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The Geopolitics of Repressions

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Abstract

This thesis studies how geopolitical concerns influence attitudes of a state toward its ethnic minorities. Using data digitized from archival sources on more than 2 million individual arrests by the Soviet secret police, I apply difference-in-differences and synthetic control method to estimate how changing German-Soviet relations influenced repressions of Germans in the Soviet Union. The results of both methods show that there was large and statistically significant increase in arrests of Germans following the German invasion into the Soviet Union in 1941. Furthermore, the impact of war appears to be highly persistent since there is almost no decline in the estimated effect on repressions for nearly 10 years after the end of the war.

Keywords

repression, geopolitics, Soviet Union, difference-in-differences, synthetic control method, archival data

Abstrakt

Tato práce zkoumá jak geopolitické zájmy ovlivňují vzah státu k jeho etnickým minoritám. Aplikuji metodu rozdílu v rozdílech (difference-in-differences) a metodu syntetické kontroly (synthetic control method) s použitím dat digitalizovaných z archivních zdrojů obsahujích více než 2 miliony záznamů individuálních zatčení sovětskou tajnou policií, abych odhadl jak změny v německo-sovětských vzazích ovlivnily represe Němců v Sovětském svazu. Výsledky obou metod ukazují, že po německé invazi do Sovětského svazu v roce 1941 došlo k výraznému a statisticky významnému nárůstu zatčení Němců. Vliv války se zdá být velmi perzistentní, jelikož nepozorujeme téměř žádný pokles odhadovaného effektu na represe skoro 10 let po konci války.

Klíčová slova

represe, geopolitika, Sovětský svaz, rozdíl v rozdílech, metoda syntetické kontroly, archivní data

Declaration of Authorship

I hereby proclaim that I wrote my bachelor thesis on my own under the leadership of my supervisor and that the references include all resources and literature I have used.

I grant a permission to reproduce and to distribute copies of this thesis document in whole or in part.

Prague, 8th May 2019

Signature

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The Bachelor's Thesis Proposal

Author of the bachelor thesis: **Martin Kosík**
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Title: **The Geopolitics of Repressions**

Research question and motivation

What determines the attitude of a state toward ethnic minorities within its borders? Why are some minorities accommodated or assimilated and others are politically excluded and repressed? Furthermore, why does the position of a state toward its minorities change in time?

Mylonas (2013) argues that geopolitical concerns play an important role. Specifically, a state is likely to choose repression and exclusion if the ethnic minority's country of origin is seen as a geopolitical enemy. The minority is then viewed by the state as unreliable and as a potential fifth column of the foreign country.

I will test this hypothesis on the case of the German minority in the Soviet Union. In 1933, Hitler's rise to power changed Germany from a neutral actor to an ideological and geopolitical enemy in the perspective of the Soviet Union. This enables us to estimate how the repression of Germans in the USSR changed before and after 1933 and compare it with other minorities. In particular, I plan to use the individual arrests by the Soviet secret police (NKVD) as a dependent variable and employ the difference-in-differences strategy.

Contribution

Existing literature on repressions has focused mostly on their consequences and legacies (Rozenas, Schutte, and Zhukov 2017; Lupu and Peisakhin 2017; Zhukov and Talibova 2018). As far as the strategic use of repressions by the state is studied, it is usually in relation to domestic factors such as institutions and economic shocks (Davenport 2007; Greitens 2016; Blaydes 2018) with less attention being given to external forces. An exception to this is a study by Mylonas (2013) which tests his theory with data on the post-World War I Balkans. However, his cross-sectional regression might suffer from omitted variable bias and reverse causality and my approach hopefully offers cleaner identification.

My bachelor thesis can also contribute to the literature on the origins of Soviet ethnic repressions. Although many scholars argue that a perceived connection to hostile external powers has played a role (Martin, 1998; Polian, 2003), the evidence has been mostly qualitative and anecdotal.

Methodology

My main source of data will be replication files from Zhukov and Talibova (2018) who use lists of victims of Soviet political repressions aggregated by Russian NGO Memorial. The difference-in-differences strategy will be used to estimate the impact of change German-Soviet relations caused by Hitler's rise to power on arrests of Germans in the USSR.

However, the parallel trends assumption, which is necessary for unbiasedness of difference-in-differences, can in some cases be violated. As a robustness check, I plan to apply the synthetic control method which constructs a synthetic control group as a linear combination of untreated units (in our case ethnicities) based on matching of pre-treatment trends and time-invariant covariates (Abadie and Gardeazabal 2003; Abadie, Diamond, and Hainmueller 2010).

Outline

1. Introduction
2. Literature review
3. Historical background
4. Data
5. Methodology
6. Results

7. Conclusion

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Contents

Introduction

What determines the attitude of a state toward ethnic minorities within its borders? Why are some minorities accommodated or assimilated and others are politically excluded and repressed? Furthermore, why does the position of a state toward its minorities change in time? For example, Soviet Union largely accommodated its minorities by in 1920s but heavily repressed them in the campaigns of mass terror 10 years later.

Mylonas (2013) argues that the geopolitical concerns play an important role. In particular, a state is likely to choose repression and exclusion if the ethnic minority's country of origin is seen as an geopolitical enemy. The minority is then viewed by the state as a potential fifth column of the foreign country that could betray the state in case of conflict.

We test this hypothesis on the case of German minority in Soviet union. The German-Soviet relations went through a series of fundamental changes in the first half of the 20th century. First, Hitlers rise to power in 1933 changed Germany from a neutral actor to an ideological and geopolitical enemy in the perspective of the Soviet Union. The hostilities ceased in August 1939 with signing of the Molotov-Ribbentrop Pact. But this period did not last long as it was abruptly ended by the German invasion into the USSR in June 1941. Our empirical strategy is to compare the change in repressions of Germans throughout these different phases with the change for other ethnic groups in the Soviet Union using the difference-in-differences design and the synthetic control method.

The source of the data on repressions is a database of Russian human rights organization Memorial (2017) which contains more than 2 million of records of individuals arrested by the Soviet secret police obtained mostly from digitized archival materials. The challenge with the data is that information on ethnicity and date of arrest is often missing which we address by imputing the missing values using names and date of trial, respectively.

The thesis has the following structure. First, we summarize the existing literature on the topic in section 1. Next, section 2 provides necessary historical context on German-Soviet relations, political repressions, and position of ethnic minorities in the USSR. This is followed by section 3 where we describe the sources of the data and provide summary statistics of our dataset. In section 4, we present the methods that we use to impute missing information on ethnicity and date of arrest. In section 5, we describe the two methods that we use to empirically estimate the effect. The results of our analysis are provided in section 6. Additional robustness checks which asses the sensitivity of results to different specifications are presented in section 7. Finally, we discuss implications of the results in the conclusion.

1 Literature Review

Existing literature on repressions has focused mostly on their consequences and legacies (Rozenas et al., 2017; Lupu and Peisakhin, 2017; Zhukov and Talibova, 2018). As far as the strategic use of repressions by the state is studied, it is usually in relation to domestic factors such as institutions and economic shocks (Davenport, 2007; Greitens, 2016; Blaydes, 2018) with less attention being given to external forces.

Davenport (2007) finds that democracy is correlated with lower levels of repression. However, it is mainly free electoral competition rather than constraints on power of the executive that accounts for this negative effect. Greitens (2016) links the severity of repression to the threat from dictator's inner circle. A dictator who fears that he would be deposed in a coup rather than by a popular uprising will fragment their coercive apparatus in order to weaken the power of a potential challenger from within. The weakened secret police will be, according to Greitens, more likely to use violence since it fails to identify the transgressors and cannot effectively deter dissent. Other scholars see repression as a substitute for co-option (Wintrobe, 1998; Svolik, 2012). Instead relying on the threat of persecution, an authoritarian ruler might buy the loyalty of the population by distributing rents to the supporters of the regime, usually through the party apparatus. Negative economic shocks can then increase repression since the rents are no longer available. Blaydes (2018) illustrates this on the case of Iraq under Hussein where the drop in oil prices after 1986 led the regime to adopt more repressive policies.

Nevertheless, these studies try to explain only the overall level of repressions and not variation across ethnic groups. Important exception is Blaydes (2018) who argues that the nature of repression depends on the legibility of the ethnic group to the state.[1] Since the state coercive institutions cannot reliably identify transgressors in less legible population (because of, for example, greater cultural and linguistic distance), they will more tend to resort

[1] The term legibility in this context means ability of a state to identify individuals in a given population and gather information on them.

to collective punishment. The logic behind this is that the members of the group will police its members to avoid collective punishment.

Our research also relates to the literature studying factors that influence position of a state towards its ethnic minorities and under what conditions conflict is likely to occur. Size and and distribution of ethnic groups have been emphasized. Several scholars pointed out that states with large number of ethnic groups are more likely to violently repress calls for autonomy or secession to discourage other ethnic minorities from making similar demands in the future (Evera, 1994; Toft, 2005; Walter, 2009). Furthermore, Toft (2005) argues that geographically concentrated groups tend to view their ethnic homeland as indivisible and non-negotiable issue which increases the likelihood of violent conflict. However, these approaches fail to explain changes in state's attitudes to minorities over short periods of time when the size and distribution of ethnic groups remains virtually constant.

More recently, the role of international factors have received greater attention. Butt (2017) argues that response of a state to a secessionist movement depends on external security environment and outside actors. Specifically, a state located in a war-prone region is more likely to suppress demands for secession because loss of territory and population would make it vulnerable to a potential future attack. Furthermore, a state responds with more violence if a separatist movement receives a support from an external power since the outside assistance makes the secessionists stronger. In addition to these strategic reasons, Butt emphasizes that receiving external support incites a strong feeling of betrayal to the central state.

International factors also feature significantly in a theory by Mylonas (2013) which we will describe in the following subsection. The empirical testing of predictions of Mylonas' theory using credible identification strategy is the main contribution of this thesis. Most studies presented in this review test their hypotheses only by qualitative comparison of selected cases. Quantitative research usually involve only cross-sectional regressions based on categorical dependent variables.

For example, Mylonas (2013) tests his theory with data on the post-World War I Balkans where the nation-building policies (categorized into 3 groups: accommodation, assimilation and exclusion) toward 90 ethnic groups are a dependent variable and information on their support by external powers is an explanatory variable (together with other control variables). However, the results of the cross-sectional regression, used in the study, might easily be biased due to omitted variables or reverse causality. We believe that our approach offers cleaner identification.

McNamee and Zhang (2019) is methodologically and thematically closet study to ours. They analyze how the 1958 split in Soviet-China relations affected the demographic composition of the population in the Soviet-Chinese border regions. Using difference-in-differences strategy, they find that, after the split both states supported expulsions of the minority group and sponsored immigration of the majority group but only in border regions without significant natural boundary (e.g. high mountains). They conclude that the states use demographic engineering as a way to protect their vulnerable border against a hostile power. Nonetheless, as McNamee and Zhang only measure the ethnic composition of the regions they cannot unambiguously identify expulsions as the main culprit since other factors could plausibly affect voluntary migration as well.

1.1 Theoretical Expectations

Our theoretical expectations are derived mostly from a model by Mylonas (2013) which connects geopolitical relations and the attitude of a state towards its minorities. The model features an ethnic minority living within a host state and an external power. Moreover, Mylonas distinguishes between hosts states with revisionist foreign policy which want change the international status quo (e.g. because they gained power or lost territory in the past) and host states that prefer the current international order.

The predictions of the theory are summarized in table 1. First, if a minority group is not supported by any external power, the theory predicts

		External Power Support		
		Yes		**No**
		Interstate Relations		
		Ally	**Enemy**	
Host's State Foreign Policy	**Revisionist**	Accommodation	Exclusion	Assimilation
	Status Quo	Accommodation	Assimilation	

Table 1: Theoretical predictions of Mylonas (2013)

that the host state will pursue policy of assimilation towards the group to "immunize" it from possible future agitation of external powers. Second, if an ethnic minority is supported by geopolitical ally then accommodation is likely since more repressive policies towards the minority could jeopardize the alliance. Third, theory predicts assimilation if a minority is supported by an geopolitical enemy and a host state pursues non-revisionist foreign policy because exclusionary policies could trigger new hostilities threatening the status quo. Finally, support of an external enemy combined with revisionist foreign policy will likely lead to exclusion of a given ethnic group since it is view as a potential "fifth column" of the external power.

Although in Mylonas' theory an external supporter of a minority can be any state, we will considers only the case of states whose political elites have ethnic ties to the given minority. Ethnic identity by its nature creates certain affinity even for co-ethnics outside given country. Empirically, the states are more likely to intervene in support of a ethnic minority to which they have ethnic ties (Davis and Moore, 1997; Saideman, 2001; Saideman, 2002). Host state can thus perceive certain implicit support from an external power based only on the ethnic ties with the minority even it is not providing any real assistance (this seems to best describe the position of German minority in the USSR). Moreover, people have strong group biases which can lead them to attribute the hostility towards the foreign power to the respective ethnic minority.

Applying the theory to our case, we first have to determine if the Soviet

Union can be considered a revisionist state. The Bolsheviks had to accept large losses of territory under the Treaty of Brest-Litovsk in 1918 so that they could focus on fighting in Russian Civil War. Thus, the USSR would certainly prefer to change the international status quo and could be arguably classified as a revisionist state.

Second, we identify several distinct phases in the Soviet-German relations (described in greater detail in subsection 2.1): neutrality (from 1921 to March 1933), hostility without war (March 1933 to August 1939), pact (August 1939 to June 1941), war (June 1941 to May 1945), and post-war period (from May 1945). The theory predicts that the policy of the Soviet state towards the German minority should change from accommodation to exclusion as the German-Soviet relations turned hostile after 1933. Mylonas (2013, p. 22) defines exclusion as "policies that aim at the physical removal of a non-core group from the host state." The Soviet political repression which usually featured either outright execution or a term in a labor camp in the Far East of the country fits this description well. Thus, the theoretical expectation is that repressions of Soviet Germans relative to other minorities should increase after 1933.

The theory would also suggest that the German repressions should decrease in the period from August 1939 to June 1941 as Germany and the USSR entered the Molotov-Ribbentrop pact. We then expect another rise in the repressions in response to the subsequent war. The theoretical predictions for the post-war period are somewhat ambiguous because Germany was partitioned into multiple occupation zones.

2 Historical Background

In this section, we provide brief historical context for selected topics. Specifically, we first describe changing geopolitical relations of Germany and the Soviet in the fist half of the 20th century. In the next subsection, we give an overview of the most important aspects of Soviet political repression. Finally, evolution of the Soviet policy towards its ethnic minorities is summarized.

2.1 German–Soviet Relations

The relations between Weimar Germany and Soviet Union can be characterized as neutral or even cooperative. Both countries were somewhat isolated in the international system dominated by the Western powers (Great Britain, France, USA) and sought to find allies. The good relations were first established by the Treaty of Rappalo in 1922 in which both countries renounced the territorial and financial claims against each other and agreed to secret military cooperation (Gatzke, 1958) and then reaffirmed by the Treaty of Berlin in 1926. Furthermore, a trade treaty was signed between the two countries in 1925 (Morgan, 1963).

Hitler was named chancellor on 30 January 1933 and effectively become a dictator on 24 March 1933 by the passing of the Enabling Act which gave him the power to enact laws without approval of the parliament. The relations with Soviet Union quickly turned hostile for several reasons. First, Hitler called in *Main Kampf* for Germany to obtain *Lebensraum* (living space) in the east, presumably at the expense of the Soviet Union and he often spoke of Judeo-Bolsheviks (Haslam, 1984, p. 6). Moreover, Hitler's anti-communist was one of factors contributing to his political success as he presented himself as the only leader strong enough to prevent a Communist revolution in Germany. This was not only empty rhetoric as Hitler soon after his rise to power banned the German Communist Party and started to persecute its members (Evans, 2004, chapter 5). Hostility also manifested itself in the German-Soviet relations as the military cooperation between the two countries was canceled in August 1939 and trade treaties were not extended.

The opposition to fascism led to change in policy of the Communist International (Comintern) with appointment Georgi Dimitrov as its general secretary in 1934. The Communist parties in democratic countries were now encouraged to form coalitions (Popular Fronts) with social democratic parties to prevent rise of fascism, in contrast to the previous aggressive and uncompromising approach. This policy was affirmed by the Seventh World Congress of the Comintern in 1935 (Haslam, 1979).

The newly formed Popular Front coalitions won elections and entered government in some European countries including France and Spain. In Spain however, the coup of nationalists against the new government in 1936 sparked a civil war. The Soviet Union heavily supported the republican government, while Germany supplied the nationalists which further increased the tensions between the two countries. As a response, Japan and Germany signed the Anti-Comintern Pact in 1936 in which they committed to cooperate for defense against communistic disintegration. Meanwhile in the Soviet Union, many people were persecuted for alleged cooperation with Germany including leading general Mikhail Tukhachevsky.

The orientation of German foreign policy began to shift in spring of 1939. Until that point, Hitler hoped that he could ally with Poland in a war against the Soviet Union or that Poland would at least allow the passing of German troops (Weinberg, 2010, chapter 26). But Poland repeatedly refused the German offers for closer relations such as to join the Anti-Comintern Pact and thus Hitler changed the strategy and in April 1939 ordered the German army to began planing for the invasion of Poland (Kotkin, 2017, p. 621). However, France and Great Britain granted security guarantees to Poland in March 1939 to deter German aggression. Hitler thus tried to negotiate neutrality of the Soviet Union to avoid simultaneously facing Western powers, Poland and the Soviet Union in war. Soviet neutrality was potentially beneficial for Stalin too. A long and costly war would weaken both the capitalist and the fascist enemies of the Soviet Union. Moreover, Stalin believed that conditions of war could bring about socialist revolutions in those countries just as in Russia in 1917. After brief negotiations, on 23 August 1939 the Molotov-Ribbentrop pact was signed between Germany and the USSR which guaranteed non-belligerence between the two countries. In addition, a secret protocol of the treaty marked the German and Soviet spheres of influence in Eastern Europe.

The pact of the two former ideological enemies caused great shock and astonishment both among Party officials and ordinary people. Victor Kravchenko (1947, p. 332), a Soviet official who later defected to the US, described in his memoir the disbelief upon hearing about the pact

> There must be some mistake, I thought, and everyone around me seemed equally incredulous. After all, hatred of Nazism had been drummed into our minds year after year. The big treason trials [...] have rested on assumption that Nazi Germany and its Axis friends [...] were preparing to attack us.

Another party official later recalled that "it left us all stunned, bewildered, and groggy with disbelief" (Robinson and Slevin, 1988, p. 137).

Nazi Germany attacked Poland on 1 September 1939 from the west and shortly after that, on 17 September, the Red Army invaded the eastern part of the country. As was agreed in the pact, Poland was partitioned between Germany and the Soviet Union. However, the mistrust between the two countries was still present as evidenced by a violent clash of German and Soviet troops near Lwów on 20 September (Kotkin, 2017, p. 685)

Hitler enjoyed major success in the first years of the war. By summer 1940, German forces defeated French army and annexed Denmark and Norway. But German industry was severely lacking raw materials needed in war effort against Britain and the US which, according to some historians, motivated Hitler to invade the resource-rich USSR (Tooze, 2008). The German attack on the Soviet Union on 22 June 1941 ended 2 years of fragile cooperation. Although Stalin received numerous warnings by his intelligence about the impeding German attack, he was generally dismissive of them as British efforts to embroil him in war with Germany (Kotkin, 2017, chapter 14).

The Eastern Front became the bloodiest theater of World War II with more than 10 million soldiers killed in combat and another 3.3 million of Soviet prisoners of war starved to death by Germans (Snyder, 2011, p. 155). Moreover, the Eastern Front was site of the worst atrocities committed on the civilian population, most notably the Holocaust.

After the surrender of Germany in May 1945 its territory was partitioned into 4 occupation zones (American, British, French, and Soviet). Various industrial disarmament programs were put in place in all occupation zones to limit and control the German military capacity. Thus, in the post-war period militarily weak Germany no longer presented a geopolitical threat as it did before. Instead, the rivalry of the Soviet Union and the United States became the new main source of tensions in the international relations.

To summarize, there were several events in the period from 1921 to 1960 that fundamentally altered the Soviet-German relations. First, Hitler's rise to power, which was definitely consolidated by the passing of The Enabling Act on 23 March 1933, brought in heightened hostilities and tensions into the Soviet-German relations. Another turning point was the Molotov–Ribbentrop Pact signed 23 August 1939 which started a brief period of limited cooperation between the two countries. On 22 June 1941, the German invasion of the Soviet Union officially terminated the pact marking the beginning of one of the most bloody conflicts of World War II. The war finally ended on 8 May 1945 with unconditional surrender of Germany.

2.2 Soviet Political Repressions

The Soviet Union had large and powerful coercive apparatus. The Soviet secret police (which was throughout the years named the Cheka, OGPU, NKVD, MVD and the KGB)[2] employed at its height (1937–1938) 270,730

[2] We will refer to the Soviet secret police as the NKVD in this text since this was the name of the agency for the largest part of the period of our interest

persons (Gregory, 2009, p. 2). The political repressions were usually carried under Article 58 of the Criminal Code. The Article 58 punished counter-revolutionary activities which included treason, espionage, counterrevolutionary propaganda, agitation and failure to report any of these crimes. In practice, this broad definition meant that anyone regarded as politically inconvenient could be arrested and prosecuted.

During the mass operations, the central office of the NKVD would typically set quotas for the number of arrests which the regional branches were supposed to reach and exceed (Gregory, 2009, chapter 6). The local NKVD officer had to decide themselves who to target to meet the quotas.

The sentences were in most cases issued extrajudicially by so-called "troikas", three-person committees composed of a regional NKVD chief, a regional party leader, and a regional prosecutor. The NKVD chief usually dominated the process as party leaders sometimes feared that they themselves would be targeted (Snyder, 2011, p. 82). Only rarely was a person acquitted from his charge. The most common sentences for political crimes in the Stalinist period were execution and prison term in a labor camp (Gulag) (Gregory, 2009, p. 21). A term in the Gulag of less then 5 years was considered lighter sentence in these cases.

