 1 presents summary statistics for the main variables included in the district-level analysis. In each district, 2803 citizens were arrested on average. During WWI and the Russian Civil War, in the average district, there were 2608 WWI veterans, 62 WWI medal recipients, and 9 and 31 WWI veterans joining the revolutionary and counter-revolutionary movements, respectively.

Table 2 reports summary statistics for variables used in the grid-cell-level analysis. The average number of arrested per grid is 732, while the average number of WWI veterans, revolutionaries, and counter-revolutionaries are 861, 6, and 15, respectively.

Table first panel of Table 3 shows the results of individual matches across the two data.

Table 1: Summary statistics (Districts)

Name	*Median*	*Mean*	*SD*	*Range*	*N*
Outcome variable					
Repression	1172.00	2803.87	5334.61	[1, 66257]	747
Explanatory variables					
WWI Veterans	2327.00	2608.52	2325.42	[1, 22056]	766
WWI heroes	36.00	61.99	79.59	[1, 607]	664
Revolutionaries	4.00	8.54	13.81	[1, 155]	617
Counter-revolutionaries	24.00	31.14	28.51	[1, 212]	627
Covariates					
Share of Military-Age Male	0.65	0.64	0.04	[0.36, 0.85]	761
Share of Literate Male	0.25	0.26	0.14	[0.01, 0.9]	761
Share of Urban Population	0.06	0.11	0.13	[0.01, 0.96]	759
Density	32.00	36.42	44.41	[0.02, 667.7]	761
Elevation	137.50	196.62	251.73	[-31, 1999]	762

Table 2: Summary statistics (Grid-cells)

Name	*Median*	*Mean*	*SD*	*Range*	*N*
Outcome variable					
Repression	275.50	731.97	1898.33	[1, 49953]	2,214
Explanatory variables					
WWI Veterans	141.00	861.49	1831.22	[1, 46550]	2,315
WWI heroes	7.00	27.45	54.19	[1, 863]	1,498
Revolutionaries	2.00	6.13	11.80	[1, 131]	856
Counter-revolutionaries	5.00	14.86	23.55	[1, 408]	1,313
Covariates					
Share of Military-Age Male	0.65	0.64	0.03	[0.36, 0.85]	2,314
Share of Literate Male	0.25	0.27	0.12	[0.01, 0.81]	2,314
Share of Urban Population	0.05	0.09	0.10	[0.01, 0.95]	2,313
Density	19.38	23.57	22.03	[0.03, 442.1]	2,315
Elevation	117.00	147.23	177.77	[-31, 1999]	2,315

The first column summarizes raw data from matching. The second column shows the overall group size. For example, 16,798 means that, out of 41,125 WWI soldiers who were awarded medals, 16,798 did not have a family member arrested during Stalin's purges. The third column lists the share of identified family arrest matches per group type. Finally, the last column shows the share of identified family arrest matches per overall number of Stalin-era arrests.

The second panel of Table 3 summarizes the overall number of family connections found across the two datasets. There are more two-way familial connections than the number of overall arrested because multiple veterans might share the same family connection with the same arrestee. The third column of the second panel shows the average number of connections per single veteran, and the last column shows the maximum number of connections per person in a given group. WWI awardees can be a cross-cutting category as both revolutionaries and counter-revolutionaries could be WWI awardees.

5. ESTIMATION STRATEGY

I utilize three different levels of analysis to build various estimation strategies that can isolate community-level and individual-level results: units are analyzed at the district level, grid-cell level, and individual level.

5.1. Community-Level Analysis

I start exploring the relationship between previous participation in war and post-war repression by looking at the aggregate, district-level measures and controlling for district-level population and socioeconomic characteristics. I begin by estimating the following equation for the number of arrestees in each district:

$$ln(\text{Repression}_{p[d]}) = \gamma \cdot ln(\text{Veteran}_{p[d]}) + \boldsymbol{\beta}' \boldsymbol{X}_{p[d]} + s\big(\text{lon}_{d[i]}, \text{lat}_{d[i]}\big) + \xi_{p[d]} + \varepsilon_{p[d]}. \quad (1)$$

Table 3: Individual Matched Data Statistics

Groups	Count	Group Size	% of group	% of Arrested
No victim match				
WWI veteran	1,644,277	1,994,352	82.45	71.82
WWI heroes	16,798	41,125	40.85	0.73
Revolutionaries	4,597	5,247	87.61	0.20
White Guard	11,323	19,511	58.03	0.49
Only one victim				
WWI veteran	107,566	1,994,352	5.39	4.70
WWI heroes	2,542	41,125	6.18	0.11
Revolutionaries	200	5,247	3.81	0.01
White Guard	1,619	19,511	8.30	0.07
At least one victim				
WWI veteran	350,075	1,994,352	17.55	15.29
WWI heroes	24,327	41,125	59.15	1.06
Revolutionaries	650	5,247	12.39	0.03
White Guard	8,188	19,511	41.97	0.36
Multiple victims				
WWI veteran	242,509	1,994,352	12.16	10.60
WWI heroes	21,785	41,125	52.97	0.95
Revolutionaries	450	5,247	8.58	0.02
White Guard	6,569	19,511	33.67	0.29

Groups	Count	Group Size	Mean per person	Max per person
Overall connections				
WWI veteran	2,923,904	1,994,352	1.47	554
WWI heroes	595,071	41,125	14.47	554
Revolutionaries	5,737	5,247	1.09	256
White Guard	99,590	19,511	5.10	554

where $ln(\text{Repression}_{p[d]})$ is the natural log of individuals arrested and resettled from district d of historical province p, and $ln(\text{Veteran}_{d[i]})$ is the number of veterans in district d as measured by the number of overall veterans, the number of veterans who later fought to defend the old regime, and the number of veterans who fought to support the revolution that brought the Soviet Union to power. I use 1897 Census data aggregated across imperial districts, controlling for province fixed effects and district characteristics that may affect the likelihood of being arrested, such as male population size, male literacy levels, the proportion of the urban population, proportion of ethnic Russian population, and district density. I cluster standard errors at the district level and include two-dimensional spatial splines for birth locations.

Interpretation of district-level analysis can create challenges, given that the administrative boundaries of the Russian Empire and the Soviet Union did not align. Furthermore, many districts underwent significant territorial, jurisdictional, and name changes over time, even within the Russian Empire, and subsequently, within the Soviet Union. I create synthetic geographic units based on a 15 x 15 km grid network to address this challenge. Then, I overlay the grid-cells separately on Imperial Russia and Soviet Union maps and retrieve quantities of interest for each grid-cell. The advantage of this approach is that the grid-cells are independent of political boundaries, exogenous to the outcome of interest, and are temporally and spatially fixed. Alternatively, I replicate the district-level analyses with administrative units based on Soviet Russia's district borders.

Similar to the district-level aggregation, I calculate the total number of veterans and arrestees in each grid-cell and include grid-cell level covariates and fixed effects. I use the following OLS specification:

$$ln(\text{Repression}_j) = \gamma \cdot ln(\text{Veteran}_j) + \boldsymbol{\beta}'\boldsymbol{X}_j + s\big(\text{lon}_{d[i]}, \text{lat}_{d[i]}\big) + \xi_j + \varepsilon_j. \quad (2)$$

where $ln(\text{Repression}_j)$ is the natural log of individuals arrested and resettled in each grid-cell, and $ln(\text{Veteran}_j)$ is the number of WWI and civil war veterans in the same grid-cell. I cluster the errors at the grid-cell level.

5.2. *Individual Analysis*

Linking individual-level outcomes with district-wide or grid-cell bound patterns is challenging because of ecological inference – the people sent to GULAG camps from the same districts or grid-cells may not be veterans themselves or their immediate family members. In the case of WWI participation, for example, soldiers were initially mainly drafted from areas with deeper state access. If the state's access to those areas drove high arrest rates in places with a higher number of veterans, the district and grid-cell-level regressions would be biased – with veteran status not affecting individual fates, but leading to seemingly more arrests.

I address the ecological inference problem by analyzing the veteran status and arrests at the individual level. To this end, I match individual war records with the arrest records from the Memorial, using the last name and grid-cells as the connecting fields. Since both data contain information on individuals' biographic details, I can examine whether any individuals sharing the same last name as the veteran and born within the same grid-cell were arrested during Stalin's repressions. For each geographic unit, I calculate the total number of individuals arrested by authorities with the same last name. I create two measures for separate analyses of individual repression: a binary variable that indicates whether at least one person sharing the same last name was arrested in the same geographic unit; and a count measure for the number of arrests with the same last name in the vicinity of the birth location. I use logarithmic transformation for the second measure to address potential skewness.

To examine the direct effect of veteran status on an individual's family members, I estimate the following two least squares models:

$$\text{Repression}_i = \gamma \cdot \text{Veteran}_i + \boldsymbol{\beta}'\boldsymbol{X}_i + s\big(\text{lon}_{d[i]}, \text{lat}_{d[i]}\big) + \xi_j + \varepsilon_j. \tag{3}$$

$$ln(\text{Repression}_{j[i]}) = \gamma \cdot \text{Veteran}_i + \boldsymbol{\beta}'\boldsymbol{X}_i + s\big(\text{lon}_{d[i]}, \text{lat}_{d[i]}\big) + \xi_j + \varepsilon_j. \tag{4}$$

In equation 3, Repression_i indicates the arrest of at least one family member of the veteran, using a single match as a positive case. Compared to Equation 3, the outcome variable in the last equation considers the overall number of the last name matches in a given grid-cell, therefore representing the intensity of exposure to repression as a function of individual participation in the war. Across both specifications, I use individual-level covariates for veterans, including ethnicity. In addition, I cluster the standard errors at the grid-cell level. This set of analyses does not focus on participation in WWI directly, as the complete data include all drafted soldiers of WWI. Therefore, for individual-level results, I focus on soldiers of WWI who distinguished themselves in battles and those soldiers who later fought in the Russian Civil War.

