Short title:

"The Real Consequences of Symbolic Politics"

Long title: "The Real Consequences of Symbolic Politics: Breaking the Soviet Past in Ukraine"

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Abstract:

Conflicts over symbolic issues are prominent in public affairs, but do they have wider political consequences, and if so, why? We study the electoral effects of *Leninopad* ("Lenin's free fall"), a sudden wave of demolitions of Soviet monuments in Ukraine. Difference-in-differences estimates show that the removals of the Soviet symbols mobilized supporters for parties with a relatively sympathetic view of Ukraine's Soviet past. We attribute this backlash effect to a signaling mechanism: the removals indicated the weakening power status of the Soviet legacy parties, which motivated their supporters to turn out in elections. This backlash dissipated once the Soviet symbols ceased being a contentious partisan issue due to the escalating secessionist war. Symbolic politics has real, non-symbolic consequences, but only when it maps onto partisan cleavages.

Key words: Symbols, authoritarianism, democratic transitions, status-threat

Note:

Supplementary material for this article is available in the appendix in the online edition. Replication files are available in the JOP Dataverse (https://dataverse.harvard.edu/dataverse/jop). The empirical analysis has been successfully replicated by the JOP replication analyst.

Some of the most contested, passionate, and often violent conflicts concern issues that have no apparent tangible value to the disagreeing parties. Relocation of a World War II monument in Estonia sparked the largest riots in the country's modern history. An attempt to remove a Civil War memorial in Charlottesville prompted violent clashes on the streets. India's Prime Minister Narendra Modi spent precious billions on record-breaking statues to Hindu figures at the risk (or perhaps with the goal) of sectarian tensions with the Muslims. The U.S. Congress and President Donald Trump found the time – in the midst of a historic pandemic – to battle over whether military bases can be named after Confederate generals.[1]

Political actors often engage in symbolic politics by fighting over and exploiting symbolic issues like linguistic conventions, topographic names, iconography, or historical narratives (Forest and Johnson, 2011; Lupu, 2003; Wedeen, 1999).[2] The preponderance of conflicts over symbolic issues seems at odds with the conventional view that sees politics as a conflict over resources and power. A great deal of political capital is spent on deciding how to name streets, which monuments to erect or remove, or how to interpret history. Does symbolic politics have tangible repercussions and if so, why?

This article proposes that conflicts over symbols matter because they are opportunities for competing groups to test and signal their power. A party that successfully challenges the status quo on an issue will be perceived as de facto more powerful by virtue of being able to prevail, even if the issue at hand is only symbolic and does not have a direct impact on the distribution of resources and power. Due to the status-threat logic (Bustikova, 2019; McClendon, 2018; Mutz, 2018), the "losers" of a conflict over symbols will be mobilized to counteract the shifting distribution of de facto power. When they map onto partisan cleavages, conflicts over symbols impact competition over votes by mobilizing turnout within

[1] "Trump Rejects Renaming Military Bases Named After Confederate Generals," *New York Times*, June 10, 2020.

[2] In the behavioral tradition, the term "symbolic politics" refers to emotional as opposed to rational (self-interested) motivation in political decision-making (Sears and Funk, 1990). We use the term in the comparative politics tradition (e.g. Forest and Johnson, 2011) where it refers to how political actors engage in symbolic acts or employ symbolic objects. Relatedly, our use of term "symbolic conflict" comes from anthropological literature where it refers to "dimension of political conflict which focuses on the manipulation of symbols" (Harrison, 1995).

the "losing" group.

We assess this theoretical intuition on the case of Ukraine. As a former Soviet state, Ukraine has had thousands of public monuments to Soviet figures. The sudden outbreak of Euromaidan protests in the fall of 2013 unleashed a mass wave of demolitions of these monuments, locally known as *Leninopad* ("Lenin's free fall"), resulting in a swift transformation of Ukraine's public spaces. We assembled a comprehensive dataset on the locations and the removals of these monuments. The granular temporal and spatial variation in the removals of the monuments provides a rare opportunity to systematically assess the wider electoral impact of symbolic politics.

Difference-in-differences estimates show that *Leninopad* mobilized supporters of the Soviet legacy parties – those with a relatively favorable interpretation of Ukraine's Soviet past. Historically, these parties had managed to thwart attempts to remove the Soviet monuments. The failure to protect the Soviet memorials during *Leninopad* served as a public signal of the diminishing influence of the Soviet legacy parties, which motivated higher turnout among their sympathizers. Using data from social media, we rule out the possibility that the effects of *Leninopad* were driven by protests that often accompanied the removals of the monuments.