With the rise in repressions in the 1930s, the Gulag system significantly expanded. At its height, it consisted of at least 476 distinct camp complexes each containing hundreds of prisoners. The Gulag system offered the Soviet state cheap source of labor that produced substantial amount the country's coal, timber, and gold supply. The mortality of prisoners was high due to heavy work, malnutrition, and cold climate (Applebaum, 2003).

The death of Stalin in 1953 marked a start of decline in political repressions in the USSR. The new Soviet leader, Nikita Khrushchev, denounced Stalin and the mass repressions of his period in his speech *On the Cult of Personality and Its Consequences* in 1956. The suppression of dissent continued in the Khrushchev and Brezhnev era but in much milder form. Khrushchev gradually dismantled the Gulag system, granted amnesty to many political prisoners and started the process of rehabilitation of victims of the Stalinist period although they were limited to only some categories of victims and offences (Applebaum, 2003; Dobson, 2009).

2.3 Ethnic Minorities in the USSR

The Soviet Union was from its inception a multi-ethnic state. According to the 1926 Census, the Russians made up only half of the total population.[3] Among other large ethnic group were Ukrainians, Belorussians and Kazakhs. A significant fraction of citizens of the USSR belonged to ethnic groups with their own independent states including Polish, German, Estonian, Latvian, Lithuanian, Finish, and Greek minorities. The Bolshevik elites were aware of the multi-ethnic nature of their newly formed state and wanted to avoid a perception of the Soviet Union as a project of Russian imperialism. Furthermore, the Bolsheviks hoped that they could exert political influence in countries with cross-border ethnic ties to Soviet diaspora nationalities by promoting the interests of minorities in the USSR. [4]

As a consequence, the Soviet policy towards its ethnic minorities in the 1920s was largely accommodating (Martin, 2001). The languages and culture of minorities were promoted and minorities were encouraged to enter local governments and party structures (so-called *korenizatsiya* policy). Some minority groups were well represented even in the NKVD (Gregory, 2009, p. 25). In some cases Autonomous Soviet Socialist Republics (ASSR) were established (including Volga German ASSR) which had given the regional minorities certain degree of independence.

This attitude changed drastically in the 1930s. First, the *korenizatsiya* policy started to be reversed in the 1932. From 1934, the NKVD started to deport ethnic minorities from the state frontier zone in Eastern Europe. This involved forced resettlement of 30 000 of Ingermanland Finns and tens of thousands of Poles and Germans to Kazakhstan and West Siberia (Polian,

[3]Full data on population of the USSR by ethnicity from the 1926 Census is available at `http://www.demoscope.ru/weekly/ssp/ussr_nac_26.php`. Population numbers for only the 38 ethnic groups featured in our dataset is provided in table A10 in the appendix.

[4]Martin (2001) refers to this argument as the *Piedmont Principle.*

2003, p. 95). In 1937 and 1938, the NKVD conducted mass operations specifically targeted at minorities with cross-border ethnic ties. Poles, Latvians, Germans, Estonians, Finns, Greeks, Chinese, and Romanians were arrested in large numbers as supposed spies and saboteurs of foreign governments. More than 320 000 people were arrested in the national operation out of which about 250 000 were executed (Martin, 1998, p. 855).

The persecutions further escalated with the World War II. Following the German invasion into the Soviet Union in 1941, Stalin ordered deportation of about 430 000 Soviet Germans (most of them living in Volga German ASSR) into Kazakhstan and Siberia (Polian, 2003, p. 134). Similar "preventive" deportation followed for Finns and Greeks as well. Between 1943-1944, forced resettlement of another six ethnic groups (Karachais, Kalmyks, Chechens, Ingushetians, Balkars, and Crimean Tatars) were carried out for alleged or actual cooperation of some of these minorities with the German troops (even if many more served in the Red Army).

3 Data

Our data on Soviet repressions come from the Victims of Political Terror in the USSR database by Russian human rights organization Memorial (2017).[5] The Memorial data has already been used in empirical research by Zhukov and Talibova (2018) to estimate the long-term effects of the Soviet repressions on political participation. The main sources of the Memorial lists are declassified Russian Interior Ministry documents, prosecutor's offices and the Commission for the Rehabilitation of Victims of Political Repression, and "Books of Memory". The years of arrests in the database span the whole existence of the Soviet Union (1917 to 1991) even though overwhelming share of them are from 1930s and 1940s since the scale and severity of repressions was greatest in this period. Vast majority records are individual arrests under Article 58. This means that the victims of other repressive activities of the Soviet state such mass forced migration, counter-insurgency operations of the Red Army during Russian Civil War or famines are mostly excluded. Therefore our research focuses on one particular type of repression (individual arrests by the NKVD).

Nevertheless, even if we restrict ourselves to the individual arrests, the Memorial database is still not complete. According to one estimate cited in (Zhukov and Talibova, 2018, p. 270), 3.8 million people were convicted under Article 58 from 1921 to 1953 (which is a subset of the period that the Memorial database covers) but at the time of our access to the database, the database contained only 2.7 million records.

Missing data presents another major challenge. Table 2 shows how many values are missing for the variables of our interest. We can see that information on ethnicity is not available for more than half of all observations. In contrast, a surname is recorded for every arrest in the dataset and a first name is missing only for negligible fraction of observations. The availability of information on names enables us to use them to infer missing ethnicity

[5] The database can be accessed and searched from `http://base.memo.ru/` (new version) or at `http://lists.memo.ru/` (older version). The TSV file with the records from the database from which we created our dataset can be downloaded from `https://github.com/MemorialInternational/memorial_data_FULL_DB/blob/master/data/lists.memo.ru-disk/lists.memo.ru-disk.zip`

Table 2: Missing Data by Variable

Variable	Number of Missing Obs.	Percent of Missing Obs.
Ethnicity	1 507 177	55.73
Date of Arrest	1 650 912	61.04
Date of Trial	943 108	34.87
First Name	14 006	0.52

Table 3: Missing Dates of Arrest and Trial

	Date of Arrest	
Date of Trial	Missing	Present
Missing	747 419	195 689
Present	903 493	857 949

of individuals. In particular, we will train a Naive Bayes classifier on the 1 197 373 observations with known ethnicity and use the model's predictions to impute the ethnicity for the remaining 1 507 177 observations (the details are described in subsection 4.1).

Date of arrest, which is also necessary for our analysis, has even higher rate of missingness than ethnicity.[6] One solution, albeit only partial, might be to use the date of trial to extrapolate the missing date of arrest where the trial date is available. As is shown in table 3, we could impute this way the missing date of arrests for 903 493 observations for which we have the date of trial. Total number of arrests used for our analysis would therefore increase from 1 053 638 to 1 957 131. However, there remains 747 419 observations for which neither the date of arrest nor the date of trail are known. Unfortunately, not much can be done address this problem.

There are more than 100 different ethnicities in the Memorial data. However, in many cases there are no more than hundred of people in the whole database that belong to a given ethnic groups. Therefore we decided to limit ourselves only to ethnic groups with at least 900 individuals in the Memorial database. This leaves us with 38 ethnic groups.

After imputations of ethnicity and the date of arrest had been applied,

[6]We consider a date missing only if not even year of arrest is available. Many observations have information on year of arrest even though the exact month or day are missing. We do not categorize these observation as having missing date of arrest since our fundamental unit of analysis is a year and thus month and day are not of high interest to us. The same applies to the date of trial.

we created our main dataset by counting number of arrest for each ethnicity by year. We decided to limit ourselves only to the period from 1921 to 1960 because there are not many arrests after 1960 (usually less than 100 in a year). With 38 ethnic groups and 40 time periods, we have 1520 observations in total. Basic descriptive statistics for each ethnicity are provided in table A4. The plot of arrest by ethnicity and year (after applying the transformation $\log(1 + y_{it})$) is shown in figure A2.

In addition to data on repressions, we also obtained some information on characteristics of the ethnic groups in our dataset that we use as covariates in the synthetic control method. In particular, we downloaded total population of the ethnic groups and their urbanization rate from the 1926 Soviet Census from the Demoscope website.[7] For each ethnic group, we also calculated the cladisitc similarity of its language to Russian based language trees from the Glottolog database (Hammarström et al., 2018). Cladistic measure of linguistic similarity counts the number of shared branching points between the two nodes on a language tree. It has been used by Fearon (2003) and Dickens (2018) among others. The complete data of all pre-treatment covariates used in the analysis are provided in table A10 in the appendix.

Furthermore, we acquired data that would allow us to test for heterogeneity in the effect by proximity to the border. The Memorial database does not include the location of arrest but it does contain either pre-arrest residential addresses or birthplaces for more than 2 million observations. Since migration of individuals was relatively rare in the Soviet Union, the pre-arrest addresses and birthplaces can serve as a proxy variables for location of arrest. However, the addresses in the Memorial database are not geocoded and therefore we do not have the exact longitude and latitude. Fortunately, Zhukov and Talibova (2018) have already geocoded the Memorial data and therefore we merged their dataset to ours.[8] The datasets were merged based

[7]Demoscope is a project of Institute of Demography of the National Research University Higher School of Economics that provides resources on demographic history of Russia and the Soviet Union. The data from the 1926 Soviet Census that we used were downloaded from `http://www.demoscope.ru/weekly/ssp/ussr_nac_26.php`

[8]The dataset from Zhukov and Talibova (2018) can be downloaded from the replications file archive of the journal available at `https://www.prio.org/JPR/Datasets/`

on first, last, and patronymic names, year of birth, and source. An unique match was found for 2 010 295 observations. We also downloaded a map of borders of the USSR in 1926 digitized by Sablin et al. (2018). We defined border frontier as an area that is within 250 kilometers of the Soviet borders (they are depicted on the map in figure A5). We then used longitude and latitude of the geocoded arrests (i.e. the location of pre-arrest addresses or birthplaces) to determine if they geographically fall within the border frontiers. Overall 355 101 of arrests were classified as being from those border areas, 1 507 224 of arrests as being outside them. 147 970 of observations fell outside of the 1926 borders of the Soviet Union which can be explained by the fact that the USSR expanded its territory after 1945. Nevertheless, we decided to drop these observations from the analysis. Finally, we applied the same procedures to the observations from the border and non-border areas as we did for the whole dataset.

4 Imputation of Missing Data

4.1 Inferring Ethnicity from Names

In this section, we explain our method for predicting ethnicity of an individual from his or her names. Using names for imputing ethnicity has several advantages. First, full name is available for every individuals in the dataset. Second, names have been shown to be highly predictive of ethnicity in a variety of applications (Mateos, 2007; Hofstra et al., 2017; Hofstra and Schipper, 2018).

Given the high number of predictors, we need a model that is not computationally demanding but at the same time achieves reasonable level of prediction accuracy. Naive Bayes classifier meets these criteria and has been for this reason used in wide range of applications including text classification (Gentzkow et al., 2019).

4.1.1 Naive Bayes Classifier

Let $\boldsymbol{x} = (x_1, x_2, x_3)$ be features used for predicting ethnicity, that is a person's first, last, and patronymic (given after father's first name) names. Using Bayes theorem, we can express the probability that particular observation belongs to ethnic group E_k given its features as

$$p(E_k \mid \mathbf{x}) = \frac{p(E_k)\ p(\mathbf{x} \mid E_k)}{p(\mathbf{x})}, \tag{4.1}$$

in other words, the posterior probability is proportional to the product of prior probability and likelihood. Assuming conditional independence of features allows us to substitute $p(\mathbf{x} \mid E_k)$ such that we get

$$p(E_k \mid \mathbf{x}) = \frac{p(E_k)\ \prod_{i=1}^{3} p(x_i \mid E_k)}{p(\mathbf{x})}. \tag{4.2}$$

All terms in this equation now can be estimated from the data: the prior probability $p(E_k)$ as a proportion of E_k in the data, $p(x_i \mid E_k)$ as a proportion of people with name x_i in the ethnic group E_k and $p(\mathbf{x})$ simply calculated such that the sum of $p(E_k \mid \mathbf{x})$ for all k is one. The Naive Bayes classifier then chooses the ethnicity with the highest posterior probability as its prediction, that is

$$\hat{y} = \underset{k \in \{1,\ldots,K\}}{\operatorname{argmax}} \; p(E_k) \prod_{i=1}^{3} p(x_i \mid E_k). \tag{4.3}$$

One potential issue is that whenever a likelihood of a certain feature is estimated to be zero then the posterior probability is always zero regardless of the prior or the likelihoods of other features. For example, suppose that a person has a typical German first name but a rare surname which does not appear in the training set at all. Then the useful information contained in the first name will be completely ignored since the zero likelihood of the surname will override any other value and we will end up with the posterior probability of zero for all ethnic groups.

To address this problem, we apply Laplace smoothing. For every ethnicity, let c_j be number of people with a name j and N be total number of member of that ethnic group in the data. Without applying any smoothing, we would estimate the likelihood $p(x_i \mid E_k)$ simply as a relative frequency, i.e. $\hat{\theta}_j = \frac{c_j}{N}$. With Laplace smoothing, we estimate the likelihood $\hat{\theta}_j$ as

$$\hat{\theta}_j = \frac{c_j + \alpha}{N + \alpha d} \qquad j = 1, \ldots, d \tag{4.4}$$

where parameter $\alpha > 0$ is a smoothing parameter. This ensures that for any finite value of N, $\hat{\theta}_j$ will never be exactly zero. In our model, relatively small value of $\alpha = 0.005$ turned out to be sufficient and was chosen.

It is important to note that the conditional independence assumption often does not hold in the data and the estimated posterior probabilities therefore have to be taken with a grain of salt. However, our main goal is the best out-of-sample accuracy of the model's predictions. In this respect, Naive Bayes classifier have been shown to perform well in many applications, despite its often violated assumptions (Domingos and Pazzani, 1997).

4.1.2 Adjusting for Unbalanced Prediction Accuracy

To reliably asses the out-of-sample performance of our model, we used 10-fold cross-validation on the data with non-missing ethnicity. That is, the data is first randomly split into 10 groups. A model is fitted to 9 group and the remaining group is used to test the model's performance. This process is then repeated 9 times until every group has been tested. Using this method, the resulting overall accuracy of our model is 79.3%. However, we are also interested in how this varies by ethnicity. For this reason we calculate sensitivity and specificity for each ethnic group.[9] The results, provided in table A3 in the appendix, show that the sensitivity differs significantly by ethnicity. Some ethnic groups with distinctive names such as Chinese or Japanese are classified with accuracy higher than 90% while for other ethnicities such as Chuvash or Udmurt it is about 10%. This severe imbalance in sensitivity and specificity across ethnic groups could potentially cause bias in the imputations.

We develop adjustments that try to correct for these biases in the model's predictions. Let P_{it} be the number of people with predicted ethnicity i arrested at time t, R_{it} be the actual number of people with ethnicity i arrested at time t, α_i and β_i be sensitivity and specificity of our classifier for ethnic group i and N_t be the total number of arrests at time t. Then the predicted arrests of a given ethnicity are sum of true positives and false positives, that is

$$P_{it} = \alpha_i R_{it} + (N_t - R_{it}) \cdot (1 - \beta_i). \tag{4.5}$$

We are interested in R_{it} but we only directly observe P_{it} and N_t. However using simple algebra, R_{it} can be expressed as

$$R_{it} = \frac{P_{it} - N_t (1 - \beta_i)}{\alpha_i + \beta_i - 1}. \tag{4.6}$$

[9]Sensitivity measures the proportion of observations in the class (in our case ethnicity) that are correctly identified by the model as such (i.e. number of true positives divided by all positives). Specificity measures the proportion of observations *not* in the class that are correctly identified as such (i.e. number of true negatives divided by all negatives).

We will refer to this method of correcting predictions as parsimonious adjustment. The parameters α_i and β_i are not known to us but we can use their estimates from the cross-validation on the training data. This assumes that the these parameters do not differ significantly for the training and test data. But this might not be the case. Suppose, for example, that Armenians are often misclassified as Chechens and that the number of Armenians in the data with missing ethnicity is disproportionately higher than in the data with information on ethnicity. Then the cross-validated specificity for Chechens in the training set will underestimate the specificity in the test set because it does not take into account the higher proportion of Armenians.

Fortunately, we can address this potential bias with a more complex model. First for all ethnic groups i and j, we define the misclassification rate b_{ij} as share of people with ethnicity j that are classified as i. Notice that for $i = j$, the misclassification rate is simply prediction accuracy for ethnicity i. It follows from the definition of the terms that predicted number of arrests for ethnic group i at time t, P_{it}, is equal to

$$P_{it} = \sum_{j=1}^{K} b_{ij} R_{jt} \qquad i = 1, \ldots, K. \tag{4.7}$$

This equation can be expressed in matrix form as

$$\mathbf{P}_t = \mathbf{B} \cdot \mathbf{R}_t, \tag{4.8}$$

where $\mathbf{P}_t = (P_{1t}, \cdots, P_{Kt})$, $\mathbf{R}_t = (R_{1t}, \cdots, R_{Kt})$, and $\mathbf{B} = (b_{ij})_{i=1,\ldots,K,\, j=1,\ldots,K}$. To express $\mathbf{R}_t$, we just apply basic linear algebra

$$\mathbf{R}_t = \mathbf{B}^{-1} \cdot \mathbf{P}_t. \tag{4.9}$$

We will call this method the full (confusion) matrix adjustment. Compared to the parsimonious adjustment (in equation 4.6), this correction no longer assumes that the test set sensitivity and specificity be accurately estimated from the training set. The full matrix adjustment makes only somewhat weaker assumption that the train and test set misclassification rates are not substantially different. On the other hand, the estimates of misclassification rate will likely be noisier (have higher variance) compared to the estimates of specificity and sensitivity because they are based on fewer observations.

One final issue that we encountered when applying these adjustments to the actual data was that some predicted values of $\mathbf{R}_t$ were negative. We decided to replace all negative values with zero in order to preserve this basic feature of the data. Finally, we scaled all values such that the total number of arrests would stay unchanged after the adjustment and rounded it to the nearest integer. The comparison of total number of arrests for each adjustment and ethnic group is provided in table A2. A graph showing the change in arrests in time by ethnicity and imputation adjustment is provided in figure A1.

4.2 Imputing Missing Date of Arrest

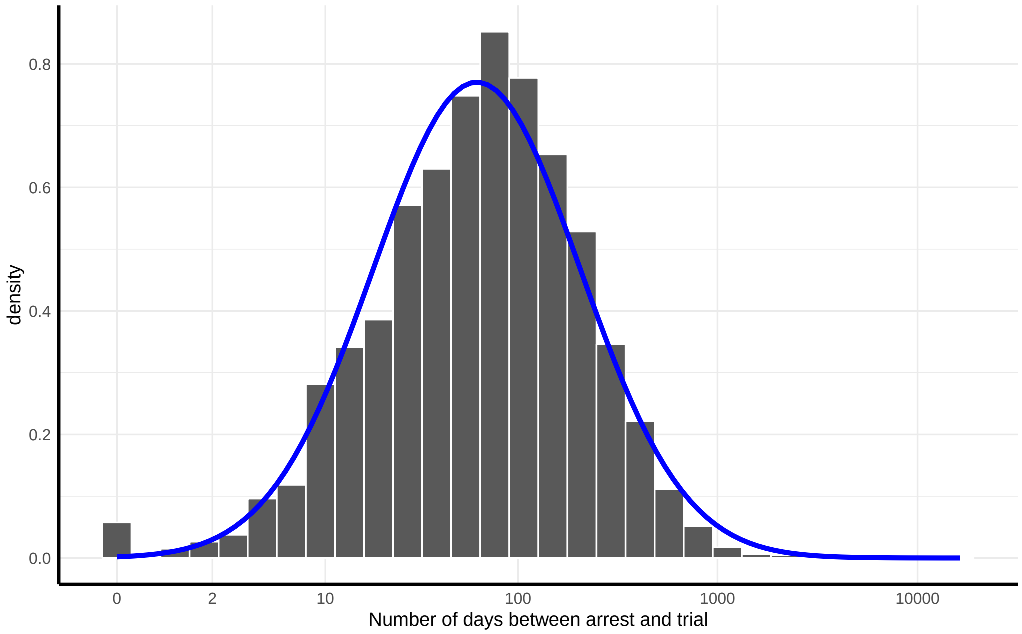
Our strategy for imputing the missing arrest dates is to predict it from the date of trial. For this reason, we model the number of days between arrest and trial and fit it to a subset of the data for which both dates are known. It is reasonable to expect that the average number of day from arrest to trial could vary considerably throughout the years. Hence we use the year of trial as a predictor for our model.

We begin by examining the data with both dates available. The histogram for number of days between arrest and trial (on scale of $\log_{10}(1 + x)$) is shown in figure 1. First, we can see that there is fairly large variance in the variable with number of days ranging from 0 to more than 1000.[10] Second, the transformed data seems to be following the normal distribution except for the density at 0 which is much higher than the normal model would predict. Moreover, the zero values are making the estimated mean of the normal distribution lower than would be appropriate for the positive values resulting in poor fit as can be seen in figure 1.

To address this problem, we model the zero and positive values separately in a two-stage process using a method described in Gelman and Hill (2006,

[10] Zero, of course, corresponds to both arrest and trial being in the same day.