Appendix **??** provides results of analysis based on a more accurate matching that identifies individuals not only by last name and location, but by the patrnomic. I use the first name of the veteran as a root for the patronymic of the arrestee, thereby identifying direct birth children of the war veterans. The advantage of this approach is that it allows me to exclude false positive matches based on common last names. However, this approach only allows for detection of birth children as opposed to veterans themselves or other members of their family (wives, grandchildren, etc.), increasing the chances for false negatives.

6. RESULTS

Overall, I find strong evidence that enlistment in previous wars increases the probability of being targeted by the state. The results are robust across all three units of analysis, demonstrating the strength and intensity of both the community-level and individual sacrifices. District-level results are presented in Table 4. An increase in the number of WWI veterans and WWI heroes in a given district from zero to 10 people leads to a 1.10 and 1.18 percentage point higher chance of arrests, respectively.[14] Similar interval changes in the number of Red Army and White Guard veterans lead to a 0.86 and 1.23 percentage point increase in repression.

Table 4: District-Level Results

	Dependent variable:			
	Log of Arrested Individuals			
	(1)	(2)	(3)	(4)
WWI veterans (general)	0.460***			
	(0.062)			
Awarded WWI veterans		0.492***		
		(0.079)		
Red Army veterans			0.358***	
			(0.092)	
White Guard veterans				0.512***
				(0.084)
District Controls	✓	✓	✓	✓
Province Fixed effects	✓	✓	✓	✓
Observations	742	653	606	620
Adjusted R^2	0.806	0.779	0.791	0.734

Note: Robust standard errors, clustered by province, are reported in parentheses. All models include province fixed effects and district-level covariates. Significance levels: $^{\dagger}p < 0.1$; $^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$.

Next, I analyze how wartime enlistment affected exposure to repression using grid-cells containing soldiers' exact birth locations. Table 5 presents the results of the grid-cell level analysis. Coefficients are consistently positive and statistically significant across all

[14] Given the logarithmic transformation, we subtract $\ln(0 + 1)$ from $\ln(10 + 1)$ and multiply by the coefficient size.

models. An increase in the number of WWI soldiers, WWI heroes, Red Army revolutionaries, and White Guard counter-revolutionaries in the soldiers' birthplaces from zero to 10 people leads to a corresponding increase in the number of arrestees by 0.84, 0.89, 1.63, and 0.96 percentage points, respectively.

Table 5: Grid-cell-Level Results

	Dependent variable:			
	Log of Arrested Individuals			
	(1)	(2)	(3)	(4)
WWI veterans (general)	0.349***			
	(0.055)			
Awarded WWI veterans		0.370***		
		(0.062)		
Red Army veterans			0.678***	
			(0.088)	
White Guard veterans				0.402***
				(0.073)
Grid-cell Controls	✓	✓	✓	✓
District Fixed Effects	✓	✓	✓	✓
Cubic Spatial Splines	✓	✓	✓	✓
Observations	1,987,701	1,946,053	1,699,214	1,909,513
Grid-cells with complete data	2214	1482	838	1302
Adjusted R^2	0.762	0.764	0.813	0.761

Note: Robust standard errors, clustered by district, are reported in parentheses. Included observations reflect districts. All models include province fixed effects and district-level covariates. Significance levels: $^{\dagger}p < 0.1$; $^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$.

I present results from equation 3 in the first panel of Table 6. WWI hero status and participation in the Russian Civil War are positively associated with the arrest of at least one member of a family or descendant. Results are similar for revolutionaries and counter-revolutionaries. The second panel of Table 6 shows the results from equation 4, which looks into the number of repressed family members. Being a revolutionary is associated with a 0.08 percentage point higher chance of repression of multiple family members. The size is much larger for the White Guard counter-revolutionaries, indicating that counter-revolutionaries, compared to the Bolshevik loyalists, saw a higher number of family members fall victim to Stalin's repressions.

Table 6: Individual-Level Results

	Dependent variable:		
	Binary Family Repression Indicator		
	(1)	(2)	(3)
Awarded WWI veterans	1.390***		
	(0.012)		
Red Army veterans		0.144***	
		(0.048)	
White Guard veterans			0.711***
			(0.016)
Individual Controls	✓	✓	✓
District Fixed effects	✓	✓	✓
Cubic Spatial Splines	✓	✓	✓
Observations	1,602,186	1,602,186	1,602,186
Adjusted R^2	0.191	0.182	0.183
	Number of Repressed Family Members		
	(1)	(2)	(3)
Awarded WWI veterans	0.736***		
	(0.036)		
Red Army veterans		0.035***	
		(0.010)	
White Guard veterans			0.284***
			(0.015)
Individual Controls	✓	✓	✓
District Fixed effects	✓	✓	✓
Cubic Spatial Splines	✓	✓	✓
Observations	1,601,593	1,601,593	1,601,593
Adjusted R^2	0.307	0.285	0.287

Note: Robust standard errors, clustered by grid-cell, are reported in parentheses. Included observations reflect disaggregated individual records, with non-missing location. All models include district fixed effects, cubic spatial splines, and individual birth and grid-cell-level covariates. Significance levels: $^{\dagger}p < 0.1$; $^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$.

In sum, the results support the punishment hypothesis: the Soviet authorities treated all civil war veterans as treacherous subjects, although the family members of counter-revolutionaries were targeted at a higher rate.

7. Alternative Explanations

The empirical findings confirm my key expectations concerning the effect of veteran status on state repression. I next attempt to rule out several alternative explanations and assess the robustness of the main findings.

7.1. Politically Neutral Veterans

I begin by reevaluating the effect of participation in World War I. In the current empirical setup, I consider three distinct groups: all veterans of World War I, veterans of WWI who chose to support the revolution, and those who continued to fight on behalf of the state. The fourth category of veterans – not included in the main specifications – is unaligned veterans of World War I. While highly unlikely, it is still possible that the Soviet state was distrustful of all participants of the Russian Civil War, because of a lack of clear information on individual loyalties and thus, punished all veterans of the civil war, but spared World War I veterans who remained neutral after the 1917 revolution. If true, we should expect to observe a null or negative effect of participation in WWI and non-participation in the Russian Civil War on Soviet repressions.

To investigate the possibility of differential treatment of politically neutral veterans, I classify WWI veterans who do not appear in civil war records in a separate group and re-run the main analyses with this group's wartime participation as the main explanatory variable. The findings in Table 7 suggest that the direction of the relationship is still positive, although the effect size is much smaller for non-aligned veterans at the district level.

Table 7: Neutral veterans and Soviet Repression

	Units of Analysis	
	District Level	Grid-cell Level
Neutral WWI veterans	0.0002 (0.0001)***	0.349 (0.055)***
Districts	742	
Grid-cells		2315
Observations	742	1,987,699
Adjusted R^2	0.80	0.762
Fixed effects	✓	✓
Cubic splines	✓	✓

Clustered robust standard errors are reported in parentheses. The dependent variable represents the number of WWI veterans who remained neutral during the civil war, specified by geographic aggregation levels. All models include district fixed effects, cubic spatial splines, and covariates. Significance levels: $^{\dagger}p < 0.1$; $^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$

7.2. All Red Army Revolutionaries

The entire veteran sample used in the paper only includes civil war participants who were veterans of World War I. This is partly due to the availability and reliability of the WWI veteran data, as the full data on civil war soldiers, although comprehensive, does not represent the entire population of participants of civil war battles. Nonetheless, the focus of the paper on only civil war soldiers who fought in WWI might produce a potential threat to inference. Suppose the Soviet authorities had detailed records of WWI soldiers without much knowledge of civil war fighters. In that case, the results for revolutionaries could be driven by the effects of WWI rather than the actual treatment of revolutionary supporters. To verify that the arrest results are not driven by only WWI participation, I re-run the analysis on the entire sample of Revolutionary Red Guard soldiers, irrespective of their involvement in World War I. Furthermore, the data includes only those Revolutionary Red Guard soldiers who have lost their lives on the battlefield fighting for the Bolshevik ideals. The results for the revolutionary soldiers remain unchanged, as shown in Table 8.

Table 8: Revolutionaries Irrespective of WWI status

	Specifications	
	District Aggregates	Weighted by Population
All revolutionaries	0.503 (0.056)***	22.604 (8.677)***
Observations	629	629
Adjusted R^2	0.772	0.479
District Controls	✓	✓
Province Fixed effects	✓	✓

Clustered robust standard errors are reported in parentheses. The dependent variable represents all revolutionary soldiers of the Russian Civil War, irrespective of their participation in WWI. The second column weights measures by the population size. All models include province fixed effects and district covariates. Significance levels: $^{\dagger}p < 0.1$; *p $<$ .05; **p $<$ .01; ***p $<$ .001

7.3. The Ethnicity Factor

One possible explanation for the current findings can rest on the ethnicity factor. We know that ethnic minority veterans of World War I enlisted in the Russian Civil War at very high rates (Talibova, 2022). Furthermore, ethnic minority enclaves of Imperial Russia saw the heaviest battles in the civil war as minority groups attempted to achieve independence and create their nation-states. It is also well-known that the last wave of Stalin's purges targeted ethnic minority areas. Although I control for ethnicity in the individual-level empirical specifications, minority ethnic background of certain geographic areas might be a potential confounder that affects both the likelihood of civil war participation and targeting by the state, creating biased results in the district and grid-cell level specifications.