Importantly, we also find that the removals of the Soviet monuments mattered only when their status was openly contested by the competing parties. Through text analysis of mass media narratives, we show that *Leninopad* stopped provoking opposition precisely when a cross-cutting cleavage – national sovereignty – emerged due to the escalating secessionist conflict. Instead of representing the entrenchment of the Soviet legacy parties, Lenin's monuments began to symbolize an assault on Ukraine's sovereignty – a non-partisan issue. As the Soviet symbols lost their polarizing partisan charge, their removals ceased having an impact on elections.

This article makes two contributions. First, it offers a theoretical framework to think about the political role of symbols. We suggest a simple logic to explain why and when conflicts over symbols are politicized and how they impact competition over real political power. Second, we provide empirical evidence that changing the symbolic status quo, under specified scope conditions, may produce an electoral backlash consistent with the proposed power-signaling logic.

With the exception of the study by Forest and Johnson (2011) on the political role of historical monuments in post-communist states, the quantitative literature on symbolic politics has emerged only very recently. Johnson, Tipler and Camarillo (2019) use an online survey experiment to estimate the effects of deliberation on the support for the removal of the Confederate memorials in the U.S. Rahnama (2020) studies how the actual removals of the Confederate memorials affected racial prejudice. Our focus is not on the impact of symbolic politics on norms, which is an independently important question, but on the distribution of power through elections. Dinas, Martínez and Valentim (2020) analyze how the Spanish flag ceased being a stigmatized symbol. While their scope is close to our secondary analysis on the changing meaning of symbols, our primary concern is the impact of symbolic politics on electoral competition.

Politically contentious symbols usually memorialize a controversial historical event, personality, or an institution: they represent past oppression and violence to some and past glory to others. In that regard, this paper also speaks to the literature on the historical legacies of exploitation (Acharya, Blackwell and Sen, 2016), state violence (Lupu and Peisakhin, 2017; Rozenas and Zhukov, 2019), and authoritarian political organizations (Grzymala-Busse, 2006). One critique of this literature is that the mechanisms reproducing the historical legacies are rarely specified (Simpser, Slater and Wittenberg, 2018). By showing how the symbolic artifacts of the past shape current electoral competition, this study suggests one such mechanism.

Symbolic Conflict as Power Signaling

Why do symbolic issues – those that do not *directly* concern resources or power – end up being politically important? We propose that this happens because of the "signaling effects" that conflicts over symbols can generate. By imposing its will on an issue – even if that issue is only symbolic – a group will appear more powerful. In and of itself, there may be no difference whether the national flag is red or green, but a group that manages to impose the green flag will appear more powerful. The desire to signal power may incentivize people to fight over the color of a flag even though intrinsically they may not care about it. In the same way as acquiring formal education allows one to signal intellectual ability (Spence, 1973), prevailing on a symbolic matter produces a valuable signal of political prowess.

The signaling effects of symbolic politics show up in many forms. Syrians routinely engaged in nauseating praises to president Hafez al-Asad without believing their own words. The regime incentivized these symbolic rituals not because it enjoyed hearing hypocritical praises, but because these rituals allowed the regime to project its awesome ability to submit people to its will (Wedeen, 1999). Or consider Vaclav Havel's famous description of a greengrocer who diligently displays slogans of devotions to the communist regime in Czechoslovakia: he does so not out of conviction, but to signal "his preparedness to conform"; if many others engage in this symbolic show of conformity, it "reinforces the perception that society is solidly behind the Party" (Kuran, 1991, p. 27).

A centuries-long struggle over the national flag in Haiti is another case in point. Haiti's founding flag of 1804 showed red and black bands. In 1820, it was replaced by a flag featuring red and blue colors, which was taken to convey the dominant role of the mulattos over blacks. Seeing themselves as the only true Haitians (the *authentiques*), the black leaders sought to reinstate the original flag. This was accomplished by president Francois Duvalier who, elected in 1957, took seven years to prevail on this question: "only in 1964 Duvalier felt strong enough to impose this flag on the country, and thus symbolically to consummate the victory of the *authentiques*" (Nicholls, 1996). This was a "new equilibrium" representing "a major shift in power from the established, predominantly mulatto, elite to a new black middle class" (Nicholls, 1996). In our interpretation, replacing the flag allowed Duvalier to solidify his authority by making this new equilibrium common knowledge.

Soon after ascending to power in Russia, Lenin initiated "the Plan for Monumental Propaganda" consisting of two parts – the "Removal of Monuments Erected in Honor of the Tsars and Their Servants" and the "Production of Projects for Monuments to the Russian Socialist Revolution." Lenin may have simply disliked the aesthetics of the tsarist monuments, but a more realistic possibility is that he conducted a public test of his power: swift removals of the memorials of the previous regime would show that the new government commands obedience from local administrators and citizens. After the communist regimes broke down, new democratic governments engaged in similar symbolic politics by replacing the communist monuments to assert their own power-status (Forest and Johnson, 2011).