Figure 1: Histogram for Number of Days between Arrest and Trial



Notes: The x-axis is shown on $\log_{10}(1 + x)$ scale.

p. 537-538). Let y be the number of days between arrest of an individual and his or her trial and X be a set of dummy variables indicating the year of trial. We also define I^y as an indicator variable that equals 1 if $y > 0$ and 0 otherwise and y^{pos} to be only positive values of y (i.e. $y^{\text{pos}} = y$ if $y > 0$). In the first stage, we predict I^y using logistic regression

$$\Pr\left(I_i^y = 1\right) = \operatorname{logit}^{-1}\left(X_i\alpha\right). \tag{4.10}$$

In the second stage, simple log-linear regression is applied to predict only the positive values y^{pos}

$$\log\left(y_i^{\text{pos}}\right) \sim \mathrm{N}\left(X_i\beta, \sigma\right). \tag{4.11}$$

We then fit the first model to the data where the exact dates of both arrest and trial are available and the second model to the subset of the same data for which $y > 0$. The results of both of these models are provided in table A6 in the appendix. The years of trial appear to be important predictors both in the first stage and even more in the second stage. However, the unexplained variance is still high making up about 77% of the total variability in the dependent variable in the second model.

We proceed to apply the fitted models to the missing data to get the predicted probability of y being positive and the mean value of y if it is positive. For each observation with missing date of arrest X_i, we then randomly draw from the Bernoulli distribution with $\text{logit}^{-1}(X_i\hat{\alpha})$ as its parameter to obtain $\hat{I}_i^y$. We also draw from the normal distribution with mean $X_i\hat{\beta}$ and exponentiate the result to get $\hat{y}_i^{\text{pos}}$. Finally, the predicted number of days is calculated simply as $\hat{y}_i = \hat{I}_i^y \cdot \hat{y}_i^{\text{pos}}$.

The histogram of the imputed values is provided in figure A3 in the appendix. The resulting distribution highly resembles the distribution in figure 1 including the fraction of zero values indicating our model captures the actual data fairly well.

Nevertheless, another complicating factor is that for significant number of observations we do not have the exact date of trial but only year. In particular, while the year of trial is recorded for all 903 455 observations where the date of arrest is to be imputed, the month of trial is missing for 369 393 of them and the day for 390 174. To fill in the missing month, we take a random sample from all months with probability equal to the relative frequency of the months of trial in the non-missing data for the years from 1921 to 1960. Even simpler method is used to impute the missing days where we just randomly choose a day within given month with uniform probability.[11] The imputed months and days of the trials are therefore only weakly informed guesses, nevertheless they enable us to carry on with the analysis.

The final step is to calculate the imputed date of arrest by subtracting the predicted number of days from the date of process (i.e. we go back in time by given number of days). Since we conduct the analysis with annual observations, we ignore predicted month and day of arrests keep only information on year. The number of arrests for each ethnicity by year (including

[11] Every date, however, has to be consistent with the calendar. This means that for January we take a sample of numbers from 1 to 31, for February from 1 to 28 and so on.

the imputed years) is then counted for the period from 1921 to 1960 which forms our final dataset.

The resulting time series of all arrests with imputed years is plotted in figure A4 in the appendix. Arrests with imputed dates seem to follow similar trends with the labeled data although there is slight divergence at the beginning and end of the series and in the 1930s.

5 Methodology

5.1 Difference-in-differences

We employ difference-in-differences design to estimate the effect of the changing geopolitical relations on repressions of Germans in the USSR. Our main specification is the following dynamic difference-in-differences model:

$$\log(1 + y_{it}) = \sum_{k=1922}^{1960} \beta_k \,\mathrm{German}_i \cdot \mathrm{Year}_t^k + \lambda_t + a_i + \mathrm{Relations}_{it} + u_{it}, \quad (5.1)$$

where y_{it} is number of arrests of people with ethnicity i in year t (from 1921 to 1960), λ is year fixed effect, a is ethnicity fixed effect (both captured by respective dummy variables) and Year_t^k are dummy variables that equals 1 if its year k equals to t and 0 otherwise. Prior to 1933 they capture the lead (anticipatory) effects used to test if pre-treatment trends are parallel. After 1933 they capture the dynamic lagged effects. The only omitted year is 1921 which thus serves as a baseline against which other coefficients are compared. The time-varying vector $\mathrm{Relations}_{it}$ is set a of dummy variables that capture other major changes in relations of a state with core group i with the USSR during this period. The list of these changes is provided in appendix in table A1.

In additional specifications used to test sensitivity of results, we also include the terms $E_i \cdot t$ and $E_i \cdot t^2$ that can capture ethnicity-specific time trends. This allows for a certain deviation from the parallel trends if it can be described by the specified (quadratic or linear) function (Angrist and Pischke, 2009, chapter 5). However, a potential issue with the ethnicity-specific time trends is that they could absorb part of the treatment effect if it increases over time (Meer and West, 2016) which is why we do not include them in our default specification.

We apply logarithmic transformation on y_{it} since it better fits the data. We use $\log(1 + y_{it})$ because some observations (although not many) have $y = 0$. As discussed in Wooldridge (2015, p. 193), the properties of standard logarithmic transformation are usually closely preserved (except for changes beginning at 0 which are not of great interest to us).

For continuous variables, log-linear models have straightforward percentage change interpretation, i.e. for variable x_j with corresponding coefficient γ_j, the estimated percentage change in y for small change in x_j is equal to $100 \cdot \gamma_j$. However, as Halvorsen and Palmquist (1980) point out, this interpretation is not correct for dummy variables. Fortunately, Kennedy (1981) derives the following unbiased estimator for percentage change effect p_j of a dummy variable x_j:

$$\hat{p}_j = 100 \cdot \left(\exp\left\{ \hat{\beta}_j - \frac{1}{2} \hat{V}\left(\hat{\beta}_j\right) \right\} - 1 \right) \tag{5.2}$$

where $\hat{\beta}_j$ is the estimated coefficient on x_j and $\hat{V}\left(\hat{\beta}_j\right)$ is an estimate of variance of $\hat{\beta}_j$. Since our main coefficients of interest are dummy variables, we will use this formula to obtain estimates of percentage change effect.

The identifying assumption for difference-in-differences model in equation 5.1 is that the number of arrest of Germans after 1933 would go in parallel to arrests of other minorities in the absence shock to German-Soviet relations conditional on our control variables.[12] Although we cannot test this assumption, we can test whether the trends were parallel prior to 1933 (pre-treatment) which could increase our confidence that they were parallel after 1933 too. This can be done by testing if the coefficients β_k on the lead effects are significantly different from zero.

As Bertrand et al. (2004) show, the usual standard errors are downward-biased for most difference-in-differences regressions since they do not account for the serial correlation within the units of interests (states, countries etc.). A common solution to this problem is to estimate standard errors using robust covariance matrix that allows for clustering (i.e. cluster-robust standard errors). However for small number of groups (generally less than 50), the cluster-robust standard errors are downward-biased and not reliable (Donald and Lang, 2007; Angrist and Pischke, 2009, chapter 8). One possible solu-

[12] In the presence of linear ethnicity-specific time trends, the identifying assumption is the parallel growth of the outcome variable of control and treatment group. This is equivalent to the parallel trends for the first differences of the outcome (Mora and Reggio, 2019).

tion might be to use $G-1$ degrees of freedom instead of $N-K$ (where G is the number of clusters, N number of observation, and K number of parameters), together with a special finite-sample correction of the covariance matrix (Angrist and Pischke, 2009; Cameron and Miller, 2015; Imbens and Kolesár, 2016). This type of standard errors is a default cluster-robust option in Stata and we thus refer to them as Stata standard errors. Nevertheless, Imbens and Kolesár (2016) have shown that for small number of clusters using Stata standard errors results in over-rejection of the null hypothesis. McCaffrey and Bell (2002) propose an alternative method called bias-reduced linearization which adjusts the standard cluster-robust variance estimator such that it is unbiased under the model specified. Effective degrees of freedom are then estimated based on Satterthwaite approximation. Imbens and Kolesár (2016) recommend using bias-reduced linearization over other methods even in moderately sized samples. One potential problem of bias-reduced linearization is that it might be undefined for certain specifications. But recently Pustejovsky and Tipton (2018) have generalized the method to models with arbitrary sets of fixed effects (including differnce-in-differences). Since we have small number of clusters (38 ethnic groups), we use the estimator by Pustejovsky and Tipton (2018) as our default option and the Stata standard errors as a robustness check.

5.2 Synthetic Control Method

As we explained in the previous section, difference-in-differences makes a fairly strong assumption regarding the absence of time-varying individual-specific heterogeneity which might be unrealistic in some empirical settings. The synthetic control method has been increasingly applied in the economic literature to overcome this issue (Abadie and Gardeazabal, 2003; Abadie et al., 2010; Billmeier and Nannicini, 2013; Cavallo et al., 2013). The method works by constructing a synthetic version of the treated unit from the control units based on matching of pre-treatment variables. The outcomes of synthetic control are then compared to the actual outcomes to estimate the treatment effect. Unlike difference-in-differences, the synthetic control method allows for the presence of certain time-varying unit-specific confounders although only if they can be captured by the factor model in equation 5.4.

Let Y_{it} be the outcome of a unit i at time t with $i = 1$ being the treated group and $i \in \{2, \ldots, J+1\}$ untreated units (we will also call them donor units). We denote D_{1t} as the treatment dummy, i.e. variable that equals 1 if $i = 1$ and $t > T_0$ and 0 otherwise (with T_0 being the start of the treatment). Let be Y_{1t}^N be a counterfactual outcome for the treated unit at time $t > T_0$ in the absence of treatment. The observed outcome Y_{it} is then assumed to be sum of the counterfactual outcome Y_{1t}^N and the effect of treatment at time t, α_{1t}, i.e.:

$$Y_{1t} = Y_{1t}^N + \alpha_{1t} D_{1t}. \tag{5.3}$$

The synthetic control method also assumes that Y_{1t}^N can be expressed by the following factor model:

$$Y_{1t}^N = \delta_t + \boldsymbol{\theta}_t \boldsymbol{Z}_i + \boldsymbol{\lambda}_t \boldsymbol{\mu}_i + \epsilon_{it}, \tag{5.4}$$

where is δ_t an unknown common factor with constant factor loadings across units, $\boldsymbol{Z}_i$ is a $(1 \times r)$ vector of observed time-invariant covariates (unaffected by the treatment), $\boldsymbol{\theta}_t$ is a $(1 \times r)$ vector of unknown parameters, $\boldsymbol{\lambda}_t$ is a $(1 \times F)$ vector of unobserved time-varying factors, $\boldsymbol{\mu}_i$ is an $(F \times 1)$ vector of unknown factor loadings and ϵ_{it} is the error term with zero mean.

Notice that if $\boldsymbol{\lambda}_t$ is constant for all t, we get the traditional difference-in-differences with time and unit-specific fixed effects. The synthetic control method thus offers more general model that, in contrast to difference-in-differences, allows the unobserved confounders vary with time.

The method works by estimating the counterfactual outcome Y_{1t}^N by constructing a synthetic control group as a convex combination of available comparison units (in our case other ethnic groups in the USSR) that most closely resembles the pre-treatment characteristics of the treated group (or more precisely, for which the average of its factor loadings $\boldsymbol{\mu}_i$ match the factor loadings of the treated unit $\boldsymbol{\mu}_1$).

More formally, we choose a vector of weights $W = (w_2, \ldots, w_J, w_{J+1})$ subject to $w_j \geq 0$ for $j = 2, \ldots, J, J+1$ and $w_2 + \cdots + w_J + w_{J+1} = 1$ that minimize $\|X_1 - X_0 W\|_V = \sqrt{(X_1 - X_0 W)^T V (X_1 - X_0 W)}$ where $X_1 = (Z_1, Y_1^{K_1}, \ldots, Y_1^{K_L})$ is a $(k \times 1)$ vector of pre-treatment characteristics of the treated unit, Y^{K_l} are linear combinations of pre-treatment outcomes, and X_0 is a $(k \times J)$ matrix with pre-treatment characteristics of untreated units analogous to X_1, and V is a $(k \times k)$ matrix that weights the importance of different pre-treatment predictors in the minimization problem. V is usually chosen among symmetric and positive semidefinite matrices to minimize the mean squared prediction error (MSPE) in the outcome in the pre-treatment period so that the V-weights would reflect the predictive power of the covariates. The effect of the treatment α_{1t} at time $t > T_0$ is then estimated as a difference between the outcome for the synthetic control and the treated unit, that is:

$$\hat{\alpha}_{1t} = Y_{1t} - \sum_{j=2}^{J+1} w_j^* Y_{jt}, \tag{5.5}$$

where w_j^* are the estimated optimal weights.

The synthetic control method, however, does not provide us with any standard errors that could measure the uncertainty in the estimates. Abadie et al. (2010) propose assessing significance using placebo tests and randomization inference. The synthetic control method is applied iteratively to every unit in the donor pool as if they were treated and the results of placebo test are then compared to the treated unit. If the estimated effect for the treated unit is much larger than the placebo effects, it implies that the effect is significant since such result would not be likely under the null hypothesis of zero treatment effect.

However, Abadie et al. (2010) point out that placebo synthetic controls with poor pre-treatment fit do not provide good comparison for estimating rareness of large effect for a treated unit with a good pre-treatment fit. They thus recommend excluding excluding placebo units with substantially higher pre-treatment MSPE relatively to the treated unit.

Nevertheless, the choice of any level of the cutoff of pre-treatment MSPE is somewhat arbitrary. Abadie et al. (2010) suggests that better way to asses significance of results might be to compare the ratios of post/pre-treatment MSPE which takes into account different values of pre-treatment fit between the treated unit and the placebo tests. First, the MSPE ratio for unit j is defined as

$$\text{MSPE ratio}_j = \frac{\sum_{t=T_0+1}^{T}\left(Y_{jt} - \hat{Y}_{jt}^{N}\right)^2}{\sum_{t=1}^{T_0}\left(Y_{jt} - \hat{Y}_{jt}^{N}\right)^2} \tag{5.6}$$

where $\hat{Y}_{jt}^{N}$ is estimated synthetic control for unit j at time t. The p-values can then be calculated as

$$p_1 = \frac{\sum_{j=2}^{J+1} \mathbb{1}\left(\text{MSPE ratio}_j \geq \text{MSPE ratio}_1\right)}{J+1}. \tag{5.7}$$

where $\mathbb{1}$ is an indicator function that equals 1 if the equation in its argument is true and 0 otherwise.

6 Results

6.1 Difference-in-differences

We first present results from our preferred specification 5.1 with geopolitical controls and no ethnicity-specific time trends. The interaction of the specific year and German dummy variables is omitted only for 1921 which therefore serves as baseline for comparison with other years. All 38 ethnic groups in the dataset are included. We imputed missing ethnicity and date of arrest as described in section 4. Full matrix adjustment (equation 4.9) was applied to the ethnicity imputations.

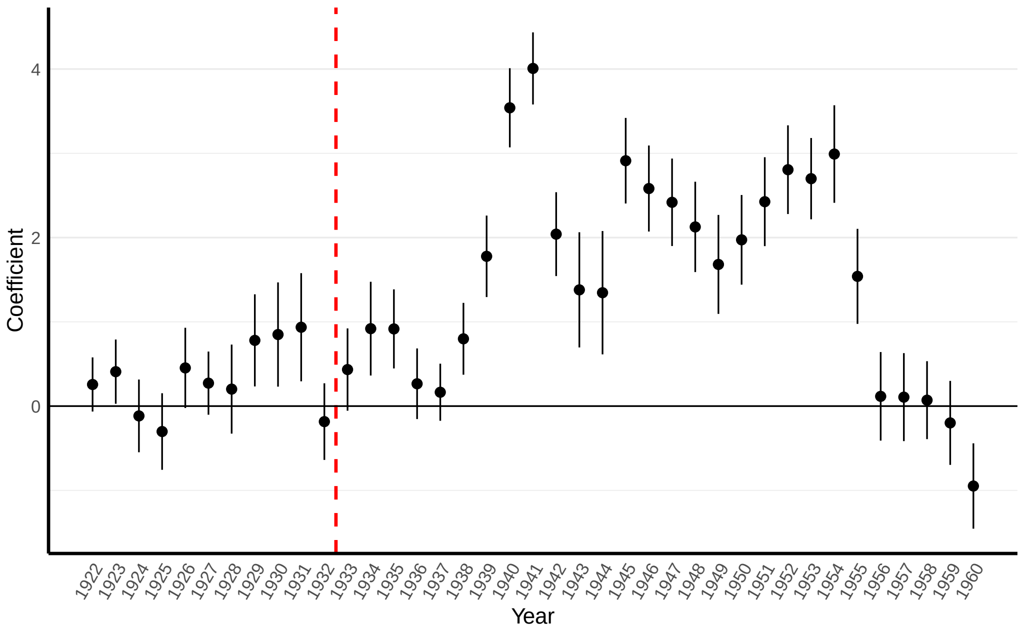
The estimated coefficients β_k from the dynamic difference-in-differences model (5.1) are provided in table A7 in the column (1) and plotted in figure 2. We can draw several conclusions from the results. First, the coefficients from 1933 to 1938 are all smaller than 1 and are not larger than the pre-1933 coefficients which implies that hostility between Germany and the Soviet Union in this period does not seem to have high impact on the repressions of Germans contrary to the theoretical predictions. Second, the political arrests of Germans start to rise in 1939 which is surprising given that Molotov-Ribbentrop pact guaranteeing neutrality Germany and the USSR was signed that year. The repressions then peak in 1940 and 1941 at 4 log points followed by sharp drop in years 1942-1944 to 2 and subsequently 1.5 log points. However, we have to be careful when interpreting those coefficients. Since the Soviet Union was during that time at war and initially lost large amounts of territory, it is plausible that the arrests of Germans declined simply because there were fewer Germans on the territory controlled by the Soviets. In any case, the impact of war on the repressions appears to be highly persistent as the estimated effect stays high at around 2 to 3 log points even after 1945. Finally, starting from 1955, the coefficients rapidly fall to zero. This period coincides with the partial relaxation of repressions and censorship following the death of Stalin in 1953 and the subsequent rise of power of Khrushchev. This is reflected in our data where the number of arrested Germans in a given year after 1954 does not exceed 50 compared to hundreds of arrests in the preceding years.

To convert these coefficients to percentage changes, we apply formula 5.2. Since the base of our comparison is very small (only 135 of arrests of Germans in 1921 compared to tens of thousands of arrests during war), the calculated percentage changes are extremely large. Whereas for years 1934 and 1935 the percentage change is around 140%, it is 475% for 1939, and as much as 5279% for 1941. In the period from 1946 to 1954 it ranges from 415% to 1812%. We see that these numbers are not necessarily very informative. Better approach might be to estimate what number of post-1933 arrests of Germans are attributable to the worse geopolitical situation. First for a given year k, we subtract the coefficient β_k from the value $\log(1 + \text{arrests}_{ik})$ for German minority and apply the transformation $\exp(x) - 1$ to the result. This gives us the estimated counterfactual of German arrests, i.e. what would be the number of German arrests if there was no treatment effect in year k. The number of repressions attributable to the effect can then be easily computed by subtracting the counterfactual number of German arrests from the actual value.

If we perform these calculations for every year after 1933 and sum the results, we get that 128 022 (83.6%) of German repressions are attributable to the effect out of the total of 153 060 in that period. However, this assumes that every deviation of the coefficients β_k from 0 is due to the treatment effect which we have serious reasons to doubt. In fact, when we repeat the same computations for the period from 1922 to 1932, the implied share of repressions attributable to the "effect" is 53.4% (9 888 out of 18 517). These estimated should thus be taken rather as an upper bound.

As we already hinted, the pre-1933 coefficients in figure 2 give us a reason to doubt the validity of our model. Even though they are small in size relative to the post-1939 coefficient, three of them (for years 1929, 1930, and 1931) are significantly different from 0 at 1% level. This provide some evidence that the pre-treatment trends for German minority were not parallel with trends for other ethnic groups. We can thus suspect that the post-treatment

Figure 2: Estimates of β_k from Specification 5.1



Notes: Ethnicity and date of arrest were imputed. Full matrix adjustment was applied on ethnic group imputations. All 38 ethnic groups are included. There are no ethnicity-specific time trends. Standard errors are clustered on the level of ethnicity and are based on cluster robust estimator by Pustejovsky and Tipton (2018). Error bars show 95% confidence intervals.

trends were not parallel either which would violate the basic identifying assumption of difference-in-differences. We address this problem by applying the synthetic control method in the next section.

Another potential issue is that some ethnic groups might have changed their treatment status in this period in various complicated ways. We tried to control for this by including a set of dummy variables that capture the most important changes in geopolitical relations (more on their definition in subsection 7.2 in the appendix). However, these dummy variables might miss more subtle changes in relations with the USSR. As a robustness check, we therefore exclude every ethnicity which constituted a core group in some independent state in the interwar period from the dataset (except for Germans, of course) and reestimate the model. This criterion removes 10 ethnic groups from the dataset. The full list of them is provided in table A10. The results of the dynamic difference-in-differences model are available in table A7 in the column (2) and plotted in figure A6 both in the appendix. The estimated coefficients change very little compared to the results with all ethnic groups included, only confidence intervals appear slightly wider since we have fewer observations. Therefore our previous conclusions are maintained.

In section 7, we perform several additional robustness checks to further asses the sensitivity of our findings. In particular, we refit the models to only data with rehabilitated individuals and allow for different ethnicity-specific time-trends, imputation adjustments, and standard errors.

6.2 Synthetic Control Method

We implemented the synthetic control method in R using the MSCMT package (Becker and Klößner, 2018). Our outcome variable is again $\log(1 + \text{arrests})$. As in difference-in-difference, we include all 38 ethnic groups and we impute missing date of arrest and ethnicity (which we adjust using the full-matrix correction). In our baseline model, the outcomes for all pre-treatment years (1921-1932) were included as predictors. This approach has been widely used in the literature (Billmeier and Nannicini, 2013; Cavallo et al., 2013; Bohn et al., 2014) and in contrast to other methods (such as using only mean of pre-treatment outcomes) it has the advantage of reducing opportunities of specification search (Ferman et al., 2018). We also include three time-invariant covariates that might potentially be predictive of post-1933 repressions: total population of the ethnic group in the USSR, its urbanization rate (both taken from the 1926 Soviet Census), and linguistic similarity to Russian. However, including all pre-treatment outcomes as predictors renders other covariates unimportant in the optimization procedure (Kaul et al., 2018). On the other hand, Botosaru and Ferman (2019) argue that if there is a long set of pre-treatment outcomes (which is our case) then a perfect balance on covariates should not be required. Since there is no clear consensus in the literature, we apply both methods and show the synthetic control method with mean of the pre-treatment outcome as predictor in section 7 as a robustness check in addition to our baseline specification with all pre-treatment outcomes as predictors that we present below.