Due to the overlap of spatial concentration of ethnic minorities in the periphery of Russia's territories, it is possible to isolate geographic areas where ethnic minorities dominated imperial districts and Soviet administrative units. To do so, I re-run my analysis on a more concentrated geographic location by eliminating districts that do not fall into present-day Russian territories. This ensures that predominantly ethnic minority areas that later became independent Soviet republics and post-Soviet states are excluded from the new sample. Appendix **??** shows the results and the list of districts excluded from the reduced sample. The results support the main findings on the positive relationship between wartime enlistment and state repressions.

7.4. Administrative Boundary Shifts

The administrative boundaries of the Soviet Union did not perfectly overlap with the district boundaries of Imperial Russia. As such, the measure of the dependent variable and some of the covariates might introduce additional errors. Grid-cell-level analysis partly addresses this problem. However, to further rule out this possibility, I replicate the district-level analyses with administrative units of the Soviet Union based on the updated Soviet district borders and using socio-demographic measures (local population size, urbanization levels, etc.) taken from the Soviet Census of 1926. As I detail in Appendix **??**, communities with a higher number of veterans of both wars were more likely to be targeted by the Soviet authorities. In short, I find no evidence of bias due to temporospatial imprecision.

8. CONCLUSION

Using novel data on soldiers of WWI and the Russian Civil War and political arrests during Stalin's rule, I study how community-level and personal sacrifices of the citizens on the battleground translate into post-war benefits. I focus on the treatment by the state – a non-tangible but extremely valuable social reward in an authoritarian setting, and find that the state does not recognize war sacrifices, nor the loyalties attached to them, when soldiers return to civilian life. Reversing the direction of the repression-loyalty relationship, often studied by scholars of legacies of political violence, this paper shows that the effect of wartime enlistment can persist for a long time and affect the fate of individuals and communities who do not partake in wartime activities directly.

My findings have important theoretical and practical implications about the dynamics of state-citizen-military relations in established autocracies. This study establishes that the absence of a liberal social contract in non-democratic countries implies citizens' primary motivation in participating in the state's war-making efforts is extrinsic. Some of these rewards are at the direct discretion of the state, while others are a natural product of military training. Insofar as the authoritarian entity is in need of civilian support for survival, either for engaging in war with an external enemy or fighting internally to gain power, it might continue to provide the expected rewards for wartime service. As soon as the political power of the regime is sealed, the state will not only resort to its usual *modus operandi*; it will punish once loyal service members to ensure against potential future civil disobedience.

While the findings in this paper are based on an analysis of a single, albeit important case, there are reasons to expect similar dynamics in authoritarian contexts and beyond. For example, there is ample scholarly evidence of the mistreatment of Black veterans of WWII in their subsequent civilian lives (Onkst, 1998; Turner and Bound, 2003; Parker, 2009), despite their anticipation of a better post-service life during enlistment (Stouffer et al., 1949). Thus, future research could measure the degree to which democratic states uphold their end of the liberal social contract in the long term.

References

Ager, Philipp, Leonardo Bursztyn, Lukas Leucht and Hans-Joachim Voth. 2021. "Killer Incentives: Rivalry, Performance and Risk-Taking among German Fighter Pilots, 1939–45." *The Review of Economic Studies* .

Alesina, A. and E.L. Ferrara. 2005. "Ethnic diversity and economic performance." *Journal of Economic Literature* 43(3):762–800.

Alesina, Alberto, Bryony Reich and Alessandro Riboni. 2020. "Nation-building, nationalism, and wars." *Journal of Economic Growth* 25(4):381–430.

Angrist, Joshua and Alan B Krueger. 1994. "Why do World War II veterans earn more than nonveterans?" *Journal of labor economics* 12(1):74–97.

Angrist, Joshua D, Stacey H Chen and Jae Song. 2011. "Long-term consequences of Vietnam-era conscription: New estimates using social security data." *American Economic Review* 101(3):334–38.

Arjona, Ana. 2016. *Rebelocracy*. Cambridge University Press.

Avrahami, Yoash and Miri Lerner. 2003. "The effect of combat service and military rank on entrepreneurial careers: The case of Israeli MBA graduates." *Journal of Political and Military Sociology* 31(1):97–118.

Balcells, Laia. 2012. "The consequences of victimization on political identities: Evidence from Spain." *Politics & Society* 40(3):311–347.

Bedard, Kelly and Olivier Deschênes. 2006. "The long-term impact of military service on health: Evidence from World War II and Korean War veterans." *American Economic Review* 96(1):176–194.

Berger, Mark C and Barry T Hirsch. 1983. "The civilian earnings experience of Vietnam-era veterans." *Journal of Human resources* pp. 455–479.

Besley, Timothy and Torsten Persson. 2008. "Wars and state capacity." *Journal of the European Economic Association* 6(2-3):522–530.

Bingley, Paul, Stéphanie Vincent Lyk-Jensen and Anders Rosdahl. 2022. "Military Service and Skill Acquisition: Evidence from a Draft Lottery.".

Boix, Carles. 2008. "Economic roots of civil wars and revolutions in the contemporary world." *World Politics* 60(3):390–437.

Brooks, Jennifer E. 2004. *Defining the Peace: World War II Veterans, Race, and the Remaking of Southern Political Tradition*. Univ of North Carolina Press.

Cárdenas, Mauricio, Marcela Eslava and Santiago Ramírez. 2016. "Why internal conflict deteriorates state capacity? Evidence from Colombian municipalities." *Defence and Peace Economics* 27(3):353–377.

Conquest, Robert. 1997. "Victims of Stalinism: A Comment." *Europe-Asia Studies* 49(7):1317–1319.

Dyadkin, Iosif G. 1983. *Unnatural Deaths in the USSR, 1928-1954*. Transaction Publishers.

Eynde, Oliver Vanden. 2016. "Military service and human capital accumulation: Evidence from colonial Punjab." *Journal of Human Resources* 51(4):1003–1035.

Gatrell, Peter. 2014. *Russia's First World War: A social and economic history*. Routledge.

Gregory, Paul R. 2009. *Terror by Quota: State Security from Lenin to Stalin*. Yale University Press.

G.U.R.K.K.A. 1926. *Imennoy spisok poter na frontakh v lichnym sostave Raboche-Krestyanskoy Krasnoy Armii za vremya grashdanskoy voyni [List of casualties at the fronts among the person-*

nel of the Workers and Peasants' Red Army during the Civil War]. Upravleniya ustroystva i slujby voisk G.U.R.K.K.A. [Directorate of the Creation and Service of the Troops of G.U.R.K.K.A.].

Gurr, Ted Robert. 1970. *Why Men Rebel*. Princeton, NJ: Princeton University Press.

Hofmeister, Alexis. 2016. "A war of letters–What do we read in soldiers'Letters of Russian Jews from the Great War?" *Revue des études slaves* 87(LXXXVII-2):181–193.

Huang, Reyko. 2016. *The wartime origins of democratization: civil war, rebel governance, and political regimes*. Cambridge University Press.

Huff, Connor and Robert Schub. 2021. "Segregation, Integration, and Death: Evidence from the Korean War." *International Organization* 75(3):858–879.

Jha, Saumitra and Steven Wilkinson. 2012. "Does combat experience foster organizational skill? Evidence from ethnic cleansing during the partition of South Asia." *American Political Science Review* 106(4):883–907.

Kessler, Gijs. 2017. "Map of the 1897 Russian Empire - uezd level.".
URL: *https://hdl.handle.net/10622/DN9QDM*

Kotkin, Stephen. 2017. *Stalin: Waiting for Hitler, 1929-1941*. Penguin Books Limited.

Krebs, Ronald R and Robert Ralston. 2022. "Patriotism or paychecks: Who believes what about why soldiers serve." *Armed Forces & Society* 48(1):25–48.

Leal, David L and Jeremy M Teigen. 2018. "Military service and political participation in the United States: Institutional experience and the vote." *Electoral Studies* 53:99–110.

Lee, Chulhee. 2012. "Military service and economic mobility: Evidence from the American civil war." *Explorations in economic history* 49(3):367–379.

Levi, Margaret. 1997. *Consent, dissent, and patriotism*. Cambridge University Press.

Lupu, Noam and Leonid Peisakhin. 2017. "The legacy of political violence across generations." *American Journal of Political Science* 61(4):836–851.

Lyall, Jason. 2020. *Divided Armies: Inequality and Battlefield Performance in Modern War*. Princeton University Press.

Mampilly, Zachariah Cherian. 2012. *Rebel Rulers: Insurgent Governance and Civilian Life During War*. Cornell University Press.

Memorial. 2014. "Zhertvy politicheskogo terrora v SSSR [Victims of political terror in the USSR].".
URL: *http://lists.memo.ru/*

Murphy, David E. 2006. *What Stalin knew: the enigma of Barbarossa*. Yale University Press.

Onkst, David H. 1998. "" First a negro... incidentally a veteran": black World War Two veterans and the GI Bill of rights in the Deep South, 1944-1948." *Journal of Social History* pp. 517–543.

Pamyati Geroev. 2020. "Pamyati Geroev Velikoy Voyni [In Memory of the Heroes of the Great War 1914-1918].".
URL: *https://gwar.mil.ru/about/*

Parker, Christopher S. 2009. "When politics becomes protest: Black veterans and political activism in the postwar South." *The Journal of Politics* 71(1):113–131.

Postnikov, Nikolay. 2014. "Tragediya, rasskazannaya v pismax [Tragedy in the letters of Russian soldiers].".
URL: *https://expert.ru/expert/2014/33/tragediya-rasskazannaya-v-pismah/*

Qian, Nancy and Marco Tabellini. 2021. Discrimination and State Capacity: Evidence from WWII US Army Enlistment. Technical report.