If symbolic change signals a shift in the de facto distribution of power, what sort of reaction should it generate? It is conceivable that the "winners" of the symbolic conflict could capitalize on their symbolic victory and demand changes on tangible issues. But the "losers" could also be mobilized to countermine the shift in the balance of power. The existing literature suggests that the latter effect should dominate, because the loss of power status tends to mobilize groups: European right-wing parties performed better as the economic status of immigrants improved (Bustikova, 2019); Polish Jews faced more pogroms in places where their political organization posed a challenge to the titular group (Kopstein and Wittenberg, 2018); many white Americans voted for Donald Trump due to the perceived threat to their status (Mutz, 2018).

For symbolic conflicts to have a backlash effect, certain scope conditions must hold. It is necessary that the demarcation lines on the symbolic issue align with the partisan divisions. Some groups may intrinsically support the status quo on a symbolic issue and some may oppose it, but if those disagreements do not map onto the partisan cleavages, then the change in the symbolic status quo will not signal the shifting distribution of the de facto political power. Changing the flag in Haiti served as a signal of the declining power of mulatto elites only because the conflict over the flag broke down precisely along racial lines; had the disagreement over the flag cut across the racial cleavage, changing the flag would not have meant a growing influence of one racial group at the expense of another.

Consider the following exotic yet instructive example of the "War of Comedians" in mid-18th century France. After an Italian opera company arrived to Paris in 1752, Parisian society was embattled over the value of French versus Italian music until the king ordered the Italians out in 1754. According to Harrison (1995, p. 257), "this initially aesthetic dispute escalated into an affair of state [because] ... it became entangled with underlying political conflicts." The progressives favored the Italian style whereas the conservatives preferred the French one. What on the surface looked like an aesthetic dispute "became a code through which opposed political interests sought implicitly to express themselves and challenge each other" (Harrison, 1995, p. 257). The conflict over aesthetics was political because it reflected the underlying partisan conflict.

These scope conditions for the backlash effect are particularly important in the context of competitive elections. If the competing parties are not publicly divided on a symbolic issue, then resolving the issue in one direction or another will say little about the de facto power of the parties, and the losing side will have little to react to. For example, were the Republicans in the U.S. to take a public stand in favor of removing the Confederate memorials, then the removals of these memorials would not signal the weakening local power of the party since now the removals would be taking place with the consent of the party; this way, arguably, this particular symbolic issue would be deactivated.

The principal prediction of this theoretical discussion is that changing the symbolic status quo, under the specified scope conditions, can mobilize a backlash. This intuition is supported by anecdotal evidence from a diverse set of cases: Russian-speakers rioted against the displacement of the Soviet memorial in Estonia; white supremacists paraded against the removals of Civil War monuments in the U.S.; racists in Bristol (UK) responded to the toppling of a statue of a slave trader by vandalizing a statue of the black poet, Alfred Fagon. But drawing conclusions from anecdotes alone is risky, since we may notice only those cases of symbolic politics that provoke a backlash. We now discuss the case where these theoretical claims can be evaluated more systematically.