The calculated optimal weights W of ethnic groups in the synthetic Ger-

Table 4: Synthetic German minority weights

Ethnic group	W-Weight
Greek	0.32
Russian	0.31
Lithuanian	0.10
Ossetian	0.08
Chuvash	0.07
Georgian	0.05
Tatar	0.05
Korean	0.02

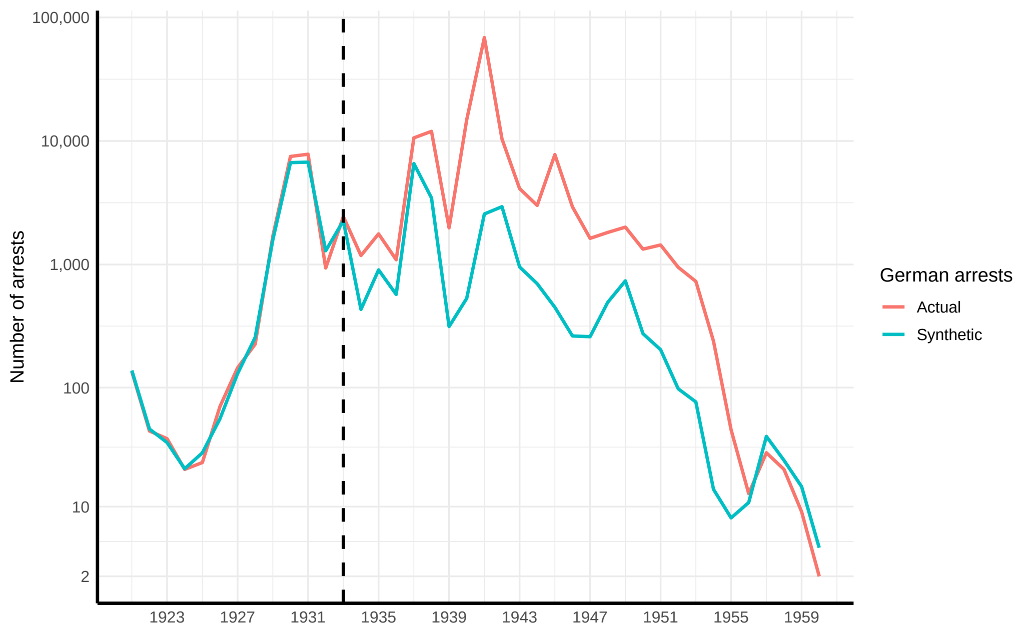
man minority are provided in table 4 (ethnic groups with zero weight are not shown). The highest contribution in the synthetic German minority have Greeks and Russians with weights 0.32 and 0.31, respectively. Lithuanians, Ossetians, Chuvashs, Georgians, Tatars, and Koreans are also represented in the synthetic control although only with weights equal or smaller than 0.10.

Figure 3 shows the arrests of the German minority and its synthetic control. The synthetic control fits the actual pre-treatment values reasonably well. In the post-treatment period, both time series follow similar general trends. However up until 1955, the actual arrests of Germans are consistently higher than the predictions of synthetic control. We can infer the estimated effect size in the post-1933 period from figure 4a which shows the difference between the actual arrest and their synthetic counterparts for each year (on $\log(1 + x)$ scale).

From 1933 to 1939, this gap is close to 1. For the period from 1941 to 1955, the estimated effect is higher but also more volatile oscillating between 1 and 3 log points. After 1955, the gap shrinks to zero. The results are similar to difference-in-differences in the overall trends although the estimated effects by the synthetic control are slightly smaller than the their difference-in-differences equivalents.

We can estimate the number of arrests attributable to the geopolitical changes as we did for difference-in-differences by transforming the actual and synthetic values from logarithmic to natural scale and subtracting them from each other. The results are that in the whole post-1933 the total number of

Figure 3: Comparison plot



Notes: The values on y-axis are shown on $\log(1+y)$ scale. Ethnicity and date of arrest were imputed. Full matrix adjustment was applied on ethnic group imputations. All 38 ethnic groups are included.

arrests for the synthetic German minority is 25 180 in contrast to 153 060 of actual German arrests which implies that the estimated effect accounts for 127 880 (83%) of all German arrests in that period. If we repeat the same calculations but only for years from 1933 to 1939, the resulting share of arrests attributable to the effect decreases to 53% (16 526 arrests out of 31 041). The same measure for the whole pre-treatment period is 8% (1 638 arrests out of 18 517).

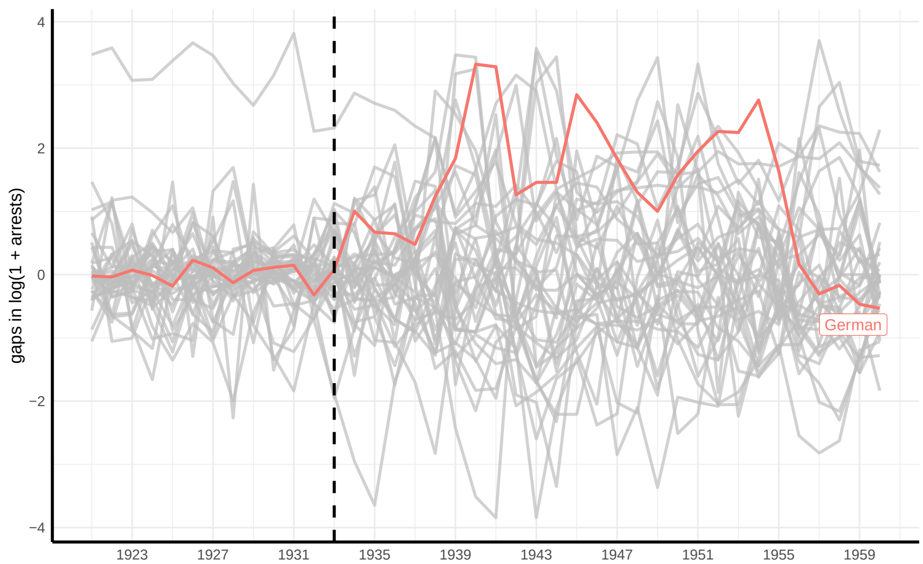
We assess the significance of our results with placebo tests by applying the same procedure to every ethnic group in the dataset. The differences between the actual values and the respective synthetic control for every placebo ethnicity are plotted in grey in figure 4a. Even in comparison with the placebo tests, the estimated effect for German ethnicity still appears relatively large for the period from 1939 to 1955, although for years 1933-1938 the effect for Germans fits within the standard range of the placebo gaps.

Figure 4a also shows that for some ethnic groups the pre-treatment gaps are fairly large. The most extreme example is the gap for Russians which stays above 2 log points for the whole pre-1933 period. This indicates that synthetic control of these ethnic groups does not capture the actual pre-treatment trends well. As we explained in subsection 5.2, the placebo synthetic controls with substantially worse pre-treatment than the treated unit should not be used in estimating significance of the treatment effect. We thus exclude the placebo ethnicities whose pre-treatment mean squared prediction error (MSPE) is 20 times higher than the same measure for German minority. Even though this is relatively lenient cutoff, it removes 8 ethnic groups that does not meet the criterion. The resulting plot is shown in figure 4b. The post-1933 gaps in German arrests now stand out little more clearly.

Nevertheless, our preferred approach for assessing uncertainty in results that avoids choice of any arbitrary level of the pre-treatment MSPE cutoff for the exclusion of poorly fit placebos is to compare the ratios of post/pre-treatment MSPE. The values of these ratios for all ethnic groups are displayed in figure 5a for the whole post-treatment period. The MSPE ratio for the German minority is the highest. The probability of German minority having the highest ratio of all under the null hypothesis of zero treatment effect is $1/38$ (≈ 0.026). In figure 5b, we also provided the MSPE ratios with the post-treatment MSPE calculated only for the years 1933-1939 to estimate the significance just for this period. The MSPE ratio for German minority is now only the fourth highest and therefore the implied p-value is $4/38$ (≈ 0.105) which would no longer be considered significant at 10% level.

Figure 4: Gaps between synthetic control and actual values for placebo tests

(a) All ethnic groups



(b) Ethnicities with pre-treatment MSPE higher than 20 times the MSPE of Germans excluded

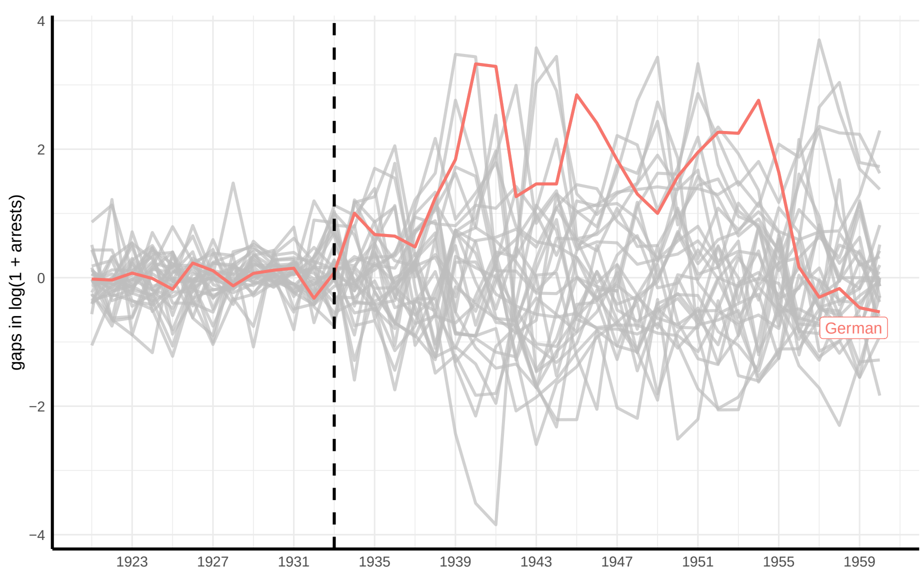
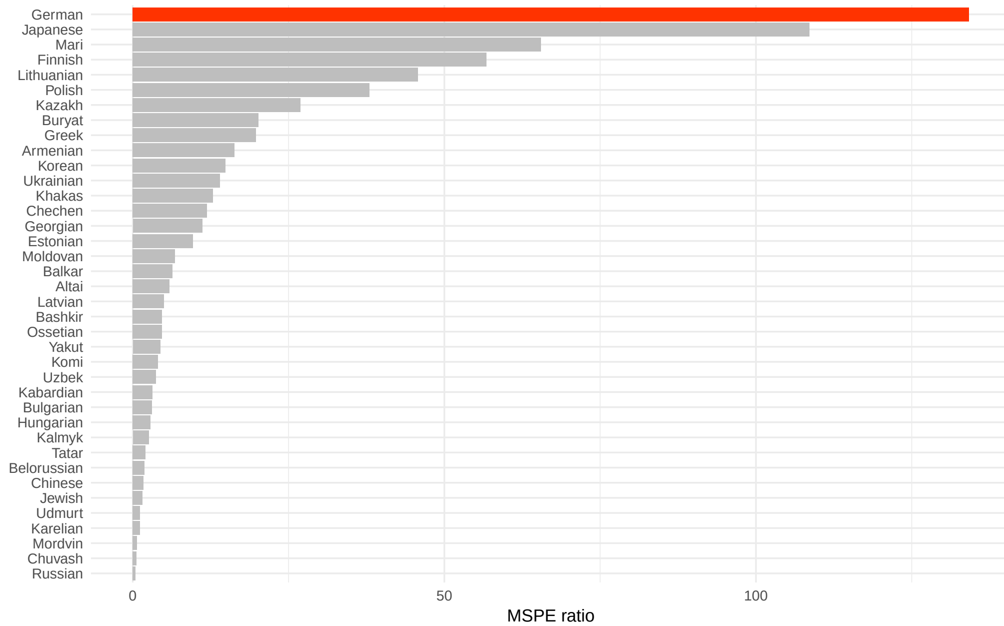
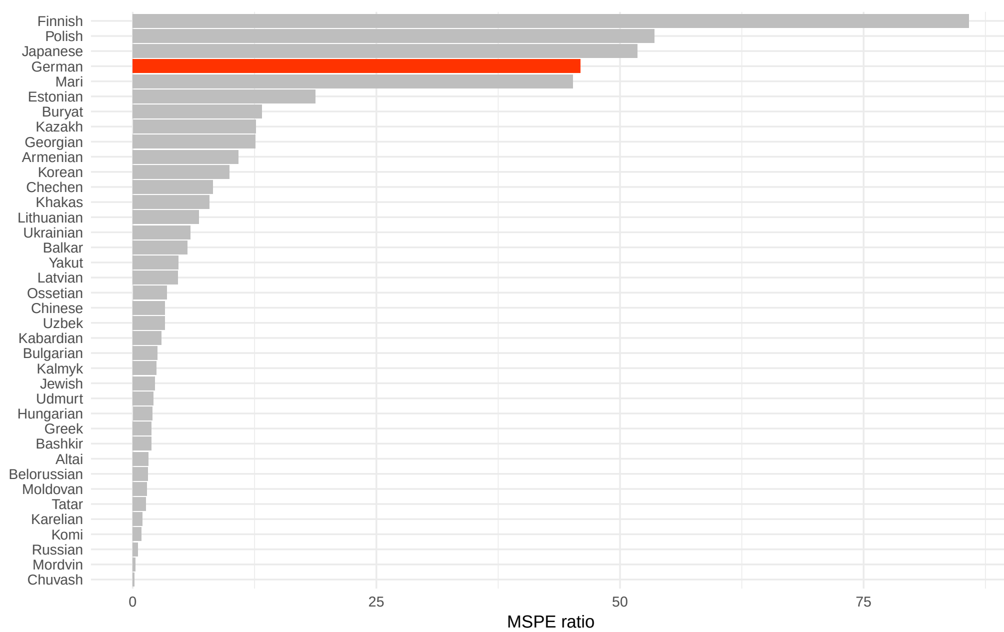


Figure 5: Ratios of post-treatment MSPE to pre-treatment MSPE

(a) The whole post-treatment period in the numerator (1933-1960)



(b) Only the period from 1933 to 1939 in the numerator



7 Robustness Checks

7.1 Difference-in-differences

Our results have shown rise of arrests of Germans during and after the war. However, the question is if these people were arrested for aiding the invading German army or only based on their ethnicity. Since the Russia's 1991 Law "On Rehabilitation of Victims of Political Repression" specified that those who joined the German army[13] were not eligible for rehabilitation, we can filter out the cases of direct cooperation by restricting our analysis to only rehabilitated victims (Frierson, 2014). In the Memorial database, there are 1 257 796 individuals classified as rehabilitated (for rest of the data we either do not have the information on rehabilitation or they were not eligible for rehabilitation). We thus re-estimate our baseline specification using only those observations. The results are provided in table A7 in the column (3) and plotted in figure A7. We see that the coefficients after 1933 change only little. Nonetheless, the pre-treatment estimates deviate from zero more than in previous specifications.

Second, we explore if there is heterogeneity in the effect by border areas. McNamee and Zhang (2019) found that the expulsions of minorities with ethnic ties to hostile power took place in border areas without natural barrier. They explain that this is motivated by state's effort to consolidate its power in a territory that is vulnerable to foreign invasion. The question is if similar logic also applies for repressions as well.[14] We see in figure A9 that the dynamics and size of the effect for non-border regions is very similar to our previous specifications The border regions, on the other hand, seem to experienced much greater increase in arrests of Germans in the years 1934-1939 (results are shown in figure A8). But the pre-1933 coefficients have much larger deviations from zero which casts stronger doubt on the parallel trends assumptions and credibility of the results. Thus, we cannot draw strong conclusions based on these results.

[13] Subsequent amendments expanded the restriction to anyone who aided the German army.

[14] We do not consider distinction between borders with and without natural barriers since most of Soviet border frontiers in Europe lack any such a barrier.

Second, we consider if the inclusion of ethnicity-specific time trends affects the results. The estimates from regressions with quadratic, linear, and no time (default) trends are provided in table A8 and plotted in figure A10 both in the appendix. The inclusion of these trends appears to increase the estimates of the effect with the coefficients for the model with linear ethnicity-specific time trends being somewhat higher compared to the baseline model with no trends and the estimates for quadratic time trends being higher still.

Third, we test the sensitivity of results to different adjustments of ethnicity imputation. As we explain in subsection 4.1.2, the adjustments were applied in order to correct for the unbalanced accuracy in prediction of our Naive Bayes classifier across ethnic groups. The results from fitting our default specification to data with different adjustments are provided in table A9 and shown in figure A11. We see that the estimates for the full matrix (used by default) and the parsimonious adjustment are virtually the same. When no adjustment is applied, the coefficients get only slightly smaller.

Finally, we use Stata cluster-robust standard errors instead of the estimator by Pustejovsky and Tipton (2018) that we have used so far (difference between them is described in subsection 5.1). The results are shown in figure A12. We see that the confidence intervals based on Stata standard errors remain almost unchanged.

7.2 Synthetic Control Method

We construct a synthetic control using mean of the outcome in the pre-1933 period instead of including outcome for every year as we did in our baseline model. This increases the importance of the time-invariant covariates (population, urbanization rate, and linguistic similarity) that are also included as predictors.

Recall that the predictors weights V are chosen to minimize pre-treatment MSPE. We can thus infer from the calculated weights V (provided in table 5) that neither urbanization rate nor linguistic similarity to Russian are good

Table 5: Pre-treatment Predictor Means

	German minority			
Variable	Actual	Synthetic	Mean of all ethnicities	V weights
Log(1 + arrests)	5.46	5.37	3.751	0.17
Total population	1 238 549.00	1 646 475.15	3 681 250.421	0.82
Urbanization rate	14.92	21.90	17.844	0.00
Ling. similarity to Russian	1.00	1.23	0.763	0.00

Note:
Log(1 + arrests) is averaged over the pre-treatment period (1921-1932). All other predictor are time-invariant. Total population and urbanization rate are taken from the 1926 Soviet Census.

Table 6: Synthetic German minority weights

Ethnic group	W-Weight
Tatar	0.45
Polish	0.41
Korean	0.14

predictors of pre-1933 repressions. Therefore the W-weights of ethnic groups in the synthetic control are chosen to mainly match the German minority on population and the mean of $\log(1 + \text{arrests})$. The calculated W-weights are shown in table 6. We see that Tatar and Polish minorities are now contributing with the largest share to the synthetic control.

When we compare the gaps between synthetic control and actual value (figure A13) with our baseline model, we notice three main differences. First, pre-treatment fit for Germany is substantially worse which is the cost of assigning greater importance to other covariates by using only the pre-treatment mean of the outcome. Second, the gap for the years 1933-1939 is slightly smaller. Finally, there is large drop in the estimated effect in the year 1944. This most likely a consequence of the sharp increase in repressions of Tatars in 1944 following their mass deportations from Crimea that year. Nonetheless, both our baseline model and its robustness check otherwise follow very similar trends. The p-value of the effect for the whole period 1933-1960 is again $1/38$ (≈ 0.026). If we consider only the time window of 1933-1939, the p-value increases to $3/38$ (≈ 0.079). The MSPE ratios for all ethnic groups based on which the p-values were calculated are provided in figure A14.

Furthermore, we apply our baseline synthetic control specification (with all pre-treatment outcomes as predictors) but only limiting ourselves to ethnic groups without independent state (e.g. Armenians, Kazakhs, etc.). The resulting synthetic control is weighted average of repressions of Tatars, Jews, Koreans, Ukrainians, Khakas, and Chuvashs as shown in the table A11. The estimated effects shown in figure A15a are similar to the baseline specification. The pre-treatment fit is slightly worse but the German minority has still the highest MSPE ratio (taken for he whole post-1933 period) as shown in figure A16a and thus the corresponding p-value is $1/28$ (≈ 0.036).

Third, we apply again the same baseline synthetic control method but only to data with rehabilitated individuals. The estimated W-weights are provided in table A12. The trends in the gaps between the actual and synthetic repressions (plotted in figure A15b) are broadly consistent with our previous estimates. The German MSPE for the whole post-treatment period is the highest of all (provided in figure A16b) and therefore the implied p-value is again $1/38$ (≈ 0.026).

Finally, we test if there are different patterns in the repressions in the border frontiers. We see in figure A17 that the post-1933 gaps in repressions in both border and non-border areas follow very similar overall trends (sharp surge with war persisting until 1955). Nonetheless, the effect size in border areas seems slightly larger. Furthermore, the pre-treatment fit of the synthetic control in the border regions is somewhat better. As a consequence, the p-value for border regions is $1/38$ but only $4/38$ (≈ 0.105) for non-border areas. Thus, there is some evidence that increase in repressions was higher in the border frontiers which is consistent with the results of McNamee and Zhang (2019).

Conclusion

We used difference-in-differences and the synthetic control method to test how changing geopolitical relations between Soviet Union and Germany affected repressions of Germans by the Soviet secret police. Both models suggest that up to 80% of repressions of Germans in the period from 1933 to 1960 might be attributable to the changes in geopolitical relations. However, this is rather an upper bound estimate since it assumes absence of any German-specific post-1933 confounders not captured by our models. The increase in repressions of Germans is the highest and most significant in the years following the German invasions in 1941.