Reiter, Dan and Allan C Stam III. 1998. "Democracy and battlefield military effectiveness." *Journal of Conflict Resolution* 42(3):259–277.

Richard, Bryant and Al Wilhite. 1990. "Military experience and training effects on civilian wages." *Applied economics* 22(1):69–81.

Rozenas, Arturas, Roya Talibova and Yuri Zhukov. 2022. "Fighting for Tyranny: State Repression and Combat Motivation." Working paper.

Rozenas, Arturas, Sebastian Schutte and Yuri Zhukov. 2017. "The Political Legacy of Violence: The Long-Term Impact of Stalin's Repression in Ukraine." *Journal of Politics* 79(4):1147–1161.

Rozenas, Arturas and Yuri Zhukov. 2019. "Mass Repression and Political Loyalty: Evidence from Stalin's' Terror by Hunger'." *American Political Science Review (forthcoming)* .

Sampson, Robert J and John H Laub. 1996. "Socioeconomic achievement in the life course of disadvantaged men: Military service as a turning point, circa 1940-1965." *American sociological review* pp. 347–367.

Shearer, David R. 2014. *Policing Stalin's socialism: Repression and social order in the Soviet Union, 1924-1953*. Yale University Press.

Skocpol, Theda. 1994. *Social revolutions in the modern world*. Cambridge University Press.

Stewart, Megan A. 2021. *Governing for Revolution: Social Transformation in Civil War*. Cambridge University Press.

Stouffer, Samuel A., Arthur A. Lumsdaine, Marion Harper Lumsdaine, Jr. Williams, Robin M., M. Brewster Smith, Irving L. Janis, Shirley A. Star and Jr. Cottrell, Leonard S. 1949. *The American Soldier: Combat and Its Aftermath*. Princeton: Princeton University Press.

Talibova, Roya. 2022. “Repression, Military Service and Insurrection.” Working paper.

Tilly, Charles. 1978. *From Mobilization to Revolution*. Addison-Wesley.

Tilly, Charles. 1992. *Coercion, capital, and European states, 990-1990*. Blackwell.

Troynitsky, N. 1899. “The First Total Census of Russian Empire in 89 Volumes.” *The Central Statistical Bureau of the Ministry of Internal Affairs of the Russian Empire, St. Petersburg* 1905.

Turner, Sarah and John Bound. 2003. “Closing the gap or widening the divide: The effects of the GI Bill and World War II on the educational outcomes of black Americans.” *The Journal of Economic History* 63(1):145–177.

Viola, Lynne. 2007. *The unknown gulag: the lost world of Stalin's special settlements*. Oxford University Press, USA.

Volkov, Sergey. 2016. “Uchastniki Belogo dvijeniya v Rossii [Participants of the White movement in Russia].”.
URL: *http://swolkov.org/*

Weinstein, Jeremy. 2007. *Inside Rebellion: The Politics of Insurgent Violence*. Cambridge: Cambridge University Press.

Young, Lauren. 2019. “The psychology of state repression: Fear and dissent decisions in Zimbabwe.” *American Political Science Review* 113(1):140–155.

Zhukov, Yuri M. and Roya Talibova. 2018. “Stalin's Terror and the Long-Term Political Effects of Mass Repression.” *Journal of Peace Research* 55(2).
URL: *http://sites.lsa.umich.edu/zhukov/wp-content/uploads/sites/ 140/2017/07/Stalin_v23.pdf*

Appendix

Contents

A1. Imperial Districts and Soviet Repression

One of the challenges of the paper is to identify the number of arrested individuals that fall within imperial district borders. When Stalin's repression unfolded in the Soviet Union, the territorial-administrative boundaries of previous imperial districts had been changed multiple times. Therefore, identifying a common territorial-administrative boundary was important for aggregating the number of arrestees and the number of veterans of wars. To ensure that the birth locations of the Soviet arrestees fall within the accurate boundaries of imperial districts, I aggregated the number of birth geocoordinates of Stalin's victims that were contained in each polygon corresponding to the pre-WWI imperial districts.

The number of arrested people corresponding to each imperial district is reported in Table A1.1 below. The table includes only those districts where the number of arrestees is above 500. There are 500 districts where the number of arrested individuals were above 500 people.

Table A1.1: List of Districts by Number of Repression Victims

District	Province	Count	% Population
Tom	Tom	66,257	23.91
Moskov	Moskov	51,144	4.25
Zmeinogor	Tom	48,042	19.79
Nalchik	Ter	39,577	38.46
Barnaul	Tom	36,132	6.19
Sankt-Peterburg	Sankt-Peterburg	23,297	1.77
Kavkaz	Kuban	22,012	8.83
Biy	Tom	21,903	6.50
Bobrov	Voronej	21,495	7.50
Ufim	Ufim	20,938	5.61
Minsk	Minsk	20,090	7.25
Kain	Tom	20,040	10.71
Nikolaev	Samar	19,868	4.02
Novouzen	Samar	19,783	4.74
Sterlitamak	Ufim	18,802	5.74
Tyukalin	Tobol	18,018	8.63
Kazan	Kazan	17,478	4.98
Akmolin	Akmolin	17,368	9.39
Om	Akmolin	17,260	17.17
Chitin	Zabaykal	16,783	12.06
Minusin	Yenisey	16,140	8.73
Belebeev	Ufim	14,939	3.45
Amur	Amur	14,824	12.32
Viteb	Viteb	14,178	8.12
Bir	Ufim	14,138	2.84
Kuznets	Tom	14,080	8.70
Orenburg	Orenburg	13,348	2.40
Pechor	Arkhangel	12,538	35.83
Perm	Perm	12,527	4.59
Yekaterinodar	Kuban	12,212	4.98
Khabarov	Primor	12,058	44.19
Sarapul	Vyat	11,820	2.90
Sunjen	Ter	11,815	20.48
Samar	Samar	11,723	3.28
Bugulmin	Samar	11,669	3.89
Menzelin	Ufim	11,637	3.06
Or	Orenburg	10,483	5.07
Pyatigor	Ter	10,385	11.44
Chelyabin	Orenburg	10,328	2.50
Kursk	Kursk	10,257	4.60

District	Province	Count	% Population
Kem	Arkhangel	10,171	28.74
Simbir	Simbir	9,992	4.42
Irkut	Irkut	9,992	6.13
Buguraslan	Samar	9,853	2.43
Saratov	Saratov	9,329	2.80
Khasavyurtov	Ter	9,162	12.94
Donetsk	Oblast Voyska Donskogo	9,141	2.01
Novoladoj	Sankt-Peterburg	9,001	10.25
Staroruss	Novgorod	8,989	4.68
Enotaev	Astrakhan	8,907	11.71
Kan	Yenisey	8,893	9.24
Buzuluk	Samar	8,794	1.78
1 Donskoy	Oblast Voyska Donskogo	8,731	3.21
Novgorod	Novgorod	8,650	4.66
Brest	Grodnen	8,439	3.86
Atbasar	Akmolin	8,378	9.70
Rostov	Oblast Voyska Donskogo	8,186	2.21
Usman	Tombov	8,180	3.90
Slonim	Grodnen	8,091	3.58
Voronej	Voronej	7,999	2.92
Krasnoyar	Yenisey	7,973	8.04
Sengileev	Simbir	7,897	5.20
Troits	Orenburg	7,806	3.88
Achin	Yenisey	7,797	6.99
Verkhotur	Perm	7,755	2.86
Solikam	Perm	7,733	3.38
Chistopol	Kazan	7,699	2.52
Lbishen	Ural	7,647	4.51
Chimkent	Syr-Darya	7,643	2.68
Tar	Tobol	7,591	4.75
Bogorod	Moskov	7,562	3.40
Borovich	Novgorod	7,490	5.12
Laishev	Kazan	7,420	4.30
Syzran	Simbir	7,398	3.06
Kokchetav	Akmolin	7,302	4.70
Krestets	Novgorod	6,903	6.61
Semipalatin	Semipalatin	6,880	4.39
Roven	Volyn	6,851	2.51
Kurgan	Tobol	6,807	2.62
Pin	Minsk	6,666	2.89

District	Province	Count	% Population
Pishpek	Semirechen	6,607	3.74
Mogilyov	Mogilyov	6,576	4.22
Kamishin	Saratov	6,552	2.13
Kustanay	Turgay	6,458	4.23
Pavlodar	Semipalatin	6,456	4.10
Arkhangel	Arkhangel	6,440	10.56
Zlatoustov	Ufim	6,425	3.46
Stavropol	Samar	6,300	2.22
Odes	Kherson	6,248	1.02
Yelabuj	Vyat	6,222	2.58
Tsarskoselsk	Sankt-Peterburg	6,185	4.13
Petropavlov	Akmolin	6,101	3.93
Astrakhan	Astrakhan	5,777	2.63
Glazov	Vyat	5,687	1.54
Malmyj	Vyat	5,660	2.02
Pskov	Pskov	5,659	2.50
Karsun	Simbir	5,603	2.58
Bakhmut	Yekaterinoslav	5,530	1.66
Irgiz	Turgay	5,471	5.54
Vesyegon	Tver	5,395	3.47
Yaran	Vyat	5,374	1.47
Verkhneural	Orenburg	5,364	2.40
Sluts	Minsk	5,191	1.99
Dorogobuj	Smolen	5,160	4.93
Temryuk	Kuban	5,154	1.50
Ostrov	Pskov	5,114	3.16
Bobruy	Minsk	5,112	2.00
Labin	Kuban	5,034	1.65
Demyan	Novgorod	5,013	6.28
Vladikavkaz	Ter	5,002	3.71
Vernen	Semirechen	4,976	2.22
Povenets	Olonets	4,964	18.82
Temir-Khan-Shurin	Dagestan	4,963	5.10
2 Donskoy	Oblast Voyska Donskogo	4,945	2.07
Yekaterinburg	Perm	4,910	1.19
Borisov	Minsk	4,902	2.06
Kiren	Irkut	4,893	8.82
Boguchar	Voronej	4,882	1.58
Yekaterinoslav	Yekaterinoslav	4,871	1.36
Ryazan	Ryazan	4,864	2.29