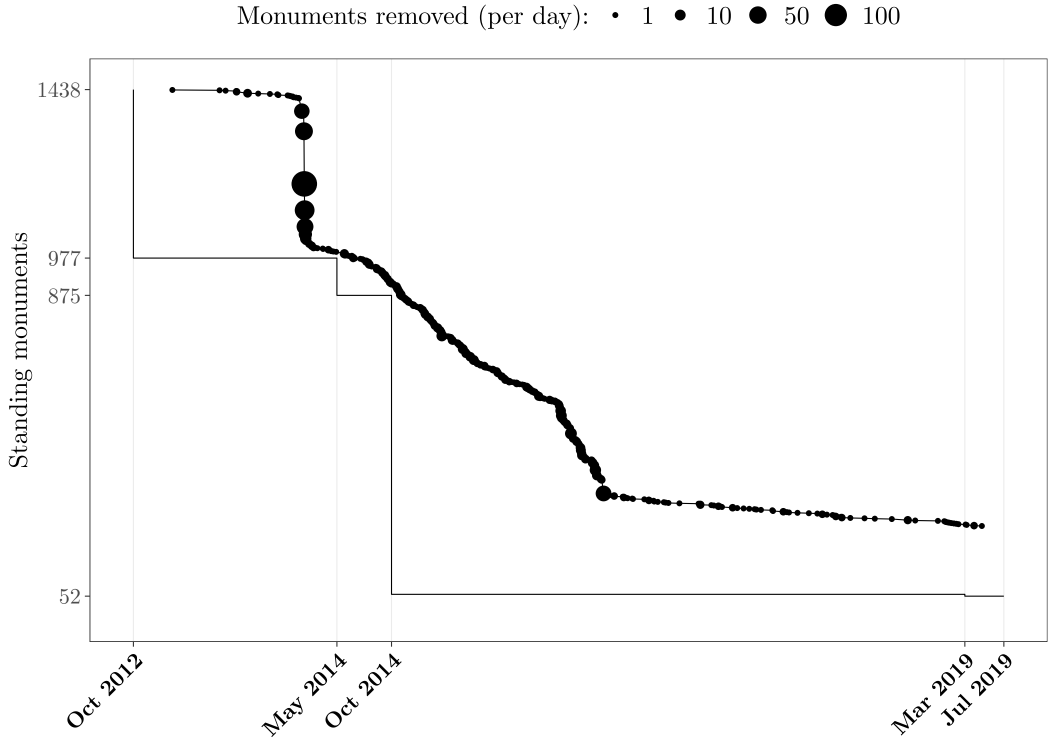
The Case and the Hypotheses

After Ukraine gained independence in 1991, it started the process of de-Sovietization by renaming streets, rewriting history books, and removing Soviet symbols from the public spaces (Budko and Horobets, 2015). These efforts were largely confined to the traditionally more nationalist western regions. In late 2013, President Viktor Yanukovich decided to reverse Ukraine's geopolitical course away from Europe towards Russia. This sparked a nation-wide wave of anti-government protests, known as Euromaidan. In early December, protesters in the capital Kyiv tore down a Lenin's monument, which ignited a chain reaction, and soon Lenins started to fall all across the country.

To give a sense of the scale of the *Leninopad*, Figure 1 shows the cumulative count of Lenin's monuments varied in time. During the last election before *Leninopad*, in October 2012, there were 1,438 monuments to Lenin, but a third of them were gone by the next election in May of 2014. When President Yanukovich fled the countryl at the end of February 2014, 340 monuments were demolished in five days. After this first explosive wave, *Leninopad* continued at a slower rate.

The status of the Soviet symbols was a contentious partisan issue, on which the competing factions disagreed publicly. The Soviet legacy parties who had espoused views sympathetic to Ukraine's Soviet past, like the Communist Party of Ukraine or the Party of Regions, denounced *Leninopad* as an illegal, "barbarian" assault on Ukraine's history (Lb.ua, 2013). The forces behind Euromaidan lauded the demolitions as an indication of Ukraine's long-overdue "farewell to the Soviet era" (iPress, 2013). *Leninopad* was also openly supported by Petro Poroshenko, the winner of the 2014 presidential election (Riafan.ru, 2014).

Historically, the local elites aligned with the Soviet legacy parties had often managed to thwart the removals of the Soviet symbols. The standing Soviet monuments served as a reminder that Ukraine's break from the Soviet past was incomplete due to the entrenchment



Note: The dotted lines trace the number of standing monuments (for which precise dates of demolitions could be found). The solid line traces the number of standing monuments prior to each round of elections: since some removals could not be identified at daily precision, the step function is generally below the dotted line. Data exclude Luhansk, Donetsk, and Crimea.

Figure 1: Monument removals in time

of the Soviet legacy parties. The unscrupulous demolitions of the Soviet monuments during *Leninopad* indicated that the Soviet legacy parties were losing de facto power, both nationally and locally, to Euromaidan forces (Gayday and Liubarec, 2016).

Since the conflict over the Soviet symbols, at least in the early stages of *Leninopad*, mapped clearly onto the partisan cleavages, this case satisfies the scope conditions under which the change in symbolic status quo should, in theory, produce a backlash. All else equal, we would expect to see higher pro-Soviet electoral mobilization in places where Lenin's monuments were removed compared to where they remained standing. The prediction here is not that *Leninopad* changed voting preferences, but that it mobilized those who already supported the Soviet legacy parties. Thus, the signaling mechanism is consistent with facts only if these two hypotheses hold concurrently:

Hypothesis 1. *Monument removals increase the overall turnout (votes cast for all parties relative to eligible voters).*

Hypothesis 2. *Monument removals increase the pro-Soviet turnout (votes cast for the Soviet legacy parties relative to eligible voters).*

Our empirical test is "hard" because it demands us to reject the signaling mechanism in a multitude of cases. For example, the evidence would be inconsistent with the signaling mechanism if we found that the removals reduced the overall turnout, but increased the pro-Soviet turnout (only Hypothesis 2 confirmed). This would suggest that some centrist voters switched to support pro-Soviet parties in response to symbolic politics being used as a diversion from real bread-and-butter issues (Solt, 2011). It could also be that the overall turnout increased while the pro-Soviet turnout decreased due to *Leninopad* (only Hypothesis 1 confirmed), which would be more consistent with the retrospective voting model ("pro-Western" voters rewarded their parties for implementing their preferred policy). A null result on *either* of the two hypotheses would also compel us to reject the signaling mechanism.