Furthermore, we find that the increased repression persist almost undiminished for nearly 10 year after the end of war when the security concerns are no longer present. This suggests that use of violence by the state might be largely driven by out-group hostility rather than the strategic considerations emphasized in the literature since after 1945 divided Germany did not posed a serious geopolitical threat anymore. The strong persistence of the hostile attitudes after the war could potentially help explain the phenomenon of conflict trap (i.e. why violence tends to reoccur in the same places). Nonetheless, our methods do not enable us to determine the underlining mechanism. It could be the bias of rank and file officers of the secret police or some directives from the top.

The effect size for the period of hostilities from 1933 to 1939 are much smaller compared to the war and post-war years. We get somewhat more conflicting results with regard to the statistical significance of these effects. For some years and specifications, the p-value is slightly smaller than 0.10, for others slightly greater. In any case, these results do not provide very strong evidence for a hypothesis that hostile relations with a foreign country that are not accompanied by war substantially increase repressions of the respective minority.

Finally, these main results are robust to numerous sensitivity checks. For example, the effect is not limited to border frontiers although it might be slightly higher there as the results from the synthetic control method suggests. We also arrive at similar conclusions if we restrict the control group only to ethnic groups without an independent state or if we consider different ethnicity imputation adjustments.

However, we also have to be aware of the limitations of this study. First, the standard errors in our results might be slightly underestimated since they do not take into account the uncertainty in the imputed values. Second, we were not able to impute missing date of arrests for about 700 000 observations with no date of trial. Moreover, the Memorial database itself does not include records of all repressed individuals in the Soviet Union. Third, to correctly estimate the treatment effect, we have to assume that the treatment has no spillovers on the control units. Yet, it is fairly plausible that circumstances of war with Germany could increase repressions of other minorities as well. Nonetheless, since we probably expect these spillovers to be positive, our estimates would in that case be biased downward.

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Appendix

Every table and graph in this thesis, the R code that generated them, and the Latex source code of this manuscript are available in the GitHub repository of this project at `https://github.com/martin-kosiik/Geopolitics-of-Repressions`. If you have any troubles with replications or any other questions, please email me at `martin.kosiik@gmail.com`.

International Relations Controls

The summary of major changes in international relations of the Soviet Union with states that have significant minorities in the USSR that we use as control variable in our default difference-in-differences specification (equation 5.1) are provided in table A1. In particular, we created a separate dummy variable for every combination of state and phase of geopolitical relations. The blank cells indicate that no special dummy variable covers that years (i.e. there was no significant change in relations with the given country in that year). For example in case of Hungarian ethnicity, we created one dummy variable for the period of war with the USSR (from 1941 to 1944) and another one covering the whole post-1945 period. We briefly describe the relevant history below to explain why we choose such classification. For more detailed information, consult Weinberg (2005) or other general overview of World War II.

In case of Japan, the Soviet Union and Japan engaged in minor border clashes near Mongolia from 1935. However, these skirmishes escalated into large scale conflict in 1938 with Battle of Lake Khasan. The war ended in 1939 with a decisive Soviet victory at Battles of Khalkhin Gol. This defeat deterred Japan from further conflict with the Soviet Union (Haslam, 1992). The two countries remained in peace until August 1945 when the USSR invaded Manchuria.

The Soviet Union invaded Finland in November 1939. This conflict ended (which became know as the Winter War) in March 1940. This peace did not last long since Finland joined the German invasion into the USSR in June

1941. Hungary was another country that allied with Germany in war against the Soviet Union.

Poland was attacked by both Germany and Soviet Union in September 1939. By the end of the month the Polish army was defeated and the Polish territory was partition between Germany and Soviet Union along the line that was agreed in the Molotov-Ribbentrop pact. This changed with German invasion in 1941 when the German army gained the control of the whole Poland. Poland stayed under German occupation for 4 years and most of its territory was liberated by the Red Army by January 1945.

Some cases are difficult to classify. For instance, China was in embroiled in a civil war from 1927 to 1949. Although the Soviet Union sometimes supported certain Chinese warlords, it is hard to identify some major changes in the relations with the Soviet Union and hence China does not appear on this list. Greece was occupied by Italy and Germany from 1941 to 1944 but the Soviet Union was not directly involved in Greece and thus Greece also do not feature on the list.

Nonetheless, this table provides only very coarse classification of changes in geopolitical relations and that is why we perform additional checks such as excluding all ethnic groups with independent states from analysis.

Table A1: Major Changes in Relations with the USSR

	State				
Year	Baltic states	Finland	Japan	Hungary	Poland
1921					
1922					
1923					
1924					
1925					
1926					
1927					
1928					
1929					
1930					
1931					
1932					
1933					
1934					
1935					
1936					
1937			War		
1938			War		
1939		War	Neutrality		War
1940	Annexation	War	Neutrality		Soviet occupation
1941	Nazi occupation	War	Neutrality	War	Nazi occupation
1942	Nazi occupation	War	Neutrality	War	Nazi occupation
1943	Nazi occupation	War	Neutrality	War	Nazi occupation
1944	Post-war	War	Neutrality	War	Nazi occupation
1945	Post-war	Post-war	War	Post-war	Post-war
1946	Post-war	Post-war	Post-war	Post-war	Post-war
1947	Post-war	Post-war	Post-war	Post-war	Post-war
1948	Post-war	Post-war	Post-war	Post-war	Post-war
1949	Post-war	Post-war	Post-war	Post-war	Post-war
1950	Post-war	Post-war	Post-war	Post-war	Post-war
1951	Post-war	Post-war	Post-war	Post-war	Post-war
1952	Post-war	Post-war	Post-war	Post-war	Post-war
1953	Post-war	Post-war	Post-war	Post-war	Post-war
1954	Post-war	Post-war	Post-war	Post-war	Post-war
1955	Post-war	Post-war	Post-war	Post-war	Post-war
1956	Post-war	Post-war	Post-war	Post-war	Post-war
1957	Post-war	Post-war	Post-war	Post-war	Post-war
1958	Post-war	Post-war	Post-war	Post-war	Post-war
1959	Post-war	Post-war	Post-war	Post-war	Post-war
1960	Post-war	Post-war	Post-war	Post-war	Post-war

Additional Tables

Table A2: Total arrest by ethnicity and imputation adjustment, 1921-1960

	Arrests			
Ethnicity	Only Labeled	Labeled + Unadj. Imput.	Labeled + Parsimon. Adj.	Labeled + Full-matrix Adj.
Russian	550 349	1 064 741	1 041 329	1 041 325
Belorussian	67 615	85 525	70 394	72 390
Polish	61 221	85 257	73 056	79 973
German	60 798	168 422	164 827	171 712
Ukrainian	54 398	91 812	94 256	96 626
Kazakh	37 125	46 541	46 340	42 775
Tatar	32 098	72 422	72 933	70 825
Jewish	31 047	43 704	42 313	42 788
Latvian	15 442	21 626	19 398	18 624
Chinese	9 693	11 507	10 642	10 490
Estonian	9 402	15 562	13 865	13 676
Chuvash	8 910	14 894	29 582	23 177
Bashkir	8 428	17 879	21 780	19 366
Finnish	8 347	14 609	13 151	13 393
Mordvin	6 011	12 646	29 026	27 908
Buryat	5 679	6 735	6 651	6 711
Mari	5 385	7 485	12 989	12 666
Lithuanian	4 651	5 474	5 259	5 626
Karelian	4 174	9 900	13 078	11 872
Korean	4 060	8 821	11 477	11 841
Komi	3 616	5 832	6 704	5 825
Ossetian	3 236	3 722	3 446	3 445
Udmurt	3 090	4 469	11 694	10 178
Armenian	2 937	4 851	4 732	4 732
Kabardian	2 733	4 437	3 833	3 946
Greek	2 246	24 504	26 316	26 914
Khakas	2 221	8 136	7 094	7 139
Altai	1 894	2 475	2 588	2 632
Yakut	1 706	3 323	3 486	3 359
Georgian	1 621	3 048	2 651	2 451
Moldovan	1 391	2 780	4 162	4 077
Kalmyk	1 294	2 169	2 072	2 015
Japanese	1 231	14 574	10 927	10 922
Uzbek	1 061	4 044	8 301	8 798
Hungarian	1 018	1 611	1 645	1 556
Bulgarian	1 015	2 477	3 721	3 408
Balkar	861	4 741	3 837	3 270
Chechen	696	8 511	11 716	12 839

Table A3: Naive Bayes Performance Measures by Ethnicity

Ethnicity	Sensitivity	Specificity
Altai	0.475	1.000
Armenian	0.799	1.000
Balkar	0.972	0.999
Bashkir	0.476	0.997
Belorussian	0.503	0.975
Bulgarian	0.365	1.000
Buryat	0.772	1.000
Estonian	0.695	0.996
Finnish	0.789	0.998
Georgian	0.560	0.999
German	0.878	0.988
Greek	0.695	0.995
Hungarian	0.316	0.999
Chechen	0.554	0.999
Chinese	0.922	0.997
Chuvash	0.102	0.995
Japanese	0.967	0.996
Jewish	0.867	0.997
Kabardian	0.881	0.999
Kalmyk	0.846	1.000
Karelian	0.155	0.995
Kazakh	0.833	0.999
Khakas	0.827	0.998
Komi	0.233	0.998
Korean	0.491	0.999
Latvian	0.673	0.995
Lithuanian	0.560	0.999
Mari	0.194	0.999
Moldovan	0.271	0.999
Mordvin	0.162	0.997
Ossetian	0.835	1.000
Polish	0.790	0.980
Russian	0.886	0.869
Tatar	0.817	0.995
Udmurt	0.075	0.999
Ukrainian	0.427	0.976
Uzbek	0.310	0.999
Yakut	0.184	0.998

Table A4: Descriptive Statistics of Arrests from 1921 to 1960 by Ethnicity, Part 1

	Only labeled data					Labels + Ethnicity imputations (no adj.)				
Ethnicity	Mean	St.dev.	Min	Max	Total	Mean	St.dev.	Min	Max	Total
Altai	42	144	0	901	1 663	44	147	0	924	1 742
Armenian	55	112	0	524	2 210	63	127	0	614	2 516
Balkar	21	63	0	370	841	24	68	0	401	970
Bashkir	199	480	0	2 071	7 964	215	513	0	2 282	8 585
Belorussian	1 558	3 291	4	18 768	62 316	1 690	3 577	4	20 458	67 584
Bulgarian	17	47	0	224	680	20	53	0	245	793
Buryat	141	428	0	2 192	5 629	145	435	0	2 217	5 792
Estonian	200	675	1	3 435	7 998	247	798	1	4 066	9 874
Finnish	162	654	0	3 237	6 493	183	699	0	3 415	7 328
Georgian	30	69	0	320	1 220	38	81	0	369	1 513
German	693	1 662	0	8 658	27 713	872	2 048	1	10 227	34 878
Greek	36	131	0	612	1 453	71	187	0	957	2 844
Hungarian	24	93	0	562	956	29	103	0	618	1 149
Chechen	16	29	0	110	624	33	53	0	249	1 303
Chinese	229	1 085	0	6 882	9 179	250	1 185	0	7 518	9 990
Chuvash	209	430	0	2 455	8 364	242	500	0	2 877	9 666
Japanese	30	95	0	547	1 216	91	183	0	891	3 654
Jewish	526	1 299	1	7 267	21 043	603	1 448	2	8 199	24 119
Kabardian	66	186	0	1 061	2 630	68	189	0	1 083	2 707
Kalmyk	6	13	0	58	245	8	14	0	58	300
Karelian	98	411	0	2 352	3 938	147	513	0	2 963	5 865
Kazakh	885	1 953	0	9 740	35 401	988	2 164	0	10 742	39 534
Khakas	32	98	0	487	1 264	48	131	0	662	1 920
Komi	85	189	0	1 137	3 395	101	226	0	1 358	4 050
Korean	93	362	0	2 203	3 712	100	379	0	2 300	4 001
Latvian	353	1 273	0	6 753	14 126	406	1 424	0	7 557	16 237
Lithuanian	101	255	0	1 365	4 028	105	263	0	1 392	4 211
Mari	60	120	0	549	2 391	63	126	0	586	2 521
Moldovan	29	49	0	211	1 162	33	56	0	259	1 328
Mordvin	130	258	0	1 377	5 197	156	313	0	1 711	6 248
Ossetian	21	34	0	158	830	23	36	0	161	907
Polish	1 077	2 722	0	14 023	43 088	1 190	2 983	0	15 460	47 598
Russian	11 786	27 149	46	157 725	471 450	14 807	33 665	54	196 301	592 263
Tatar	688	1 406	0	6 275	27 539	764	1 562	0	7 098	30 560
Udmurt	72	135	0	781	2 864	77	146	0	849	3 071
Ukrainian	1 160	2 668	10	14 694	46 384	1 329	3 025	12	16 819	53 175
Uzbek	26	58	0	268	1 059	69	157	0	746	2 752
Yakut	39	68	0	348	1 571	52	86	0	426	2 084

Table A5: Descriptive Statistics of Arrests from 1921 to 1960 by Ethnicity, Part 2

	Labels + Arrest date imputations					Labels + Arrest date + Ethnicity imput. (no adj.)				
Ethnicity	Mean	St.dev.	Min	Max	Total	Mean	St.dev.	Min	Max	Total
Altai	47	146	0	903	1 894	62	161	0	955	2 475
Armenian	73	140	0	665	2 937	121	184	0	863	4 851
Balkar	22	64	0	375	861	119	226	0	1 058	4 741
Bashkir	211	508	0	2 100	8 428	447	1 133	0	5 548	17 879
Belorussian	1 690	3 459	5	19 637	67 615	2 138	4 076	8	22 668	85 525
Bulgarian	25	54	0	245	1 015	62	96	0	347	2 477
Buryat	142	431	0	2 201	5 679	168	451	0	2 244	6 735
Estonian	235	756	1	3 872	9 402	389	949	1	4 832	15 562
Finnish	209	718	0	3 534	8 347	365	852	0	3 991	14 609
Georgian	41	86	0	383	1 621	76	128	0	577	3 048
German	1 520	3 568	2	20 096	60 798	4 211	10 367	2	63 686	168 422
Greek	56	148	0	687	2 246	613	1 134	0	4 727	24 504
Hungarian	25	97	0	584	1 018	40	115	0	670	1 611
Chechen	17	32	0	143	696	213	434	0	2 225	8 511
Chinese	242	1 121	0	7 111	9 693	288	1 247	0	7 879	11 507
Chuvash	223	449	0	2 500	8 910	372	736	0	3 328	14 894
Japanese	31	95	0	550	1 231	364	773	0	4 199	14 574
Jewish	776	1 761	1	8 475	31 047	1 093	2 333	3	10 318	43 704
Kabardian	68	194	0	1 113	2 733	111	232	0	1 197	4 437
Kalmyk	32	105	0	620	1 294	54	147	0	837	2 169
Karelian	104	433	0	2 471	4 174	248	636	0	3 579	9 900
Kazakh	928	2 035	0	10 065	37 125	1 164	2 370	0	11 537	46 541
Khakas	56	138	0	552	2 221	203	494	0	2 296	8 136
Komi	90	195	0	1 169	3 616	146	283	0	1 534	5 832
Korean	102	384	0	2 270	4 060	221	496	0	2 406	8 821
Latvian	386	1 358	0	7 181	15 442	541	1 594	5	8 463	21 626
Lithuanian	116	279	0	1 518	4 651	137	303	1	1 655	5 474
Mari	135	280	0	1 451	5 385	187	370	0	1 535	7 485
Moldovan	35	55	0	225	1 391	70	102	0	409	2 780
Mordvin	150	291	0	1 550	6 011	316	635	0	2 510	12 646
Ossetian	81	192	0	1 160	3 236	93	210	0	1 245	3 722
Polish	1 531	3 315	0	15 503	61 221	2 131	4 178	0	18 510	85 257
Russian	13 759	30 374	53	173 860	550 349	26 619	52 769	63	237 714	1 064 741
Tatar	802	1 631	0	6 741	32 098	1 811	4 264	1	20 929	72 422
Udmurt	77	142	0	814	3 090	112	193	0	948	4 469
Ukrainian	1 360	2 997	17	16 484	54 398	2 295	4 324	24	21 486	91 812
Uzbek	27	58	0	268	1 061	101	196	0	912	4 044
Yakut	43	71	0	351	1 706	83	127	0	479	3 323

Table A6: Arrest Date Imputation - Model Results

	Dependent variable:	
	I^y	$log(y^{\text{pos}})$
	logistic	*OLS*
	(1)	(2)
(Intercept)	-0.771^{***} (0.161)	0.888^{***} (0.025)
Year of Trial - 1922	1.630^{***} (0.586)	1.038^{***} (0.033)
Year of Trial - 1923	0.955^{*} (0.510)	0.976^{***} (0.039)
Year of Trial - 1924	2.128^{**} (1.004)	1.122^{***} (0.043)
Year of Trial - 1925	1.019^{*} (0.586)	1.112^{***} (0.043)
Year of Trial - 1926	0.508^{*} (0.284)	0.972^{***} (0.027)
Year of Trial - 1927	0.346 (0.234)	0.904^{***} (0.024)
Year of Trial - 1928	-0.260^{**} (0.123)	0.422^{***} (0.016)
Year of Trial - 1929	-0.209^{**} (0.101)	0.307^{***} (0.012)
Year of Trial - 1930	0.012 (0.103)	0.754^{***} (0.012)
Year of Trial - 1931	0.166 (0.111)	0.695^{***} (0.013)
Year of Trial - 1932	0.299^{***} (0.106)	0.463^{***} (0.012)
Year of Trial - 1933	0.193 (0.139)	0.457^{***} (0.016)
Year of Trial - 1934	-0.198^{*} (0.116)	0.602^{***} (0.014)
Year of Trial - 1935	-0.206^{*} (0.112)	0.874^{***} (0.014)
Year of Trial - 1936	0.858^{***} (0.099)	-0.298^{***} (0.011)
Year of Trial - 1937	1.116^{***} (0.101)	0.486^{***} (0.012)
Year of Trial - 1938	1.845^{***} (0.151)	2.010^{***} (0.013)
Year of Trial - 1939	1.560^{***} (0.162)	1.579^{***} (0.013)
Year of Trial - 1940	0.463^{***} (0.113)	0.705^{***} (0.013)
Year of Trial - 1941	0.282^{***} (0.109)	0.641^{***} (0.013)
Year of Trial - 1942	0.234^{**} (0.114)	0.833^{***} (0.013)
Year of Trial - 1943	-0.422^{***} (0.118)	0.804^{***} (0.015)
Year of Trial - 1944	0.175 (0.127)	0.936^{***} (0.015)
Year of Trial - 1945	0.264^{*} (0.142)	1.182^{***} (0.016)
Year of Trial - 1946	0.164 (0.161)	0.987^{***} (0.018)
Year of Trial - 1947	0.231 (0.179)	0.860^{***} (0.020)
Year of Trial - 1948	0.810^{***} (0.192)	0.735^{***} (0.017)
Year of Trial - 1949	0.512^{***} (0.186)	0.953^{***} (0.019)
Year of Trial - 1950	0.532^{***} (0.188)	0.908^{***} (0.019)
Year of Trial - 1951	-0.080 (0.197)	0.844^{***} (0.024)
Year of Trial - 1952	0.077 (0.269)	0.619^{***} (0.031)
Year of Trial - 1953	0.003 (0.589)	1.680^{***} (0.070)
Year of Trial - 1954	-0.526 (0.462)	2.253^{***} (0.071)
Year of Trial - 1955	-0.713^{*} (0.425)	1.324^{***} (0.071)
Year of Trial - 1956	0.950^{***} (0.367)	0.683^{***} (0.029)
Year of Trial - 1957	0.595 (0.367)	0.813^{***} (0.034)
Year of Trial - 1958	-0.232 (0.333)	1.036^{***} (0.044)
Year of Trial - 1959	-0.716 (0.516)	1.042^{***} (0.087)
Year of Trial - 1960	4.292^{***} (0.094)	3.697^{***} (0.011)
Observations	812,592	805,800
R^2		0.235
Adjusted R^2		0.235
Log Likelihood	$-38{,}300.970$	
Akaike Inf. Crit.	76,681.930	
Note:		*p<0.1; **p<0.05; ***p<0.01