District	Province	Count	% Population
Ostrogoj	Voronej	4,844	1.77
Mariin	Tom	4,839	3.51
Tambov	Tambov	4,805	1.14
Mamadysh	Kazan	4,741	2.50
Ural	Ural	4,617	1.57
Spass	Ryazan	4,612	2.94
Yakut	Yakut	4,600	3.20
Balagan	Irkut	4,546	3.12
Buin	Simbir	4,514	2.48
Kovel	Volyn	4,492	2.12
Guryev	Ural	4,460	5.14
Batalpashin	Kuban	4,385	2.04
Ishim	Tobol	4,361	1.62
Nijegorod	Nijegorod	4,290	1.93
Aulieatin	Syr-Darya	4,265	1.54
Orlov	Orlov	4,254	2.04
Yadrin	Kazan	4,197	2.72
Novogrud	Minsk	4,180	1.69
Shuy	Vladimir	4,177	2.64
Iman	Primor	4,149	9.97
Lipets	Tambov	4,126	2.51
Gdov	Sankt-Peterburg	4,064	2.79
Khvalyn	Saratov	4,053	2.10
Igumen	Minsk	4,036	1.72
Ust-Medvedits	Oblast Voyska Donskogo	3,997	1.62
Okhan	Perm	3,969	1.48
Balashov	Saratov	3,960	1.27
Yaroslav	Yaroslav	3,939	1.89
Petrozavodsk	Olonets	3,914	4.91
Alatyr	Simbir	3,892	2.46
Verkhneudin	Zabaykal	3,886	2.31
Porkhov	Pskov	3,870	2.20
Viley	Vilen	3,859	1.86
Ud	Primor	3,829	21.00
Cherkass	Oblast Voyska Donskogo	3,797	1.58
Nijneudin	Irkut	3,757	4.64
Opoches	Pskov	3,736	2.75
Verkhnedneprov	Yekaterinoslav	3,715	1.76
Cherdyn	Perm	3,705	3.50
Sal	Oblast Voyska Donskogo	3,698	4.85

District	Province	Count	% Population
Aktyubin	Turgay	3,683	3.20
Penzen	Penzen	3,680	2.27
Sviyaj	Kazan	3,679	2.91
Urjum	Vyat	3,596	1.24
Roslavl	Smolensk	3,579	1.90
Stavropol	Stavropol	3,557	2.15
Tsarevokokshay	Kazan	3,554	3.16
Yelets	Orlov	3,499	1.25
Khopyor	Oblast Voyska Donskogo	3,483	1.38
Kotelnich	Vyat	3,477	1.26
Grodnen	Grodnen	3,465	1.69
Valday	Novgorod	3,453	3.63
Liven	Orlov	3,453	1.19
Shadrin	Perm	3,442	1.11
Novokhopyor	Voronej	3,439	1.79
Tobol	Tobol	3,430	2.68
Aleksandrov	Arkhangel	3,397	36.56
Spass	Kazan	3,377	1.93
Totem	Vologod	3,354	2.28
Vladimir-Volyn	Volyn	3,354	1.21
Mtsen	Orlov	3,354	3.22
Kiev	Kiev	3,334	0.62
Vyat	Vyat	3,316	1.73
Tetyush	Kazan	3,307	1.78
Maykop	Kuban	3,268	1.15
Orshan	Mogilyov	3,199	1.71
Kharkov	Kharkov	3,146	0.90
Olgin	Primor	3,127	7.52
Osin	Perm	3,113	0.97
Pinej	Arkhangel	3,061	10.63
Balakhnin	Nijegorod	3,047	2.15
Ardatov	Simbir	3,027	1.60
Yenisey	Yenisey	3,002	4.45
Krapiven	Tul	2,994	2.91
Zvenigorod	Moskov	2,985	3.54
Ust-Sysol	Vologod	2,915	3.24
Insar	Penzen	2,905	1.63
Luj	Sankt-Peterburg	2,866	2.15
Yalutorov	Tobol	2,834	1.50
Dmitrov	Moskov	2,826	2.36

District	Province	Count	% Population
Tsaryov	Astrakhan	2,816	1.42
Serdob	Saratov	2,806	1.25
Saran	Penzen	2,794	1.95
Nerchin	Zabaykal	2,785	2.95
Pavlov	Voronej	2,778	1.77
Yey	Oblast Voyska Donskogo	2,763	1.00
Turgay	Turgay	2,755	3.17
Aleksandrov	Vladimir	2,711	2.70
Zemlyan	Voronej	2,706	1.35
Maloarkhangel	Orlov	2,698	1.54
Slobod	Vyat	2,684	1.26
Serpukhov	Moskov	2,645	2.36
Zaysan	Semipalatin	2,633	2.77
Romanovo-Borisogleb	Yaroslav	2,629	3.49
Podol	Moskov	2,615	3.03
Gorodishen	Penzen	2,609	1.51
Velikoluk	Pskov	2,565	2.07
Lepel	Viteb	2,522	1.61
Ustyujen	Novgorod	2,498	2.50
Pokrov	Vladimir	2,478	1.57
Nijnedevits	Voronej	2,463	1.47
Taganrog	Oblast Voyska Donskogo	2,456	0.59
Lepsin	Semirechen	2,420	1.34
Tikhvin	Novgorod	2,411	2.43
Solvychegod	Vologod	2,403	2.04
Lipnov	Plots	2,400	2.71
Ustyuj	Vologod	2,378	1.65
Sudogod	Vladimir	2,375	2.45
Aleksandrov	Stavropol	2,363	1.31
Kozlov	Tambov	2,360	0.70
Borisogleb	Tambov	2,350	0.77
Disnen	Vilen	2,341	1.14
Lid	Vilen	2,333	1.13
Tsaritsyn	Saratov	2,332	1.44
Nerchinsko-Zavod	Zabaykal	2,332	3.08
Koven	Koven	2,320	1.02
Krasnin	Smolensk	2,293	2.24
Gorbatov	Nijegorod	2,278	1.70
Surgut	Tobol	2,266	29.25
Kasimov	Ryazan	2,260	1.35

District	Province	Count	% Population
Orlov	Vyat	2,235	1.05
Belostok	Grodnen	2,234	1.08
Bronnits	Moskov	2,229	1.71
Lukoyanov	Nijegorod	2,223	1.15
Sebej	Viteb	2,211	2.40
Kopal	Semirechen	2,187	1.60
Orgeev	Bessarab	2,180	1.02
Yegoryev	Ryazan	2,160	1.41
Petrov	Saratov	2,157	0.97
Nijnelomov	Penzen	2,155	1.40
Selengin	Zabaykal	2,153	2.11
Semyonov	Nijegorod	2,142	1.92
Krasnoslobod	Penzen	2,136	1.22
Kaluj	Kaluj	2,125	1.84
Temnikov	Tambov	2,113	1.53
Kobrin	Grodnen	2,097	1.14
Akshin	Zabaykal	2,094	6.00
Nikol	Vologod	2,077	0.91
Kolomen	Moskov	2,071	1.85
Morshan	Tambov	2,065	0.76
Tsivil	Kazan	2,065	1.26
Zhitomir	Volyn	2,056	0.47
Kurmysh	Simbir	2,037	1.26
Ardatov	Nijegorod	2,032	1.43
Arzamas	Nijegorod	2,022	1.46
Vel	Vologod	2,021	1.97
Klin	Moskov	2,017	1.75
Rostov	Yaroslav	1,994	1.34
Tyumen	Tobol	1,986	1.64
Groznen	Ter	1,981	0.88
Velij	Viteb	1,963	1.96
Andiy	Dagestan	1,958	3.95
Krasnoyar	Astrakhan	1,952	2.96
Kuznets	Saratov	1,950	1.09
Kirsanov	Tambov	1,949	0.74
Tifliss	Tifliss	1,917	0.82
Murom	Vladimir	1,913	1.56
Kholm	Pskov	1,910	2.17
Yuryevets	Kostrom	1,909	1.57
Smolen	Smolensk	1,909	1.32

District	Province	Count	% Population
Lomjin	Lomjin	1,884	1.60
Pereyaslav	Poltav	1,862	1.00
Volokolam	Moskov	1,860	2.30
Yelnin	Smolensk	1,845	1.34
Kungur	Perm	1,844	1.35
Shlisselburg	Sankt-Peterburg	1,838	3.35
Rybin	Yaroslav	1,834	1.97
Novosil	Tul	1,831	1.28
Zhizdrin	Kaluj	1,809	0.75
Volkovyss	Grodnen	1,800	1.21
Turkmenskoe pristavstvo	Stavropol	1,790	7.49
Melenkov	Vladimir	1,785	1.25
Karkaralin	Semipalatin	1,779	1.04
Dukhovshin	Smolensk	1,778	1.43
Taruss	Kaluj	1,775	3.05
Oster	Chernigov	1,767	1.18
Verkholen	Irkut	1,767	2.54
Varnavin	Kostrom	1,751	1.43
Polots	Viteb	1,745	1.23
Ryaj	Ryazan	1,735	1.25
Simferopol	Tavrich	1,731	1.22
Chembar	Penzen	1,723	1.12
Vyazem	Smolensk	1,706	1.62
Kazalin	Syr-Darya	1,694	1.21
Kineshem	Kostrom	1,691	1.18
Kamishlov	Perm	1,684	0.68
Feodosiy	Tavrich	1,680	1.45
Vetluj	Kostrom	1,678	1.39
Mokshan	Penzen	1,642	1.51
Temir	Ural	1,618	1.70
Shigrov	Kursk	1,614	1.08
Lebedyan	Tambov	1,612	1.11
Oboyan	Kursk	1,611	0.89
Ust-Kamenogor	Semipalatin	1,608	1.55
Luts	Volyn	1,603	0.63
Krasnoufim	Perm	1,603	0.62
Novorjev	Pskov	1,582	1.39
Makaryev	Nijegorod	1,575	1.45
Bel	Smolensk	1,568	0.95
Cherepovets	Novgorod	1,565	0.99