Data

Our initial source of data on the Soviet monuments was a crowd-sourced platform `Leninstatues.ru` containing (often incomplete and imprecise) records on the locations and the demolitions of 2,410 monuments to Lenin in Ukraine.[3] We then cross-validated these data, collected additional information, and geo-referenced them.

We first compared our starting list against the official registry of Ukraine's objects of cultural heritage (Ministry of Culture of Ukraine, 2016). The two lists could be compared because, fortunately, they use the same nomenclature to reference the monuments. All

[3] Lenin is the only major Soviet political figure whose monuments survived into Ukraine's independence. Monuments to Stalin and other major Soviet figures were largely removed before the break-up of the Soviet Union.

monuments listed in the official registry appeared on our initial list, which is reassuring. We also used data from the official registry to identify more precise locations of some of the monuments and the dates of their demolitions.

We also cross-validated these data against news reports on media websites and search engine queries on demolitions of Lenin's monuments. We found reports on the demolitions of eight monuments that were not mentioned on *Leninstatues.ru*, which we then added to our database. The fact that we were able to find only eight additional monuments indicated that the coverage of our data was fairly complete.

From the media reports, we also obtained more precise dates of statue demolitions and their locations. One issue we encountered was that multiple demolitions took place in close proximity to one another that could not be easily discriminated (e.g., they occurred in the same town). In those cases, we compared the images of demolitions presented in mass media to the images posted on *Leninstatues.ru*. Lenin's monuments come in a variety of forms (seated, standing, wearing a hat, etc.), so differentiating them and improving the precision of data proved laborious, but straightforward.

We then geocoded the locations of the monuments using Google Maps and Yandex Maps services. When complete addresses were available, we used automated geocoding. If the precise location could not be determined from a specified address, we used the satellite mode of Google Maps to identify the monument or an empty pedestal (in cases where the satellite picture was taken after a removal). Using a combination of these procedures, we geocoded over 99% of the monuments.

Figure 2 shows the locations of Lenin's monuments. A vast majority of monuments in western Ukraine were removed in early 1990's. Most of the standing monuments are located in the conflict regions of Luhansk and Donetsk, which we excluded from the analyses. Since our analyses only include monuments that were standing when *Leninopad* began, most of our observations are from central regions of Ukraine.

The temporal variation in the monument removals was shown earlier in Figure 1. Precise