Table A7: Difference-in-differences results

	Model		
	(1)	(2)	(3)
β_{1922}	0.257 (0.158)	0.273 (0.184)	−0.111 (0.177)
β_{1923}	0.409** (0.188)	0.560*** (0.216)	0.284 (0.178)
β_{1924}	−0.116 (0.213)	0.046 (0.268)	−0.862*** (0.191)
β_{1925}	−0.302 (0.224)	−0.230 (0.286)	−1.624*** (0.221)
β_{1926}	0.453* (0.235)	0.523* (0.316)	−1.589*** (0.201)
β_{1927}	0.272 (0.185)	0.321 (0.239)	−0.459** (0.199)
β_{1928}	0.202 (0.260)	0.152 (0.338)	−0.809*** (0.260)
β_{1929}	0.780*** (0.270)	0.675** (0.321)	0.481* (0.282)
β_{1930}	0.850*** (0.305)	0.650* (0.358)	0.571* (0.328)
β_{1931}	0.936*** (0.316)	0.695* (0.362)	0.706** (0.338)
β_{1932}	−0.184 (0.224)	−0.329 (0.279)	−0.339 (0.222)
β_{1933}	0.434* (0.241)	0.292 (0.291)	−0.114 (0.227)
β_{1934}	0.919*** (0.274)	0.871** (0.346)	1.272*** (0.304)
β_{1935}	0.916*** (0.231)	0.959*** (0.294)	0.961*** (0.239)
β_{1936}	0.265 (0.207)	0.274 (0.265)	0.526** (0.232)
β_{1937}	0.165 (0.167)	0.202 (0.212)	0.393* (0.204)
β_{1938}	0.799*** (0.210)	1.130*** (0.232)	1.162*** (0.229)
β_{1939}	1.778*** (0.238)	1.985*** (0.276)	2.022*** (0.218)
β_{1940}	3.540*** (0.231)	3.571*** (0.249)	3.620*** (0.210)
β_{1941}	4.007*** (0.211)	4.006*** (0.201)	4.066*** (0.191)
β_{1942}	2.041*** (0.245)	2.129*** (0.253)	2.085*** (0.238)
β_{1943}	1.380*** (0.337)	1.235*** (0.378)	0.893** (0.359)
β_{1944}	1.346*** (0.361)	1.239*** (0.403)	1.418*** (0.341)
β_{1945}	2.912*** (0.250)	2.940*** (0.275)	2.432*** (0.265)
β_{1946}	2.582*** (0.252)	2.556*** (0.280)	2.445*** (0.288)
β_{1947}	2.419*** (0.256)	2.382*** (0.278)	2.556*** (0.242)
β_{1948}	2.127*** (0.264)	2.251*** (0.278)	2.247*** (0.237)
β_{1949}	1.681*** (0.290)	1.803*** (0.298)	2.025*** (0.260)
β_{1950}	1.973*** (0.262)	2.049*** (0.289)	2.065*** (0.270)
β_{1951}	2.426*** (0.260)	2.447*** (0.306)	2.642*** (0.243)
β_{1952}	2.806*** (0.259)	2.774*** (0.311)	2.706*** (0.248)
β_{1953}	2.699*** (0.238)	2.596*** (0.262)	2.765*** (0.248)
β_{1954}	2.991*** (0.285)	2.940*** (0.342)	2.941*** (0.263)
β_{1955}	1.540*** (0.278)	1.595*** (0.331)	1.496*** (0.279)
β_{1956}	0.116 (0.259)	0.129 (0.321)	0.294 (0.254)
β_{1957}	0.106 (0.257)	0.136 (0.309)	0.142 (0.228)
β_{1958}	0.071 (0.228)	0.059 (0.273)	0.138 (0.215)
β_{1959}	−0.199 (0.246)	−0.177 (0.287)	−0.550** (0.249)
β_{1960}	−0.948*** (0.250)	−1.053*** (0.291)	−1.665*** (0.252)
Eth. with ind. state excluded	No	Yes	No
Only rehabilitated ind.	No	No	Yes
Geopol. relations controls	Yes	No	Yes
Ethnicity-spec. time trends	No	No	No
Observations	1,520	1,120	1,520
Adjusted R^2	0.850	0.845	0.836

Notes: Cluster-robust standard errors are in the parentheses. The coefficients from model (1) are plotted in the figure 2, from model (2) in the figure A6, and from model (3) in the figure A7. For additional information, refer to the notes of the respective figures. *p<0.1; **p<0.05; ***p<0.01

Table A8: Difference-in-differences results - Ethnicity-specific time trends

	Model		
	(1)	(2)	(3)
β_{1922}	0.257 (0.158)	0.287* (0.158)	0.287* (0.158)
β_{1923}	0.409** (0.188)	0.470** (0.185)	0.470** (0.185)
β_{1924}	−0.116 (0.213)	−0.025 (0.214)	−0.025 (0.214)
β_{1925}	−0.302 (0.224)	−0.180 (0.228)	−0.180 (0.228)
β_{1926}	0.453* (0.235)	0.606** (0.239)	0.606** (0.239)
β_{1927}	0.272 (0.185)	0.455** (0.191)	0.455** (0.191)
β_{1928}	0.202 (0.260)	0.415 (0.271)	0.415 (0.271)
β_{1929}	0.780*** (0.270)	1.024*** (0.294)	1.024*** (0.294)
β_{1930}	0.850*** (0.305)	1.124*** (0.320)	1.124*** (0.320)
β_{1931}	0.936*** (0.316)	1.240*** (0.334)	1.240*** (0.334)
β_{1932}	−0.184 (0.224)	0.151 (0.254)	0.151 (0.254)
β_{1933}	0.434* (0.241)	0.799*** (0.257)	0.799*** (0.257)
β_{1934}	0.919*** (0.274)	1.315*** (0.289)	1.315*** (0.289)
β_{1935}	0.916*** (0.231)	1.342*** (0.246)	1.342*** (0.246)
β_{1936}	0.265 (0.207)	0.722*** (0.220)	0.722*** (0.220)
β_{1937}	0.165 (0.167)	0.652*** (0.196)	0.652*** (0.196)
β_{1938}	0.799*** (0.210)	1.315*** (0.225)	1.315*** (0.225)
β_{1939}	1.778*** (0.238)	2.343*** (0.249)	2.343*** (0.249)
β_{1940}	3.540*** (0.231)	4.102*** (0.227)	4.102*** (0.227)
β_{1941}	4.007*** (0.211)	4.591*** (0.185)	4.591*** (0.185)
β_{1942}	2.041*** (0.245)	2.654*** (0.221)	2.654*** (0.221)
β_{1943}	1.380*** (0.337)	2.024*** (0.302)	2.024*** (0.302)
β_{1944}	1.346*** (0.361)	1.986*** (0.317)	1.986*** (0.317)
β_{1945}	2.912*** (0.250)	3.596*** (0.190)	3.596*** (0.190)
β_{1946}	2.582*** (0.252)	3.295*** (0.210)	3.295*** (0.210)
β_{1947}	2.419*** (0.256)	3.162*** (0.204)	3.162*** (0.204)
β_{1948}	2.127*** (0.264)	2.901*** (0.209)	2.901*** (0.209)
β_{1949}	1.681*** (0.290)	2.486*** (0.237)	2.486*** (0.237)
β_{1950}	1.973*** (0.262)	2.808*** (0.214)	2.808*** (0.214)
β_{1951}	2.426*** (0.260)	3.291*** (0.184)	3.291*** (0.184)
β_{1952}	2.806*** (0.259)	3.702*** (0.198)	3.702*** (0.198)
β_{1953}	2.699*** (0.238)	3.625*** (0.175)	3.625*** (0.175)
β_{1954}	2.991*** (0.285)	3.948*** (0.219)	3.948*** (0.219)
β_{1955}	1.540*** (0.278)	2.527*** (0.224)	2.527*** (0.224)
β_{1956}	0.116 (0.259)	1.134*** (0.212)	1.134*** (0.212)
β_{1957}	0.106 (0.257)	1.154*** (0.191)	1.154*** (0.191)
β_{1958}	0.071 (0.228)	1.149*** (0.165)	1.149*** (0.165)
β_{1959}	−0.199 (0.246)	0.910*** (0.186)	0.910*** (0.186)
β_{1960}	−0.948*** (0.250)	0.191 (0.214)	0.191 (0.214)
Ethnicity-spec. time trends	None	Linear	Quadratic
Eth. with ind. state excluded	No	Yes	No
Geopol. relations controls	Yes	Yes	Yes
Observations	1,520	1,520	1,520
Adjusted R^2	0.850	0.871	0.871

Notes: Cluster-robust standard errors are in the parentheses. The coefficients from these models are plotted in the figure A10. For additional information, refer to the notes of the figures A10. *p<0.1; **p<0.05; ***p<0.01

Table A9: Difference-in-differences results - Ethnicity Imputation Adjustments

	Model		
	(1)	(2)	(3)
β_{1922}	0.257 (0.158)	0.263* (0.151)	0.227** (0.110)
β_{1923}	0.409** (0.188)	0.477** (0.207)	0.338** (0.141)
β_{1924}	−0.116 (0.213)	−0.035 (0.212)	−0.038 (0.135)
β_{1925}	−0.302 (0.224)	−0.293 (0.222)	−0.140 (0.178)
β_{1926}	0.453* (0.235)	0.486** (0.231)	0.211 (0.150)
β_{1927}	0.272 (0.185)	0.278 (0.182)	0.143 (0.135)
β_{1928}	0.202 (0.260)	0.107 (0.252)	0.023 (0.163)
β_{1929}	0.780*** (0.270)	0.644*** (0.249)	0.410** (0.170)
β_{1930}	0.850*** (0.305)	0.699** (0.278)	0.476** (0.200)
β_{1931}	0.936*** (0.316)	0.850*** (0.313)	0.557*** (0.210)
β_{1932}	−0.184 (0.224)	−0.376* (0.222)	−0.317* (0.169)
β_{1933}	0.434* (0.241)	0.281 (0.206)	0.186 (0.165)
β_{1934}	0.919*** (0.274)	0.871*** (0.291)	0.627*** (0.203)
β_{1935}	0.916*** (0.231)	0.820*** (0.201)	0.602*** (0.147)
β_{1936}	0.265 (0.207)	0.173 (0.234)	0.050 (0.183)
β_{1937}	0.165 (0.167)	0.096 (0.174)	0.011 (0.148)
β_{1938}	0.799*** (0.210)	0.757*** (0.227)	0.626*** (0.178)
β_{1939}	1.778*** (0.238)	1.944*** (0.245)	1.385*** (0.168)
β_{1940}	3.540*** (0.231)	3.774*** (0.255)	3.059*** (0.175)
β_{1941}	4.007*** (0.211)	4.194*** (0.215)	3.463*** (0.153)
β_{1942}	2.041*** (0.245)	1.986*** (0.243)	1.702*** (0.190)
β_{1943}	1.380*** (0.337)	1.457*** (0.401)	1.031*** (0.296)
β_{1944}	1.346*** (0.361)	1.260*** (0.387)	1.002*** (0.298)
β_{1945}	2.912*** (0.250)	2.987*** (0.259)	2.544*** (0.204)
β_{1946}	2.582*** (0.252)	2.575*** (0.253)	2.263*** (0.214)
β_{1947}	2.419*** (0.256)	2.389*** (0.252)	2.066*** (0.215)
β_{1948}	2.127*** (0.264)	2.039*** (0.265)	1.749*** (0.211)
β_{1949}	1.681*** (0.290)	1.523*** (0.281)	1.311*** (0.227)
β_{1950}	1.973*** (0.262)	1.944*** (0.249)	1.695*** (0.199)
β_{1951}	2.426*** (0.260)	2.345*** (0.251)	2.020*** (0.220)
β_{1952}	2.806*** (0.259)	2.831*** (0.267)	2.365*** (0.210)
β_{1953}	2.699*** (0.238)	2.697*** (0.235)	2.296*** (0.201)
β_{1954}	2.991*** (0.285)	3.042*** (0.297)	2.657*** (0.250)
β_{1955}	1.540*** (0.278)	1.551*** (0.283)	1.233*** (0.236)
β_{1956}	0.116 (0.259)	0.106 (0.263)	−0.180 (0.220)
β_{1957}	0.106 (0.257)	0.120 (0.256)	−0.168 (0.224)
β_{1958}	0.071 (0.228)	0.092 (0.231)	−0.191 (0.219)
β_{1959}	−0.199 (0.246)	−0.172 (0.251)	−0.452** (0.220)
β_{1960}	−0.948*** (0.250)	−0.918*** (0.259)	−1.246*** (0.230)
Ethnicity imputation adjust.	Full-matrix	Parsimonoius	None
Ethnicity-spec. time trends	None	None	None
Eth. with ind. state excluded	No	No	No
Geopol. relations controls	Yes	Yes	Yes
Observations	1,520	1,520	1,520
Adjusted R^2	0.850	0.845	0.900

Notes: Cluster-robust standard errors are in the parentheses. The coefficients from these models are plotted in the figure A11. For additional information, refer to the notes of the figures A11.
*p<0.1; **p<0.05; ***p<0.01

Table A10: Pre-treatment characteristics of ethnic groups in the USSR

Ethnic group	Total population	Ling. similarity to Russian	Urbanization rate	Ind. state
Altai	39 062	0	0.30	0
Armenian	1 567 568	1	35.45	0
Balkar	33 307	0	1.23	0
Bashkir	713 693	0	2.12	0
Belorussian	4 738 923	4	10.32	0
Bulgarian	111 296	3	6.26	0
Buryat	237 501	0	1.05	0
Estonian	154 666	0	23.00	1
Finnish	134 701	0	10.55	1
Georgian	1 821 184	0	16.93	0
German	1 238 549	1	14.92	1
Greek	213 765	1	21.21	1
Hungarian	5 476	0	63.33	1
Chechen	318 522	0	0.98	0
Chinese	10 247	0	64.87	1
Chuvash	1 117 419	0	1.60	0
Japanese	93	0	76.34	1
Jewish	2 599 973	1	82.43	0
Kabardian	139 925	0	1.27	0
Kalmyk	129 321	0	1.29	0
Karelian	248 120	0	2.91	0
Kazakh	3 968 289	0	2.18	0
Khakas	45 608	0	1.08	0
Komi	375 871	0	2.56	0
Korean	86 999	0	10.52	0
Latvian	141 703	2	42.31	1
Lithuanian	41 463	2	63.16	1
Mari	428 192	0	0.84	0
Moldovan	278 905	1	4.86	0
Mordvin	1 340 415	0	2.19	0
Ossetian	272 272	1	7.86	0
Polish	782 334	3	32.75	1
Russian	77 791 124	5	21.32	1
Tatar	2 916 536	0	15.48	0
Udmurt	504 187	0	1.21	0
Ukrainian	31 194 976	4	10.54	0
Uzbek	3 904 622	0	18.66	0
Yakut	240 709	0	2.20	0

Note:
Total population and urbanization rate of the ethnic group in the USSR is taken from 1926 census. The linguistic similarity to Russian is measured by the number of common nodes in the language tree (cladistic similarity). Independent state equals one if the ethnic group was a core group in an independent country that existed in the interwar period.

Table A11: Synthetic German minority weights, Only ethnicities without ind. state

Ethnic group	W-Weight
Tatar	0.53
Jewish	0.19
Korean	0.13
Ukrainian	0.11
Khakas	0.03
Chuvash	0.01

Table A12: Synthetic German minority weights, Only rehabilitated individuals

Ethnic group	W-Weight
Polish	0.32
Tatar	0.32
Korean	0.27
Mari	0.05
Greek	0.03

Additional Figures

Figure A1: Number of Predicted Arrests by Ethnicity, Year, and Prediction Adjustment

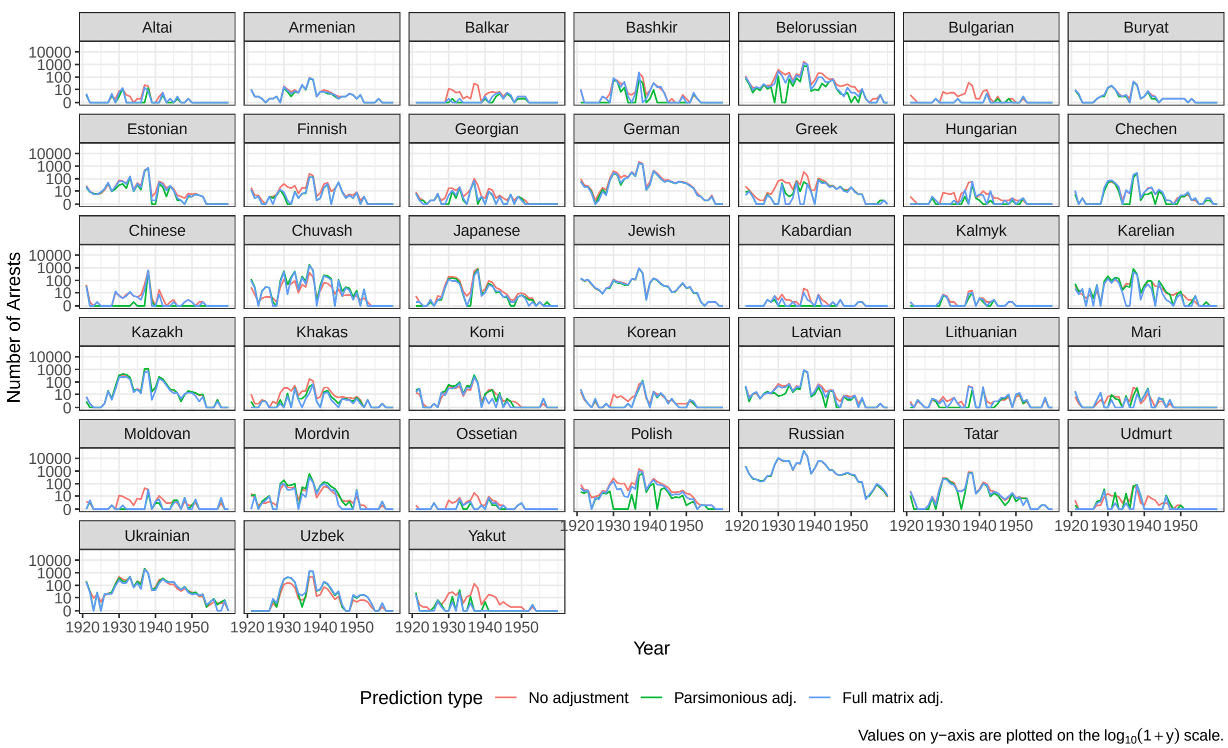


Figure A2: Histograms of Arrests by Ethnicity and Year

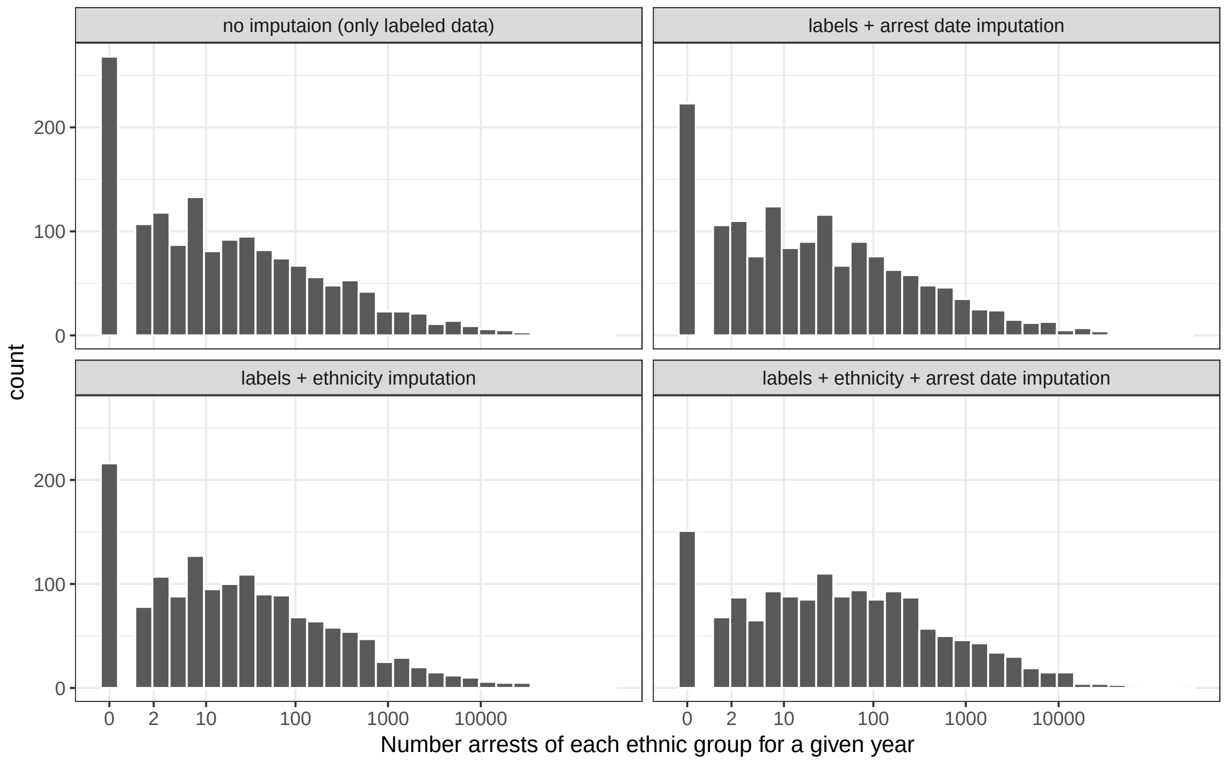


Figure A3: Histogram of Imputed Number of Days between Arrest and Process

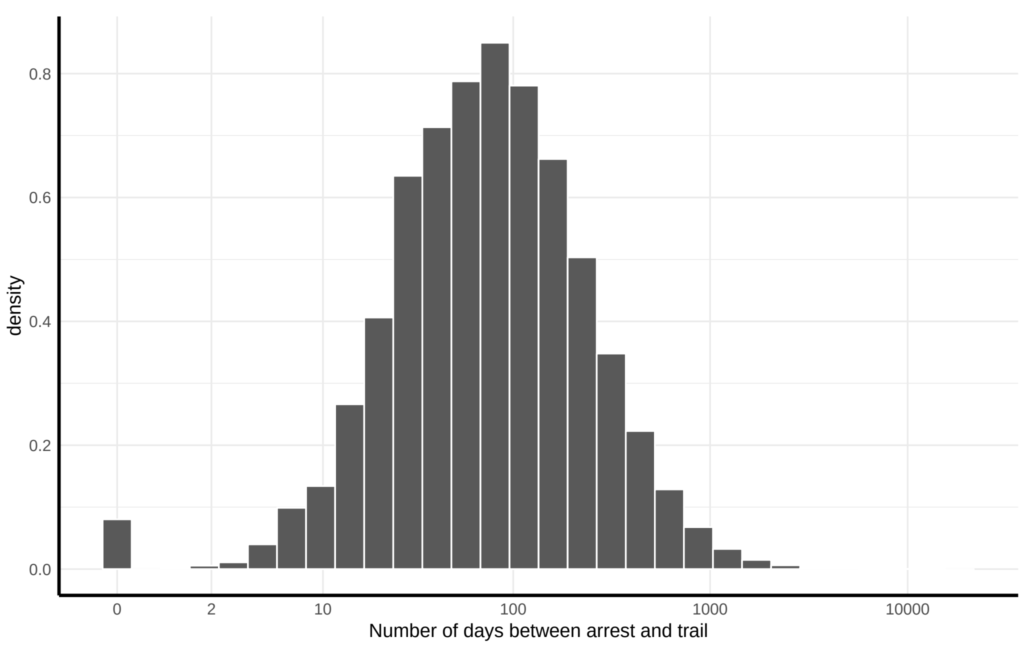
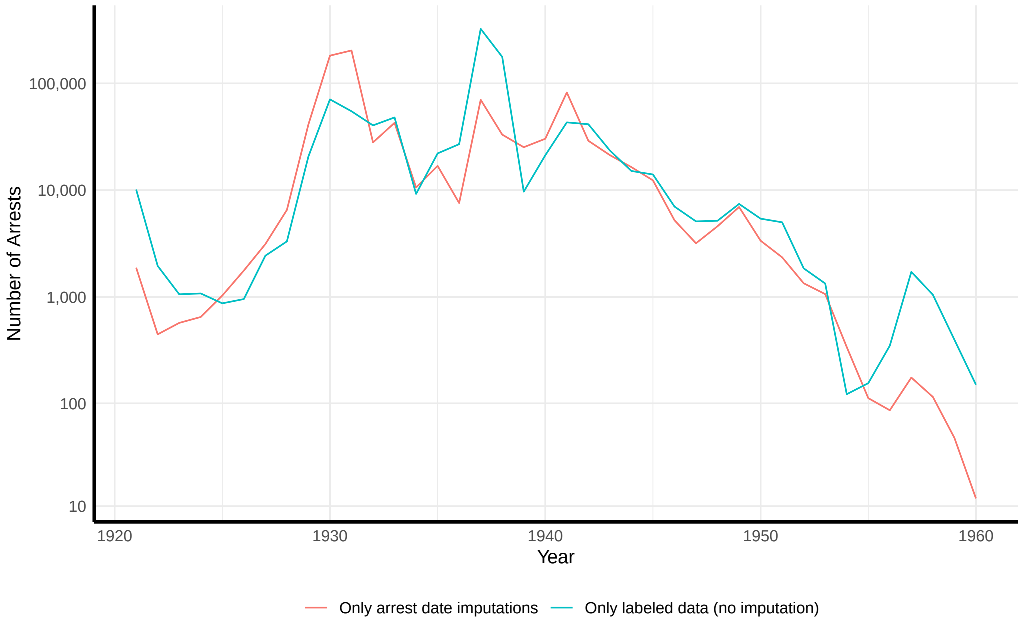