District	Province	Count	% Population
Spass	Tambov	1,560	1.29
Chernoyar	Astrakhan	1,560	1.56
Tim	Kursk	1,553	1.10
Kherson	Kherson	1,535	0.26
Tiraspol	Kherson	1,529	0.64
Bolkhov	Orlov	1,515	1.10
Korotoyak	Voronej	1,511	0.96
Zmiev	Kharkov	1,509	0.65
Ananyev	Kherson	1,508	0.57
Nolin	Vyat	1,502	0.83
Krements	Volyn	1,499	0.68
Porech	Smolensk	1,492	1.13
Toropets	Pskov	1,482	1.54
Vologod	Vologod	1,470	0.85
Novorossiy	Chernomor	1,468	4.21
Novotorj	Tver	1,457	1.00
Cheboksar	Kazan	1,447	1.14
Bejets	Tver	1,432	0.58
Biryuchen	Voronej	1,386	0.69
Vladimir	Vladimir	1,365	0.85
Petropavlov	Kamchatka	1,365	16.32
Meshov	Kaluj	1,364	1.41
Shenkur	Arkhangel	1,338	1.74
Balt	Podol	1,332	0.34
Yaren	Vologod	1,328	2.90
Yuryev	Vladimir	1,327	1.43
Gorodok	Viteb	1,326	1.18
Suzdal	Vladimir	1,322	1.23
Baku	Baku	1,316	0.72
Tashkent	Syr-Darya	1,308	0.29
Vol	Saratov	1,305	0.71
Sennen	Mogilyov	1,300	0.80
Vyshnevolots	Tver	1,297	0.72
Gorets	Mogilyov	1,293	1.06
Zvenigorod	Kiev	1,279	0.47
Kadnikov	Vologod	1,272	0.67
Sapojkov	Ryazan	1,270	0.79
Klimovich	Mogilyov	1,266	0.88
Atkar	Saratov	1,266	0.44
Gorokhovets	Vladimir	1,242	1.35

District	Province	Count	% Population
Kozel	Kaluj	1,238	0.99
Zaray	Ryazan	1,237	1.08
Aleksandrov	Yekaterinoslav	1,235	0.45
Belozer	Novgorod	1,233	1.42
Belgorod	Kursk	1,226	0.70
Zadon	Voronej	1,220	0.99
Perekop	Tavrich	1,219	2.37
Keren	Penzen	1,219	1.15
Gomel	Mogilyov	1,208	0.54
Starooskol	Kursk	1,202	0.82
Vilen	Vilen	1,197	0.33
Cherikov	Mogilyov	1,195	0.80
Venden	Liflyand	1,179	0.95
Turin	Tobol	1,172	1.71
Kovrov	Vladimir	1,170	1.06
Kolim	Yakut	1,165	14.77
Barguzin	Zabaykal	1,153	4.53
Kargopol	Olonets	1,149	1.40
Pavlograd	Yekaterinoslav	1,146	0.46
Sichyov	Smolensk	1,141	1.13
Rij	Liflyand	1,137	0.29
Yamburg	Sankt-Peterburg	1,136	1.39
Kholmogor	Arkhangel	1,135	3.15
Skopin	Ryazan	1,134	0.64
Bykhov	Mogilyov	1,125	0.90
Tver	Tver	1,116	0.67
Fatej	Kursk	1,116	0.89
Bryan	Orlov	1,105	0.54
Mojay	Moskov	1,096	2.03
Sochin	Chernomor	1,093	8.08
Oshmyan	Vilen	1,078	0.46
Krom	Orlov	1,075	0.98
Grayvoron	Kursk	1,074	0.61
Makaryev	Kostrom	1,072	0.74
Varshav	Varshav	1,070	0.13
Sergach	Nijegorod	1,067	0.67
Vyaznikov	Vladimir	1,061	1.23
Karachev	Orlov	1,055	0.78
Valuy	Voronej	1,055	0.56
Kozmodemyan	Kazan	1,049	0.99

District	Province	Count	% Population
Yukhnov	Smolensk	1,048	0.87
Medyn	Kaluj	1,042	1.00
Ostashkov	Tver	1,036	0.80
Olonets	Olonets	1,022	2.56
Ranenburg	Ryazan	1,020	0.67
Mosal	Kaluj	1,015	0.67
Tul	Tul	1,015	0.48
Onej	Arkhangel	1,003	2.55
Rjev	Tver	1,003	0.70
Nerekht	Kostrom	1,003	0.67
Ruz	Moskov	1,001	1.80
Prujan	Grodnen	1,000	0.72
Petergof	Sankt-Peterburg	981	0.70
Yelisavetgrad	Kherson	972	0.16
Nevel	Viteb	958	0.87
Kashir	Tul	953	1.43
Aleksandriy	Kherson	946	0.23
Peremishl	Kaluj	942	1.54
Korochan	Kursk	934	0.59
Vytegor	Olonets	926	1.65
Dmitriev	Kursk	926	0.73
Yelatom	Tambov	913	0.65
Okhot	Kamchatka	906	19.15
Kirillov	Novgorod	894	0.74
Kaytago-Tabasaran	Dagestan	893	0.98
Bolshederbetov	Stavropol	888	0.38
Korchev	Tver	873	0.73
Pereslav	Vladimir	871	1.00
Sudjan	Kursk	871	0.58
Amudaryin	Syr-Darya	871	0.45
Mikhaylov	Ryazan	858	0.57
Narovchat	Penzen	858	0.73
Irbit	Perm	857	0.54
Shats	Tambov	845	0.52
Epifan	Tul	842	0.73
Mangyshlak	Zakaspiy	834	1.22
Dmitrov	Orlov	830	0.79
Mstislav	Mogilyov	812	0.79
Dankov	Ryazan	810	0.77
Rechits	Minsk	807	0.36

District	Province	Count	% Population
Verey	Moskov	794	1.47
Lgov	Kursk	782	0.60
Maloyaroslavets	Kaluj	763	1.86
Vasilsur	Nijegorod	763	0.60
Tuapsin	Chernomor	762	8.42
Perov	Syr-Darya	762	0.57
Akhtyr	Kharkov	761	0.47
Berdyan	Tavrich	760	0.25
Beryozov	Tobol	757	3.54
Kutnov	Varshav	755	0.92
Bogorodits	Tul	754	0.49
Drissen	Viteb	749	0.77
Novomoskov	Yekaterinoslav	749	0.29
Novograd-Volyn	Volyn	746	0.21
Kalyazin	Tver	728	0.65
Ryl	Kursk	722	0.44
Bratslav	Podol	719	0.30
Akkerman	Bessarab	718	0.27
Khorol	Poltav	710	0.41
Gjat	Smolensk	694	0.71
Kazikumukh	Dagestan	678	1.49
Knyaginin	Nijegorod	677	0.64
Borov	Kaluj	676	1.27
Kyurin	Dagestan	673	0.87
Lodeynopol	Olonets	665	1.44
Danilov	Yaroslav	664	0.94
Verkhoyan	Yakut	662	4.64
Melitopol	Tavrich	656	0.17
Kashin	Tver	638	0.53
Ostrov	Lomjin	635	0.64
Molog	Yaroslav	633	0.54
Mirgorod	Poltav	629	0.40
Trok	Vilen	610	0.30
Mozyr	Minsk	610	0.34
Izyum	Kharkov	608	0.22
Chauss	Mogilyov	606	0.68
Bogodukhov	Kharkov	606	0.38
Lyubim	Yaroslav	603	0.92
Jarkent	Semirechen	597	0.49
Bel	Grodnen	589	0.29

District	Province	Count	% Population
Duben	Volyn	586	0.30
Belyov	Tul	570	0.73
Novoskol	Kursk	570	0.36
Litin	Podol	568	0.27
Troitskosav	Zabaykal	568	1.73
Sventsyan	Vilen	566	0.33
Mariupul	Yekaterinoslav	564	0.22
Poshekhon	Yaroslav	562	0.51
Pudoj	Olonets	561	1.68
Suraj	Chernigov	560	0.30
Starits	Tver	544	0.37
Uglich	Yaroslav	543	0.57
Yefremov	Tul	542	0.32
Gryazovets	Vologod	540	0.51
Sosnits	Chernikov	535	0.31
Mezen	Arkhangel	534	2.13
Trubchev	Orlov	520	0.40
Sev	Orlov	509	0.33
Zubtsov	Tver	503	0.49
Rogachyov	Mogilyov	500	0.22

A2. Alternative Functional Forms for Spatial Splines

Most models in the grid-cell level and individual-level analyses include natural cubic polynomials, which controls for smooth functions of latitude and longitude ($x + y + x^2 + y^2 + xy + +x^3 + y^3 + x^2y + xy^2$). I check the robustness of the results to alternative functional forms of the spatial interpolation by using different orders of polynomials in the models: linear, quadratic, and quartic. Table A2.2 reports estimates from specifications with alternative polynomials in latitude and longitude.