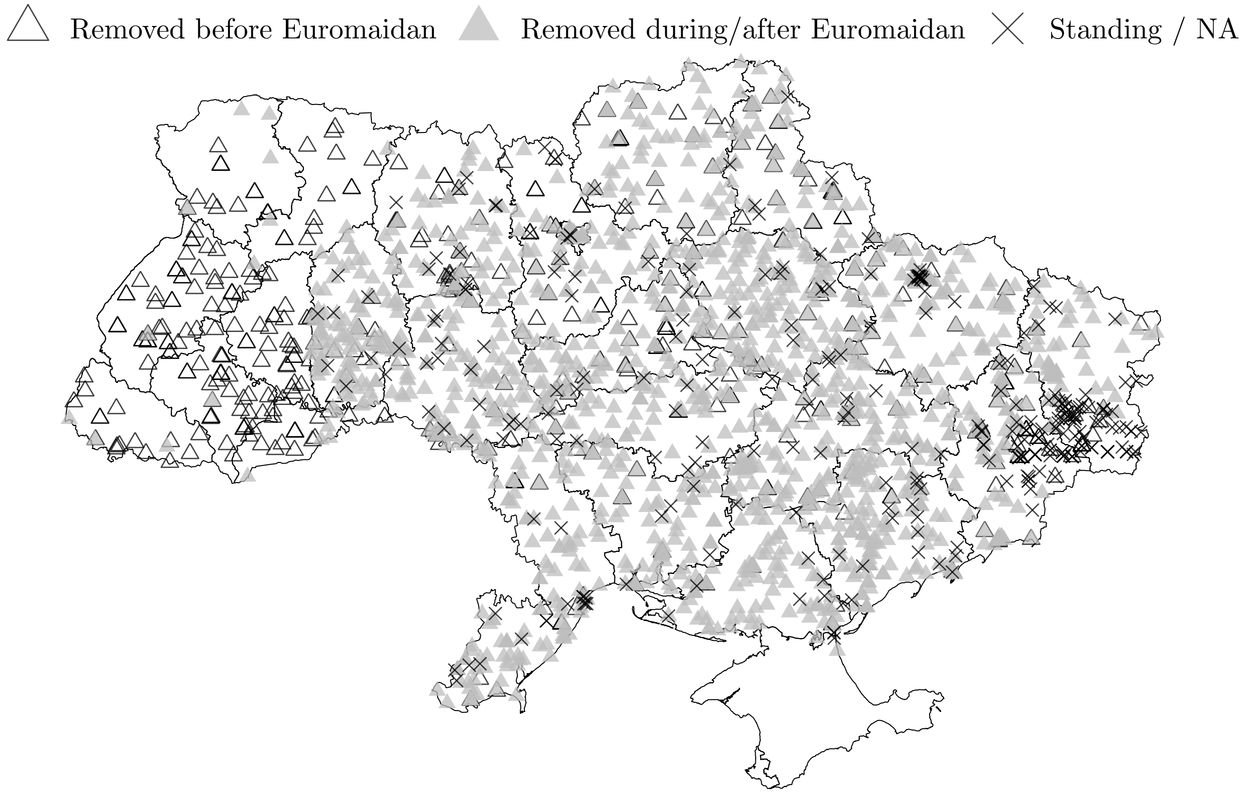


Figure 2: Locations of the Soviet monuments

demolition dates could not be obtained for some monuments, but in all except 93 cases, we were able to identify the inter-election period in which the monument was removed. This kind of time-stamping is sufficient for the type of analysis we do.

We analyze the electoral effects of the *Leninopad* on four elections: the presidential elections in May 2014, the parliamentary elections in October 2014, the first round of the presidential election in March 2019, and the parliamentary elections in July 2019. We exclude the runoff presidential election in 2019 because neither of the two candidates in that election – the incumbent Petro Poroshenko and his challenger Volodymyr Zelensky – represented the Soviet legacy position (see Appendix A). We obtained results of these elections at the level of electoral precinct from the Central Election Commission of Ukraine (CECU). To study the pre-treatment trends in voting behavior, we also collected data on all national-level elections going back to 2004.[4]

The two outcomes of interest are the percentage of eligible voters who turned out (overall turnout) and the percentage of pro-Soviet votes relative to the vote-eligible population (pro-Soviet turnout). We code parties as 'pro-Soviet' if they espouse sympathetic views towards Ukraine's Soviet past, organize celebrations of Soviet holidays or otherwise promote Soviet nostalgia, or call for Ukraine's closer integration with Russia. Some of the Soviet legacy parties, like the Communist Party of Ukraine, are direct successors of the Soviet regime. Others, like the Party of Regions, are not direct successors of the Soviet regime party, but they do share ideological affinities with it. We coded presidential candidates as 'pro-Soviet' if they were members of pro-Soviet parties or served in Yanukovich's government. Appendix A lists pro-Soviet parties and candidates and presents a validation study of our coding scheme.

Empirical Strategy

Our empirical strategy is based on variants of the following difference-in-differences (DiD) regression:

$$\mathbb{E}(y_{it}) = \alpha_i + \gamma_t + \beta \cdot D_{it} + \sum_{j=1}^{23} t \cdot \text{Oblast}_{j[i]} + \sum_{k=1}^{K} \eta_k \cdot t \cdot x_{ik},$$

where y_{it} is either overall or pro-Soviet turnout in precinct i on election t. The precinct fixed effect α_i captures unobserved time-invariant characteristics of the precincts and election fixed effects γ_t capture election-specific shocks. The variable D_{it} is the treatment status of precinct i at time t. The temporal trends are allowed to vary by oblast ($Oblast_{j[i]}$) and pre-treatment characteristics of the precincts (x_{ik}).

We estimate two versions of the above regression. First is the generalized DiD regression (or multi-period DiD), which includes all ten elections ($t = 1, ..., 10$) from December 2004

[4]We did not have geographic boundaries for precincts prior to 2012. To merge the pre- and post-2012 data, we geocoded the addresses of the polling stations in 2004-2010 using a combination of Yandex and Google mapping services and then, for each precinct in 2012-2014, we found a precinct with the nearest polling station in each election from 2004 to 2010.

to July 2019 and in which the treatment variable $D_{it} = 0, 1, 2, ...$ measures the number of monuments removed in a precinct i up to election t. The coefficient of interest β captures the effect of one removed monument. This specification includes six elections that took place before *Leninopad* started ($D_{it} = 0$ for all i and $t \leqslant 6$). Assuming that the trends are linear, we can use the pre-treatment elections to estimate the pre-treatment oblast- and covariate-specific trends that are then extrapolated into the post-treatment time frame (see Angrist and Pischke, 2008, 178).[5] In all analyses, we exclude non-treatable precincts – those that had no monuments prior to *Leninopad*.