Figure A4: Time Series of Arrests

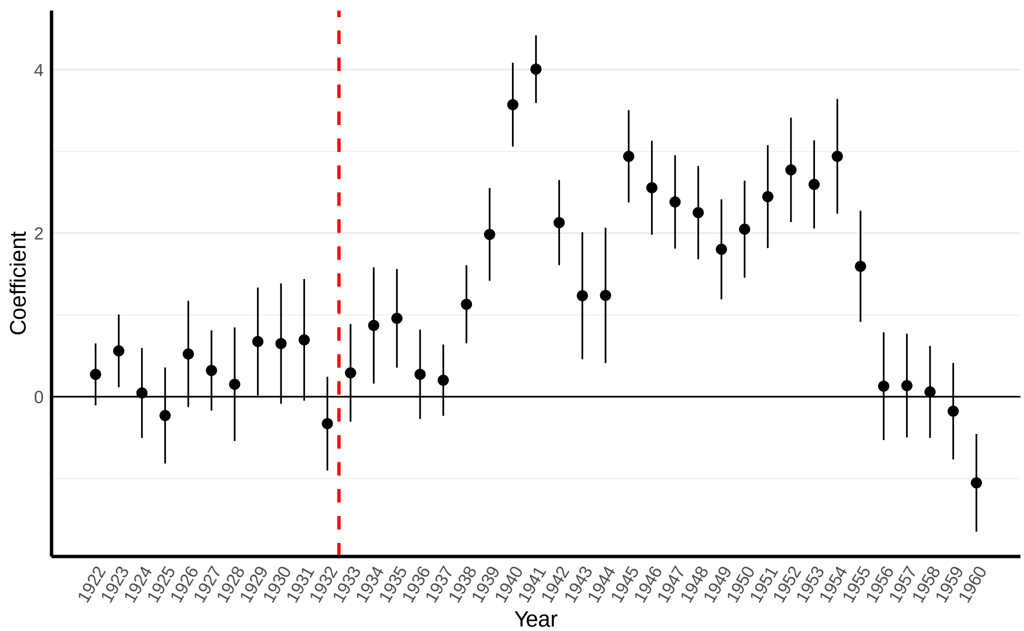


Note: Values on the y-axis are plotted on the $\log_{10}(1+y)$ scale.

Figure A5: Map of the Soviet Union in 1926

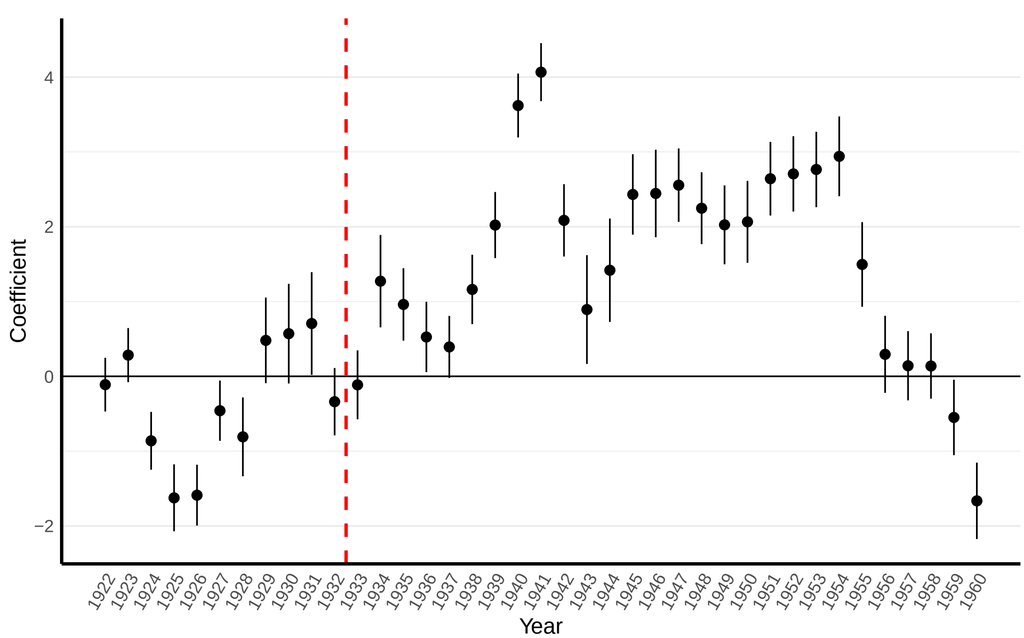
Notes: The shaded area shows the 250 km border buffer. The regions within are governorates (*guberniye*) and Autonomous Soviet Socialist Republics. The source of the map is Sablin et al. (2018).

Figure A6: Dynamic DiD, Only Ethnicities without Independent State



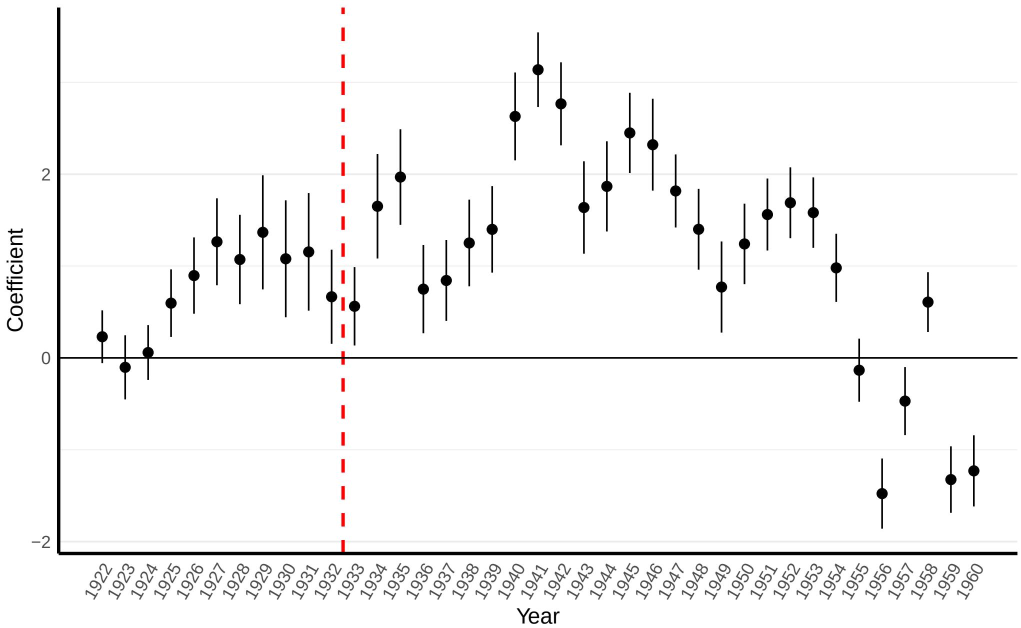
Notes: Only ethnic groups without independent state are included in the control group. Ethnicity and date of arrest were imputed. Full matrix adjustment was applied on ethnic group imputations. The quadratic ethnicity-specific time trends are included. Standard errors are clustered on the level of ethnicity and are based on cluster robust estimator by Pustejovsky and Tipton (2018). Error bars show 95% confidence intervals.

Figure A7: Dynamic DiD, Only Rehabilitated Individuals



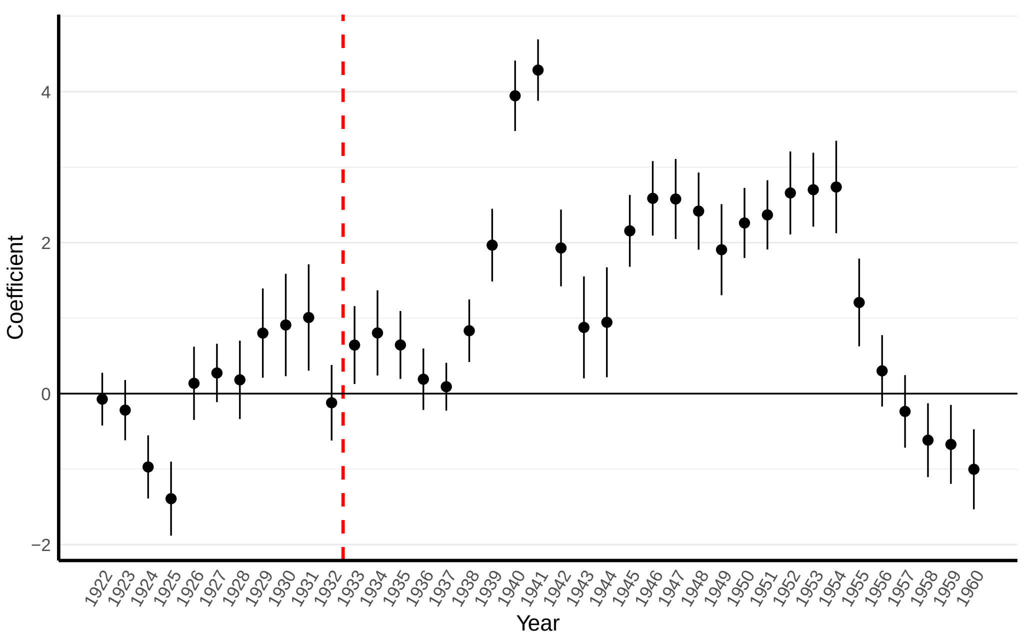
Notes: All 38 ethnic groups are included. Ethnicity and date of arrest were imputed. Full matrix adjustment was applied on ethnic group imputations. Controls for major changes in relations with the USSR are included. Standard errors are clustered on the level of ethnicity and are based on cluster robust estimator by Pustejovsky and Tipton (2018). Error bars show 95% confidence intervals.

Figure A8: Dynamic DiD, Only Border Regions



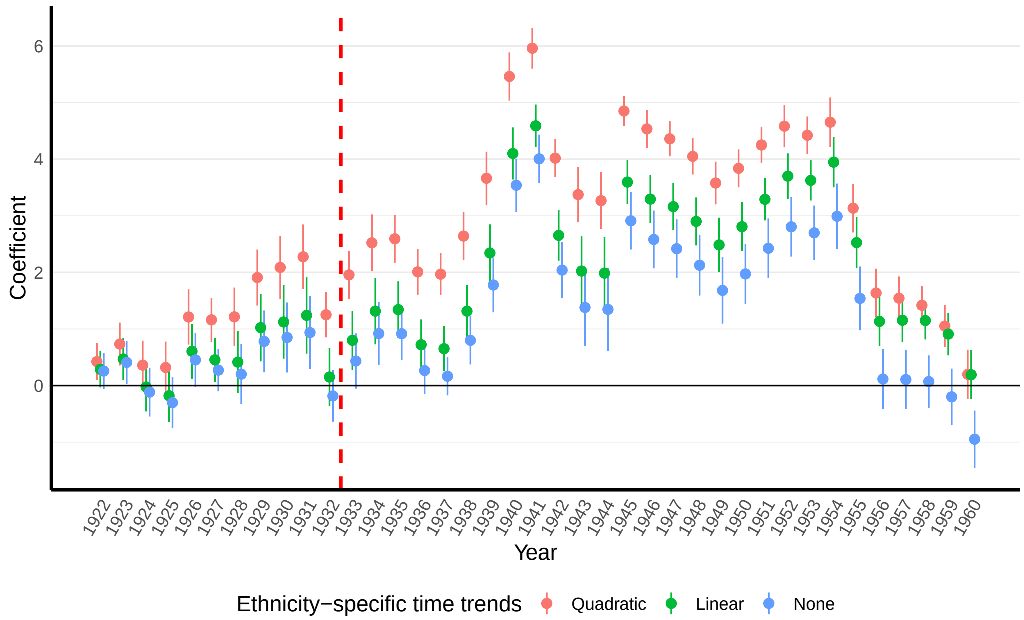
Notes: All 38 ethnic groups are included. Ethnicity and date of arrest were imputed. Full matrix adjustment was applied on ethnic group imputations. Controls for major changes in relations with the USSR are included. Standard errors are clustered on the level of ethnicity and are based on cluster robust estimator by Pustejovsky and Tipton (2018). Error bars show 95% confidence intervals.

Figure A9: Dynamic DiD, Border Regions Excluded



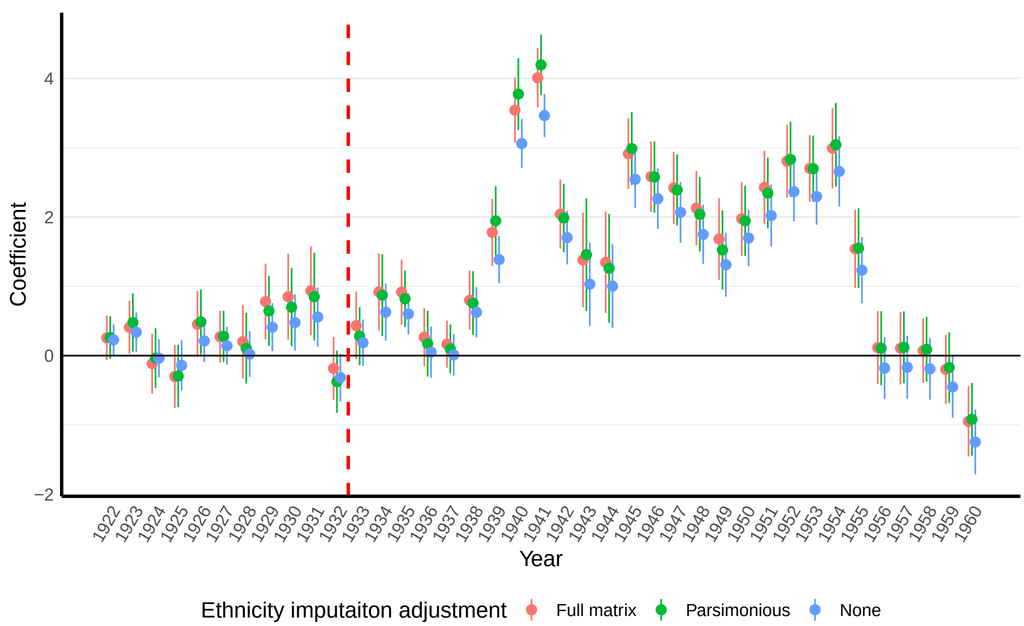
Notes: All 38 ethnic groups are included. Ethnicity and date of arrest were imputed. Full matrix adjustment was applied on ethnic group imputations. Controls for major changes in relations with the USSR are included. Standard errors are clustered on the level of ethnicity and are based on cluster robust estimator by Pustejovsky and Tipton (2018). Error bars show 95% confidence intervals.

Figure A10: Comparison of Ethnicity-specific Time Trends for DiD



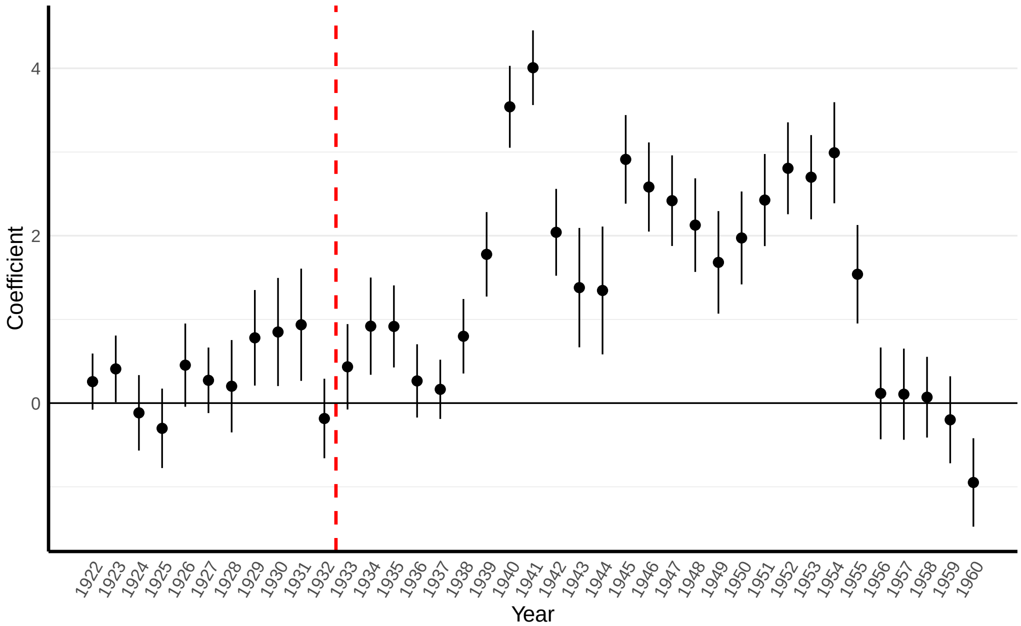
Notes: All 38 ethnic groups are included. Ethnicity and date of arrest were imputed. Full matrix adjustment was applied on ethnic group imputations. Standard errors are clustered on the level of ethnicity and are based on cluster robust estimator by Pustejovsky and Tipton (2018). Error bars show 95% confidence intervals.

Figure A11: Comparison of Ethnicity Imputation Adjustments for DiD



Notes: All 38 ethnic groups are included. Ethnicity and date of arrest were imputed. Standard errors are clustered on the level of ethnicity and are based on cluster robust estimator by Pustejovsky and Tipton (2018). Error bars show 95% confidence intervals.

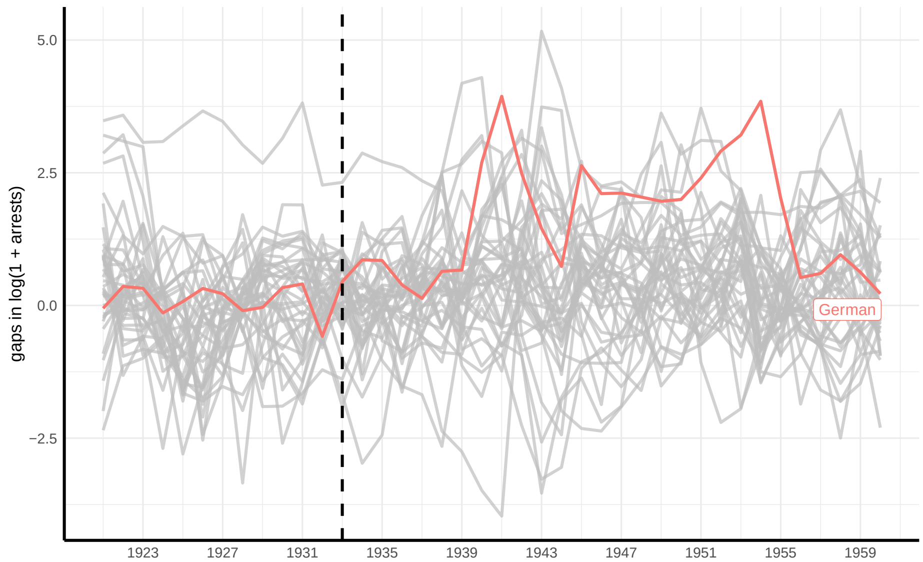
Figure A12: Dynamic DiD, Stata Standard Errors



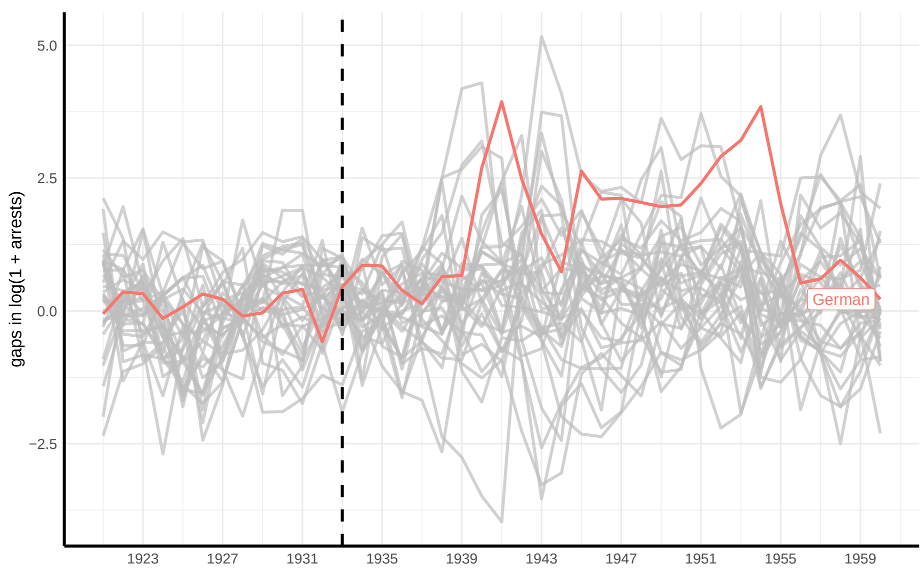
Notes: All 38 ethnic groups are included. Ethnicity and date of arrest were imputed. Full matrix adjustment was applied on ethnic group imputations. We used Stata standard errors clustered on ethnicity. Error bars show 95% confidence intervals.