Table A2.2: Alternative Functional Forms for Spatial Interpolation

	Arrests					
	Gridcell-level			Individual-level		
	Linear	Quadratic	Quartic	Linear	Quadratic	Quartic
WWI veterans (general)	0.335 (0.080)***	0.351 (0.084)***	0.369 (0.084)***			
Awarded WWI veterans	0.343 (0.091)***	0.369 (0.095)***	0.391 (0.093)***	0.737 (0.036)***	0.737 (0.036)***	0.737 (0.036)***
Red Army veterans	0.575 (0.118)***	0.672 (0.121)***	0.716 (0.118)***	0.038 (0.010)***	0.037 (0.009)***	0.036 (0.009)***
White Guard veterans	0.357 (0.114)***	0.395 (0.117)***	0.420 (0.113)***	0.283 (0.015)***	0.284 (0.015)***	0.284 (0.015)***

Note: Outcome = the number of arrested individuals in a specified geographic location (with logarithmic transformation). Robust standard errors, clustered by district, are reported in parentheses. Models use alternative functional forms for the longitude and latitude (linear, quadratic, and quartic). All models include covariates. Significance levels: $^{\dagger}p < 0.1$; *p < .05; **p < .01; ***p < .001

A3. Alternative Specifications of Repression

To address potential concerns concerning the logarithmic transformation of the outcome variable (arrests) and explanatory variables (counts of war participants), I use alternative formulations for the arrests and war participant counts. Given that the data for the arrests and war participants are right-skewed, I use a square root and cube root transformation of the count variables on the left and right-hand sides of the equations. I transform the outcome and explanatory variables simultaneously to allow for the proper scaling of coefficients. Tables A3.3 and A3.4 present the results of district-level and grid-cell-level analyses with square root and cube root transformed variables.

Table A3.3: District-Level Results with Alternative Transformations

	Dependent variable:							
	Square Root of Arrested Individuals				Cube Root of Arrested Individuals			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
WWI veterans (general)	0.562^{***}				0.533^{***}			
	(0.082)				(0.064)			
Awarded WWI veterans		2.679^{***}				1.445^{***}		
		(0.616)				(0.285)		
Red Army veterans			2.047^{**}				1.113^{***}	
			(0.947)				(0.375)	
White Guard veterans				4.576^{***}				2.066^{***}
				(0.968)				(0.370)
District Controls	✓	✓	✓	✓	✓	✓	✓	✓
Province Fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
Observations	742	653	606	620	742	653	606	620
Adjusted R^2	0.699	0.661	0.682	0.647	0.751	0.709	0.735	0.685

Note: Robust standard errors, clustered by province, are reported in parentheses. Included observations reflect districts. All models include province fixed effects and district-level covariates. Significance levels: $^{\dagger}p < 0.1$; $^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$.

Table A3.4: Grid-cell-Level Results with Alternative Transformations

	Dependent variable:							
	Square Root of Arrested Individuals				Cube Root of Arrested Individuals			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
WWI veterans (general)	0.138^{***}				0.205^{***}			
	(0.082)				(0.023)			
Awarded WWI veterans		0.996^{***}				0.760^{***}		
		(0.094)				(0.069)		
Red Army veterans			2.555^{**}				1.546^{***}	
			(0.365)				(0.211)	
White Guard veterans				1.386^{***}				0.943^{***}
				(0.153)				(0.104)
Grid-cell Controls	✓	✓	✓	✓	✓	✓	✓	✓
District Fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
Cubic Spatial Splines	✓	✓	✓	✓	✓	✓	✓	✓
Observations	1,443,564	1,417,403	1,231,101	1,396,016	1,443,564	1,417,403	1,231,101	1,396,016
Grid-cells	1311	726	904	991	1311	726	904	991
Adjusted R^2	0.791	0.794	0.829	0.800	0.779	0.783	0.819	0.787

Note: Robust standard errors, clustered by district, are reported in parentheses. All models include province fixed effects and district-level covariates. Significance levels: $^{\dagger}p < 0.1$; $^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$.

A4. Alternative Grid-Cell Sizes

The results of the grid-cell level analysis may be biased due to the size of the grid-cells. Below, I also test whether the estimates are robust to alternative grid-cell sizes. Tables A4.5, A4.6, and A4.7 show results of regressions using 10x10, 20x20, and 25x25 grid-cell sizes, respectively.

Table A4.5: 10x10 Grid-cell Results

	Dependent variable:			
	Log of Arrested Individuals			
	(1)	(2)	(3)	(4)
WWI veterans (general)	0.367***			
	(0.081)			
Awarded WWI veterans		0.463***		
		(0.057)		
Red Army veterans			0.586***	
			(0.112)	
White Guard veterans				0.402***
				(0.099)
Grid-cell Controls	✓	✓	✓	✓
District Fixed Effects	✓	✓	✓	✓
Cubic Spatial Slines	✓	✓	✓	✓
Observations	1,992,318	1,873,800	1,831,321	1,948,494
Grid-cells with complete data	1225	596	805	880
Adjusted R^2	0.773	0.758	0.805	0.767

Note: Robust standard errors, clustered by district, are reported in parentheses. Included observations reflect districts. All models include province fixed effects and district-level covariates. Significance levels: $^{\dagger}p < 0.1$; $^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$.

Table A4.6: 20x20 Grid-cell Results

	Dependent variable:			
	Log of Arrested Individuals			
	(1)	(2)	(3)	(4)
WWI veterans (general)	0.378***			
	(0.044)			
Awarded WWI veterans		0.420***		
		(0.055)		
Red Army veterans			0.744***	
			(0.089)	
White Guard veterans				0.459***
				(0.067)
Grid-cell Controls	✓	✓	✓	✓
District Fixed Effects	✓	✓	✓	✓
Cubic Spatial Slines	✓	✓	✓	✓
Observations	1,979,176	1,911,387	1,584,680	1,865,302
Grid-cells with complete data	3383	960	1762	2056
Adjusted R^2	0.758	0.765	0.821	0.762

Note: Robust standard errors, clustered by district, are reported in parentheses. Included observations reflect districts. All models include province fixed effects and district-level covariates. Significance levels: $^{\dagger}p < 0.1$; $^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$.

Table A4.7: 25x25 Grid-cell Results

	Dependent variable:			
	Log of Arrested Individuals			
	(1)	(2)	(3)	(4)
WWI veterans (general)	0.399***			
	(0.043)			
Awarded WWI veterans		0.463***		
		(0.057)		
Red Army veterans			0.957***	
			(0.079)	
White Guard veterans				0.502***
				(0.073)
Grid-cell Controls	✓	✓	✓	✓
District Fixed Effects	✓	✓	✓	✓
Cubic Spatial Slines	✓	✓	✓	✓
Observations	1,969,169	1,873,800	1,523,455	1,821,033
Grid-cells with complete data	4648	2602	1023	2156
Adjusted R^2	0.747	0.758	0.839	0.757

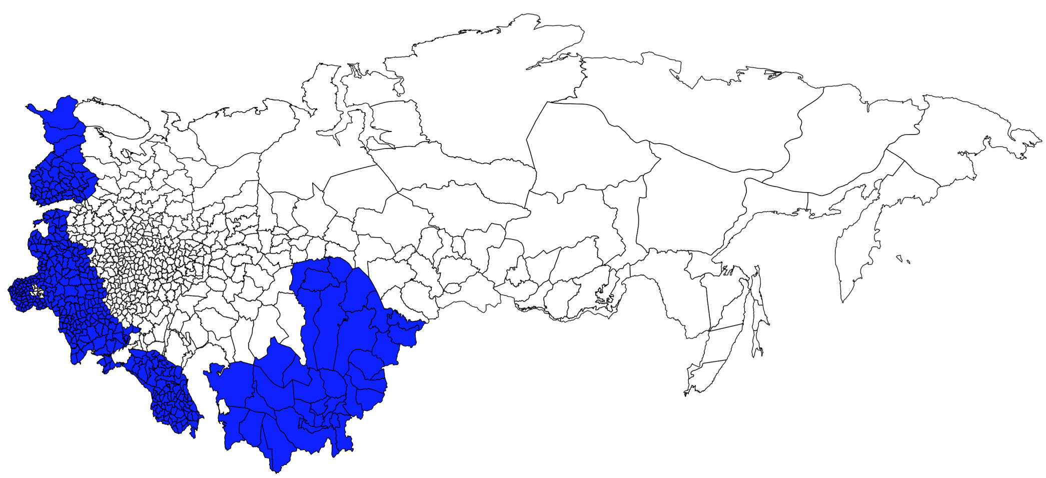
Note: Robust standard errors, clustered by district, are reported in parentheses. Included observations reflect districts. All models include province fixed effects and district-level covariates. Significance levels: $^{\dagger}p < 0.1$; $^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$.

A5. Ethnic Minority Districts

The findings of the paper might reflect the ethnic characteristics of the districts. The data show that ethnic minority veterans of World War I enlisted at higher rates in the Russian Civil War. Ethnic minority enclaves of Imperial Russia witnessed more battles in the civil war than Russian-dominated areas, as minority groups attempted to achieve independence and create their nation-states. The last wave of Stalin's terror specifically targeted ethnic minority areas. Therefore, the ethnic background of some geographic regions might be a potential confounder that affects both the likelihood of civil war participation and targeting by the state, creating biased results in the district and grid-cell level specifications.