We also estimate the above regression in a standard two-period DiD setting with a binary treatment. We arrange the five elections starting with October 2012 into four consecutive pairs so that, within each pair, $t = 0$ and $t = 1$ refer to pre- and post-treatment periods, respectively. The precinct is considered as treated if it had at least one monument removed between the two elections ($D_{i0} = 0$ for all i and $D_{i1} = 1$ if at least one monument was removed in precinct i).[6] Recent literature suggests that, in some settings, the two-period DiD is more credible than the multi-period specification (Imai and Kim, 2021). Reassuringly, our results are consistent across both versions.

With each subsequent round of elections, the number of treatable precincts (those with any monuments at the baseline) shrinks, as no new monuments were erected. For this reason, we cannot compare the March 2019 and July 2019 elections because by March 2019, only 49 precincts had standing monuments. Thus, the two-period DiD regressions compare the following pairs: (1) October 2012 vs May 2014, (2) May 2014 vs October 2014, (3) October 2014 vs March 2019, and (4) October 2014 vs July 2019.

Since the outcome variables are fractional, they are measured more accurately in precincts with more voters. We account for this variable measurement error by weighting precincts by

[5] A more flexible version of this regression with oblasts and covariates interacted with time as factor yields very similar results (see Appendix B.1).

[6] In over 90% of cases, only one monument was removed. Alternative definitions of the treatment lead to identical results (see Appendix B.3).

vote-eligible population (the denominator of the dependent variables).[7] Standard errors are two-way clustered by the precinct, per standard DiD practice, and by oblast, to account for spatial auto-correlation.

Whether a monument was removed or not sometimes was dictated by factors orthogonal to politics. In Kharkiv, for example, activists failed to remove a monument because it was too tall and made of bronze and granite (Abramovich, 2014). In Odessa, a diamond saw blade could not be found to cut through a monument made of solid granite (Gordon, 2016). We do not claim that the removals were exogenous across the board, however. Our empirical strategy relies on a weaker assumption that election outcomes in the treated precincts would have trended in the same way had they not been treated.

We see two key threats to this assumption of common trends. It could be that political actors were more eager to remove monuments in precincts where they expected pro-Soviet electoral mobilization to rise. In Ukraine's fluid party system, it is very unlikely that anyone could anticipate *changes* in election returns at such small geographic scale as precinct. But given the importance of regional politics (Katchanovski, 2006), it is possible that these trends could be anticipated on a larger, regional scale. Oblast-level time trends are included to partial out such anticipatory effects.

The literature also suggests that factors like urbanization and development (Birch, 2000) or geographic proximity to Russia (Peisakhin and Rozenas, 2018) are predictive of voting patterns in Ukraine. Since it is possible that monument removals were more likely to occur in urbanized places and/or places further from Russia, we also include covariate-specific time trends. The covariates include include precinct size category (according to the official classification of precincts as small, intermediate, or large), the density of roads in the precinct, the longitude and latitude of a precinct's centroid and their product. We also allow time-trends to vary by proximity to Kyiv, since this is where *Leninopad* started. We further corroborate the common trends assumption through specification with precinct-specific trends, synthetic

[7] The estimates are very similar if we do not use weights (see Appendix B.4).

control analysis and falsification tests.

Results

Table 1 shows the output from different multi-period DiD regressions. Column 1 uses the most basic specification with only precinct and election fixed effects. In column 2, we add oblast-level time trends, and in column 3, we add covariate-specific trends. In column 4, we allow each precinct to have its own time trends (which subsumes oblast and covariate-specific trends). The estimates are similar across the specifications. A removal of one monument increased the overall turnout by 3.3 to 4.3 percentage points and it also increased the turnout among pro-Soviet voters from 1.5 to 2.4 percentage points, depending on the specification.

	(1)	(2)	(3)	(4)
Effect on overall turnout	3.6^{***}	3.4^{***}	3.3^{***}	4.3^{***}
	(0.6)	(0.6)	(0.6)	(0.8)
Effect on pro-Soviet turnout	2.4^{***}	1.6^{***}	1.5^{***}	1.8^{***}
	(0.5)	(0.3)	(0.3)	(0.4)
Precincts FE	✓	✓	✓	✓
Election FE	✓	✓	✓	✓
Oblast FE × time		✓	✓	
Covariates × time			✓	
Precincts FE × time				✓

Coefficients represent the effect of one removal on the respective outcome (in percentage points). Ten rounds of elections are included ($N = 11,860$). Standard errors in the parentheses are clustered by precinct and oblast. Significance levels: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$.