Figure A13: Gaps between synthetic control and actual values for placebo tests

(a) All ethnic groups



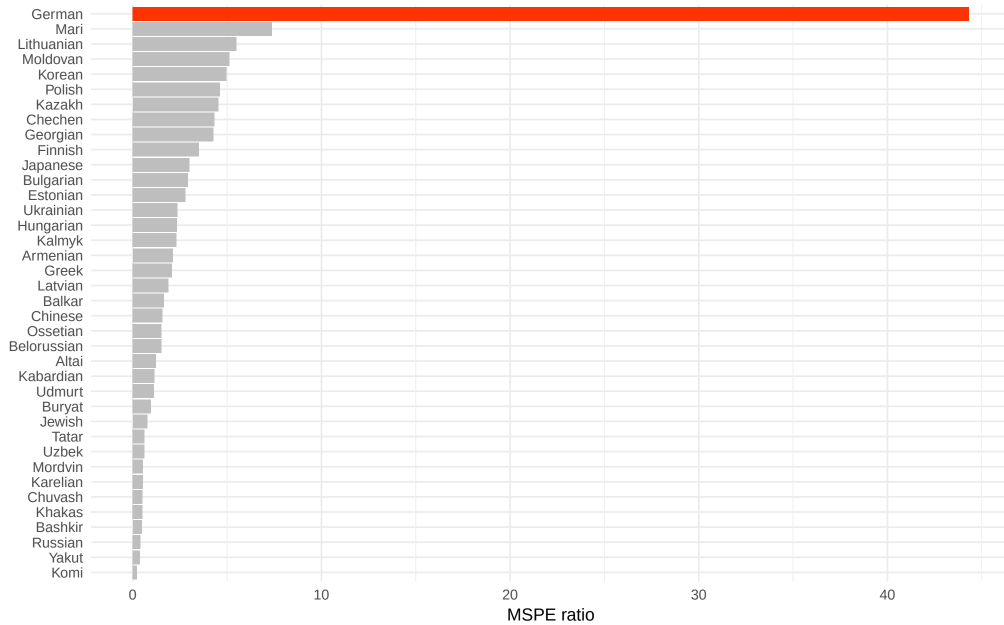
(b) Ethnic groups with pre-treatment MSPE higher than 20 times the MSPE of Germans excluded



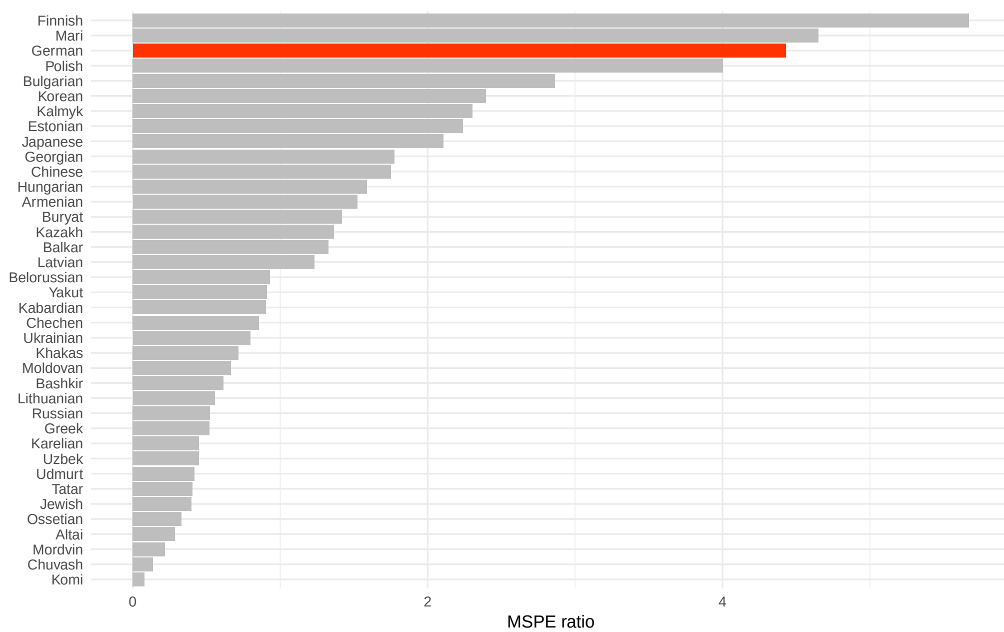
Notes: The predictors are the mean of log $(1 + \text{arrests})$ in the pre-treatment period, total population of the ethnic group in the USSR and its urbanization rate (both taken from the 1926 Soviet census), and linguistic similarity to Russian. Ethnicity and date of arrest were imputed. Full matrix adjustment was applied on ethnic group imputations. All 38 ethnic groups are included.

Figure A14: Ratios of post-treatment MSPE to pre-treatment MSPE

(a) The whole post-treatment period in the numerator (1933-1960)



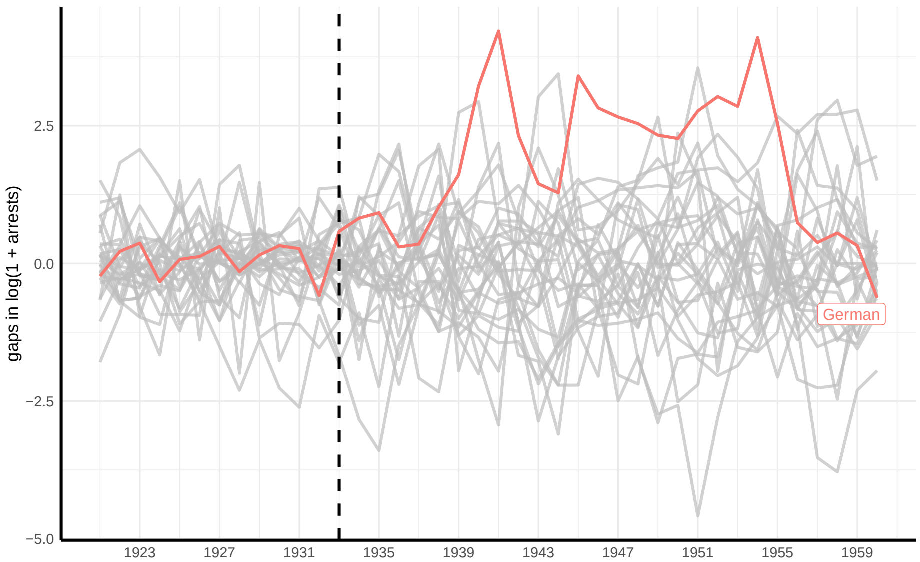
(b) Only the period from 1933 to 1939 in the numerator



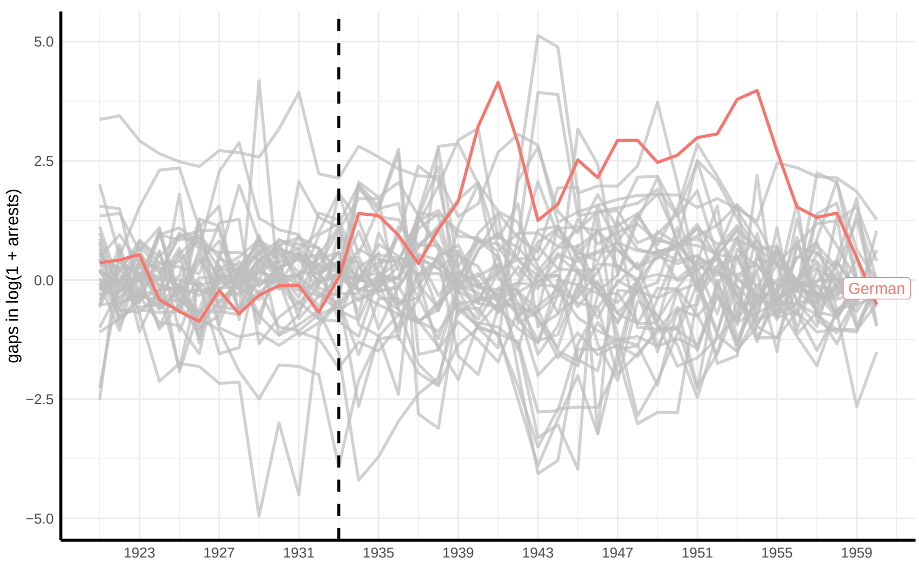
Notes: The same as for the figure A13.

Figure A15: Gaps between synthetic control and actual values for placebo tests

(a) Only ethnicities without independent state



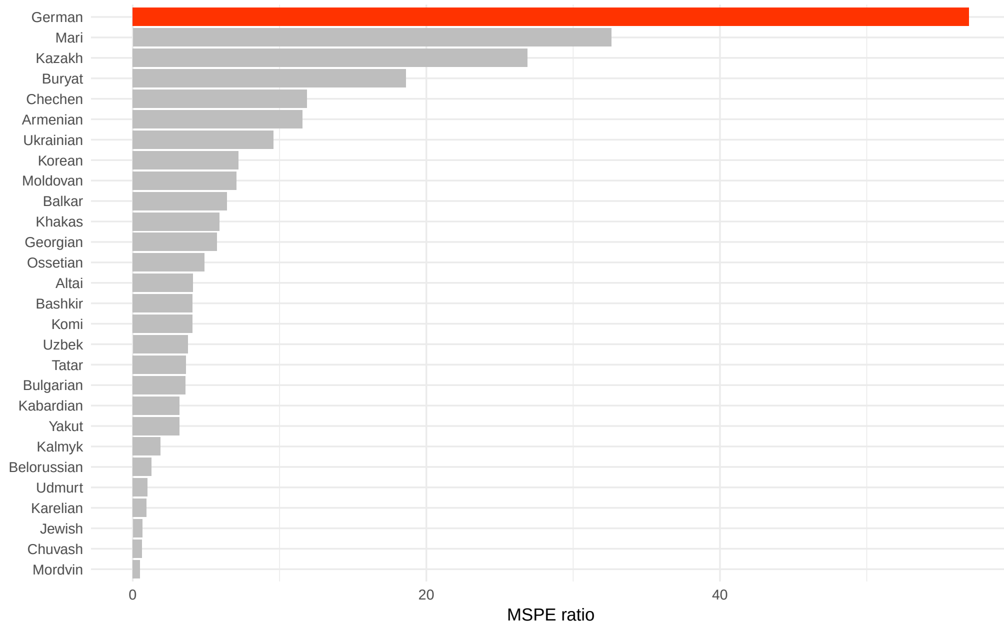
(b) Only rehabilitated individuals



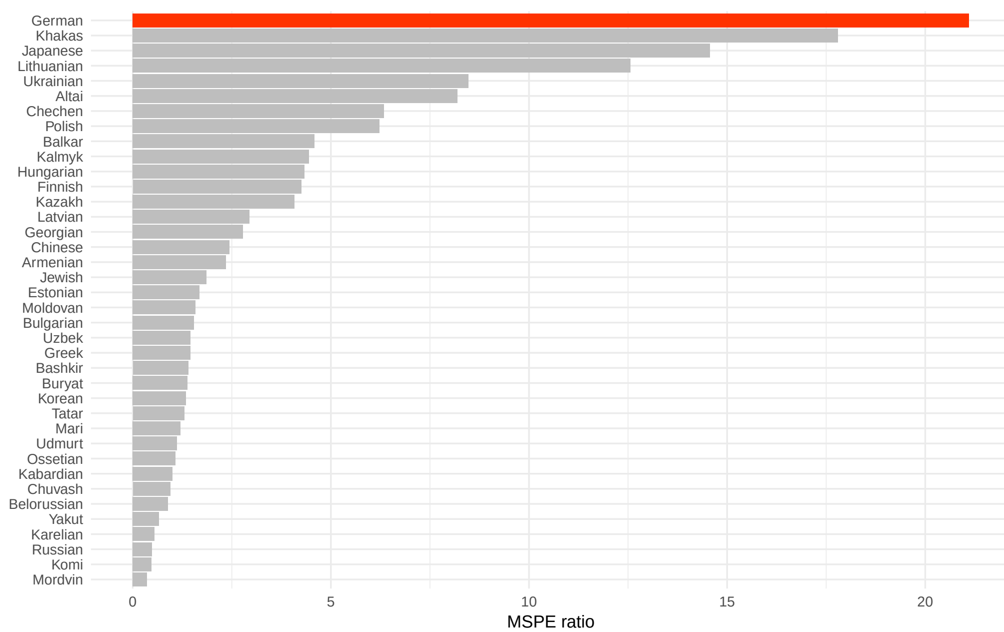
Notes: All pre-treatment outcomes were used as predictors. Ethnicity and date of arrest were imputed. Full matrix adjustment was applied on ethnic group imputations.

Figure A16: Ratios of post-treatment MSPE to pre-treatment MSPE

(a) Only ethnicities without independent state



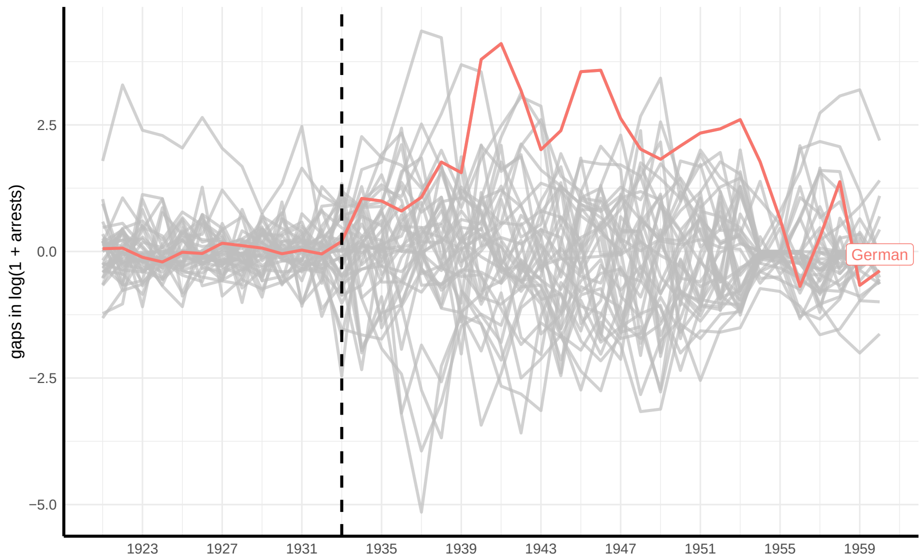
(b) Only rehabilitated individuals



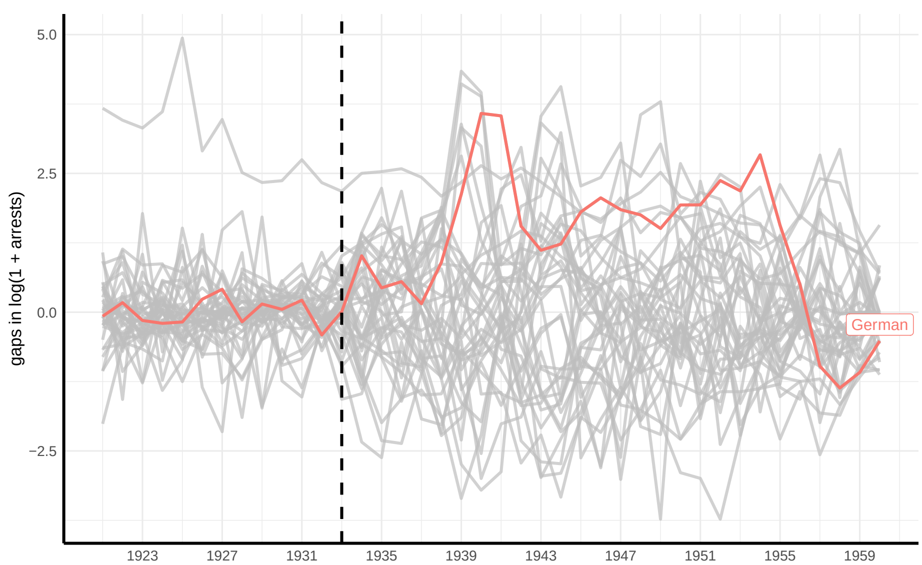
Notes: The whole post-treatment period in the numerator (1933-1960) for both figures. Otherwise same as for the figure A15.

Figure A17: Gaps between synthetic control and actual values for placebo tests

(a) Only Border Regions



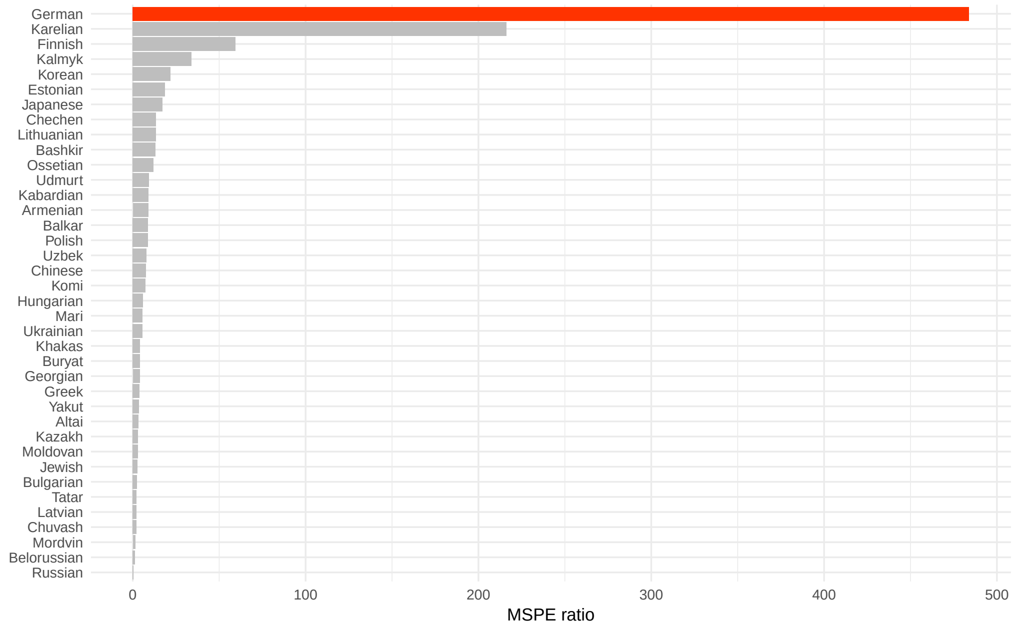
(b) Border Regions Excluded



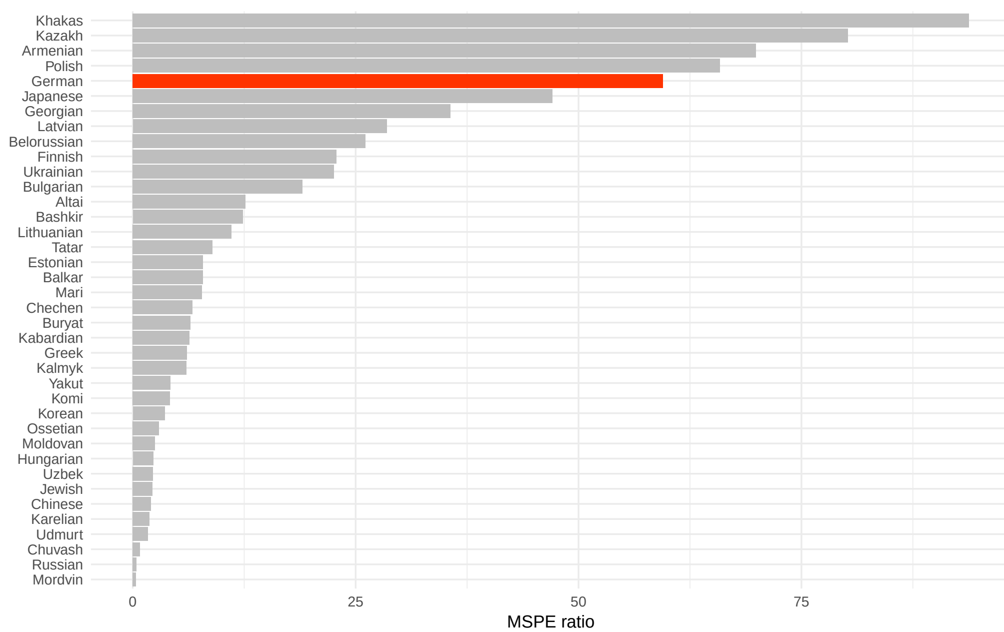
Notes: All pre-treatment outcomes were used as predictors. Ethnicity and date of arrest were imputed. Full matrix adjustment was applied on ethnic group imputations.

Figure A18: Ratios of post-treatment MSPE to pre-treatment MSPE

(a) Only Border Regions



(b) Border Regions Excluded



Notes: The whole post-treatment period in the numerator (1933-1960) for both figures. Otherwise same as for the figure A17.