Ethnic minorities were spatially concentrated in the periphery of Russia's territories, making it possible to empirically isolate geographic areas where ethnic minorities dominated imperial districts and Soviet administrative units. To this end, I re-run the main set of analyses on a concentrated geographic location by eliminating districts that do not fall into present-day Russian territories. This ensures that predominantly ethnic minority areas that later became independent Soviet republics and post-Soviet states are excluded from the sample. Table A5.8 lists the name of provinces, the districts of which have been excluded to isolate the ethnicity effect, and Figure A5.1 highlights these districts on Imperial Russia's map.

Figure A5.1: Excluded Minority Districts



Tables A5.9, A5.10, and A5.11 present the results of replicated main analyses while excluding territories with predominantly minority ethnic populations.

Table A5.8: Excluded Provinces

Province Name	Number of Districts
Uleaborgskaya Guberniya	6
Vazaskaya Guberniya	6
Abo-Byornoborgskaya Guberniya	8
Tavastgusskaya Guberniya	6
Nyulandskaya Guberniy	4
Sankt-Mikhelskaya Guberniya	4
Kuopioskaya Guberniya	6
Viborgskaya Guberniya	9
Estlyandskaya Guberniya	4
Liftlyandskaya Guberniya	9
Kurlyandskaya Guberniya	10
Kovenskaya Guberniya	7
Vitebskaya Guberniya	12
Suvalskaya Guberniya	7
Vilenskaya Guberniya	7
Lomjinskaya Guberniya	8
Plotskaya Guberniya	7
Varshavskaya Guberniya	14
Kalishskaya Guberniya	8
Petrokovskaya Guberniya	8
Keletskaya Guberniya	7
Radomskaya Guberniya	7
Lyublinskaya Guberniya	10
Kholmskaya Guberniya	8
Grodnenskaya Guberniya	9
Minskaya Guberniya	9
Volynskaya Guberniya	12
Podolskaya Guberniya	12
Kievskaya Guberniya	12
Bessarabskaya Guberniya	8
Khersonskaya Guberniya	6
Poltavskaya Guberniya	15
Chernigovskaya Guberniya	15
Mogilevskaya Guberniya	11
Tavricheskaya Guberniya	9
Yekaterinoslavskaya Guberniya	8

Province Name	Number of Districts
Kubanskaya Oblast	6
Chernomorskaya Guberniya	3
Kutaisskaya Guberniya	8
Batumskaya Oblast	2
Karskaya Oblast	4
Erivanskaya Guberniya	7
Yelisavetpolskaya Guberniya	8
Bakinskaya Guberniya	6
Dagestanskaya Oblast	9
Tiflisskaya Guberniya	10
Terskaya Oblast	12
Stavropolskaya Guberniya	7
Akmolinskaya Oblast	5
Semipalatinskaya Oblast	5
Semirechenskaya Oblast	6
Syr-darinskaya Oblast	6
Zakaspiyskaya Oblast	5
Khivinskoe Khanstvo	1
Samarkandskaya Oblast	4
Bukharskoe Khanstvo	1
Ferganskaya Oblast	5

Table A5.9: District-Level Results for Ethnic Russian Territories

	Dependent variable:			
	Log of Arrested Individuals			
	(1)	(2)	(3)	(4)
WWI veterans (general)	0.329***			
	(0.047)			
Awarded WWI veterans		0.316***		
		(0.076)		
Red Army veterans			0.350***	
			(0.069)	
White Guard veterans				0.401***
				(0.071)
District Controls	✓	✓	✓	✓
Province Fixed effects	✓	✓	✓	✓
Observations	385	373	319	372
Adjusted R^2	0.600	0.574	0.578	0.590

Note: Robust standard errors, clustered by province, are reported in parentheses. Included observations reflect districts. All models include province fixed effects and district-level covariates. Significance levels: $^{\dagger}p < 0.1$; $^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$.

Table A5.10: Grid-cell-Level Results for Ethnic Russian Territories

	Dependent variable:			
	Log of Arrested Individuals			
	(1)	(2)	(3)	(4)
WWI veterans (general)	0.316***			
	(0.055)			
Awarded WWI veterans		0.317***		
		(0.057)		
Red Army veterans			0.670***	
			(0.116)	
White Guard veterans				0.336***
				(0.061)
Grid-cell Controls	✓	✓	✓	✓
District Fixed Effects	✓	✓	✓	✓
Cubic Spatial Slines	✓	✓	✓	✓
Observations	739,408	735,743	612,949	732,507
Grid-cells with complete data	1083	843	508	785
Adjusted R^2	0.696	0.702	0.758	0.707

Note: Robust standard errors, clustered by district, are reported in parentheses. Included observations reflect districts. All models include province fixed effects and district-level covariates. Significance levels: $^{\dagger}p < 0.1$; $^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$.

Table A5.11: Individual-Level Results for Ethnic Russian Territories

	Dependent variable:		
	Binary Family Repression Indicator		
	(1)	(2)	(3)
Awarded WWI veterans	1.410***		
	(0.013)		
Red Army veterans		0.268***	
		(0.063)	
White Guard veterans			0.717***
			(0.017)
Individual Controls	✓	✓	✓
District Fixed effects	✓	✓	✓
Cubic Spatial Splines	✓	✓	✓
Observations	1,033,625	1,033,625	1,033,625
Adjusted R^2	0.142	0.132	0.133
	Number of Repressed Family Members		
	(1)	(2)	(3)
Awarded WWI veterans	0.785***		
	(0.038)		
Red Army veterans		0.087***	
		(0.023)	
White Guard veterans			0.311***
			(0.017)
Individual Controls	✓	✓	✓
District Fixed effects	✓	✓	✓
Cubic Spatial Splines	✓	✓	✓
Observations	1,033,252	1,033,252	1,033,252
Adjusted R^2	0.286	0.261	0.263

Note: Robust standard errors, clustered by grid-cell, are reported in parentheses. Included observations reflect disaggregated individual records, with non-missing location. All models include district fixed effects, cubic spatial splines, and individual birth and grid-cell-level covariates. Significance levels: $^{\dagger}p < 0.1$; *p < .05; **p < .01; ***p < .001.

A6. Individual Record Matching

The main individual-level analysis in the paper is based on individual record matching on two identifying fields: last name and grid-cell numbers. If a person born around the same birth location as the war veteran shares a last name with the veteran, I consider it a match for a family member. However, this approach creates a potential for a significant number of false matches, especially with regard to common last names in Russia. To avoid bias produced by false matches, I propose an alternative approach, which attempts to increase the accuracy of the matching procedure, albeit at the cost of slightly increasing false negative matches.

In Russian culture, patronymics are a standard feature of a person's full name. Patronymics are generally based on the given name of a person's father and usually come after the last and first names. The standard full name is written as "Efimov Aleksey Ivanovich," where "Efimov" is the last name, "Aleksey" is the first name, and "Ivanovich" is the patronymic. This person's patronymic indicates that his father's name was "Ivan." The "-ich" suffix is the standard ending of a patronymic. Using these well-known features of the Russian full names, I separate the patronymics of the arrestees from the full name string and stem the patronymic to retain the root name that should, in theory, correspond to the first name of the person's father. Because the length of the characters in the root of the patronymic depends on a person's last name, and since "-ich" is not a universal ending for patronymics and thus not a unique qualifier, I only use the first four letters of the patronymic to extract the potential root of the name. Similarly, I separate the first name of the war veterans. Then I match the records across the two datasets using three unique identifiers: cell number, last name, and first name-patronymic combination.

Table A6.12 below demonstrates a random sample from the matched combinations.

Table A6.13 below presents the results of the replicated individual-level analysis with the new matching scheme that reflects the association between war participation and the likelihood of the veteran's birth children's arrest during Stalin's repressions.

Table A6.12: Individual Record Linkage Sample

Cellnumber	Last Name	Patronymic Stemmed	Matches
837	Gutman	Abra	3
3833	Akchurin	Abdu	1
3271	Afuksenov	Avra	2
2960	Boger	Adam	2
1884	Danilovich	Adam	3
1573	Grunichev	Alek	2
1884	Kovalev	Egor	2
2031	Loginov	Seme	6
3719	Ivanov	Emel	2
3085	Zotov	Logi	4
987	Skuba	Lyudv	1
1880	Bolshakov	Maks	2
2928	Smirnov	Yakov	10
2642	Tarasov	Maks	4
1863	Virolaynen	Matv	2
1880	Ritter	Vlad	2
2944	Dergilev	Vasi	3
1446	Bortnik	Fedo	5
2926	Chernyshov	Mikha	1

Table A6.13: Individual-Level Results for Birth Children

	Dependent variable:		
	Binary Family Repression Indicator		
	(1)	(2)	(3)
Awarded WWI veterans	1.368***		
	(0.019)		
Red Army veterans		0.510***	
		(0.126)	
White Guard veterans			0.687***
			(0.034)
Individual Controls	✓	✓	✓
District Fixed effects	✓	✓	✓
Cubic Spatial Splines	✓	✓	✓
Observations	1,157,126	1,157,126	1,157,126
Adjusted R^2	0.211	0.196	0.197
	Number of Repressed Family Members		
	(1)	(2)	(3)
Awarded WWI veterans	0.127***		
	(0.017)		
Red Army veterans		0.007***	
		(0.003)	
White Guard veterans			0.045***
			(0.006)
Individual Controls	✓	✓	✓
District Fixed effects	✓	✓	✓
Cubic Spatial Splines	✓	✓	✓
Observations	1,157,126	1,157,126	1,157,126
Adjusted R^2	0.107	0.099	0.099

Note: Robust standard errors, clustered by grid-cell, are reported in parentheses. Included observations reflect disaggregated individual records, with non-missing location. All models include district fixed effects, cubic spatial splines, and individual birth and grid-cell-level covariates. The outcome count variable is log-transformed. Significance levels: $^{\dagger}p < 0.1$; *p < .05; **p < .01; ***p < .001.