Table 1: Estimates from multi-period DiD regressions

Table 2 reports estimates from two-period DiD regressions. Here we cannot include precinct-level trends, but we do include oblast-specific and covariate-specific trends – the specification that yielded the most conservative estimates in the multi-period setting (column 3 in Table 1). We see that the results in multi-period regressions were driven entirely by the elections of May 2014, during which a monument removal increased the overall and the

	Overall turnout	Pro-Soviet turnout	Precincts
Oct 2012 - May 2014	1.6 (0.5)**	1.7 (0.4)***	1,296
May 2014 - Oct 2014	−0.5 (0.4)	0.1 (0.2)	887
Oct 2014 - Mar 2019	−1.3 (0.7)	−0.6 (0.9)	792
Oct 2014 - Jul 2019	−0.2 (0.7)	−0.8 (0.8)	792

Coefficients represent the effect of at least one removal. Only precincts with standing monuments at the baselines are included. Standard errors (in parentheses) are clustered by precinct and oblast. Significance levels: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$.

Table 2: Two-period DiD regressions

pro-Soviet turnout by 1.6 and 1.7 percentage points, respectively. Monument removals had no statistically detectable effects in any subsequent elections. These conclusions are robust to alternative specifications, definitions of the treatment, and regression weights; also, they are not driven by any particular oblast (see Appendices B.1 - B.5).

Table 3 decomposes two-period DiD estimates for this set of elections. In October 2012, the overall turnout in treated and control precincts was nearly identical. By May 2014, the overall turnout decreased by 1.1 percentage points in the control precincts, but it increased by 0.5 percentage points in the treated ones. Under common trends, without *Leninopad*, the average turnout in May 2014 would have been 1.6 percentage points lower than observed.

Euromaidan and annexation of Crimea by Russia drastically depleted support for the Soviet legacy candidates. In control precincts, pro-Soviet turnout dropped by 21.2 percentage points, but in the treated precincts, turnout dropped by 19.5 percentage points – 1.7 percentage points less. Given that the average pro-Soviet turnout in May 2014 was around 8%, the difference of 1.7% seems substantial.[8]

Can the effect of removals on pro-Soviet turnout be attributed to mobilization or to party-switching? The party-switching hypothesis would be plausible if removals had increased pro-Soviet turnout without changing the overall turnout (voters switched parties). Instead,

[8]Note that pro-Soviet turnout in the treatment group was hitting the lower bound in May 2014, which raises a concern that the coefficient for pro-Soviet turnout was driven by the floor effects. We show in Appendix B.6 that this is unlikely because the results are very similar if we limit our analyses to precincts where the floor effects were not binding.

	Control			Treatment			
Turnout	Oct-2012	May-2014	Δ_T	Oct-2012	May-2014	Δ_C	$\Delta_T - \Delta_C$
Overall	57.2	56.1	−1.1	57.5	58.0	0.5	1.6
Pro-Soviet	31.0	9.9	−21.2	21.1	1.7	−19.5	1.7

Table 3: Decomposition of the DiD effects

we see that the overall turnout increased *by a nearly identical magnitude* as did pro-Soviet turnout suggesting that we should favor the mobilization hypothesis.

Two additional pieces of evidence reinforce this interpretation. In general, higher turnout favored pro-Soviet parties (see Appendix C.1). Also, if it happened at all, party-switching towards pro-Soviet parties must have come from the "centrist" voters rather than nationalist voters with polar opposite preferences. If so, we should see a negative effect of removals on the *centrist turnout*. We found no support for this prediction in the data: the estimated DiD effect of removals on the centrist turnout is insignificant and positive (see Appendix C.2).

The mobilization hypothesis suggests an important unobservable confounder: Lenin's monuments could have been removed in places where the local tensions mobilized the population to both remove the monuments and also take part in elections rendering our results spurious. Adjusting for this type of confounding directly beyond what we already do is difficult, but we can tease out and test one implication of this argument: if higher mobilization accounts for both removals and later turnout, then the removals should be associated with higher turnout for nationalist parties whose supporters often were behind the removals. Instead, we find that slightly *fewer* nationalist voters were mobilized by the removals (see Appendix C.2), which is the opposite to what this type of confounding implies.

The Common Trends

Our inferences assume that the analyzed outcomes trended independently of the monument removals. We have accounted for a number of channels through which this assumption could have been violated, including a specification with precinct-level linear trends. But this solution is only partial if the underlying trends are non-linear. Also, as Table 3 shows, pro-Soviet turnout is imbalanced at the baseline (fortunately, the overall turnout is balanced). Even though DiD design does not require outcome variables to be balanced at the baseline, stark imbalances are concerning.

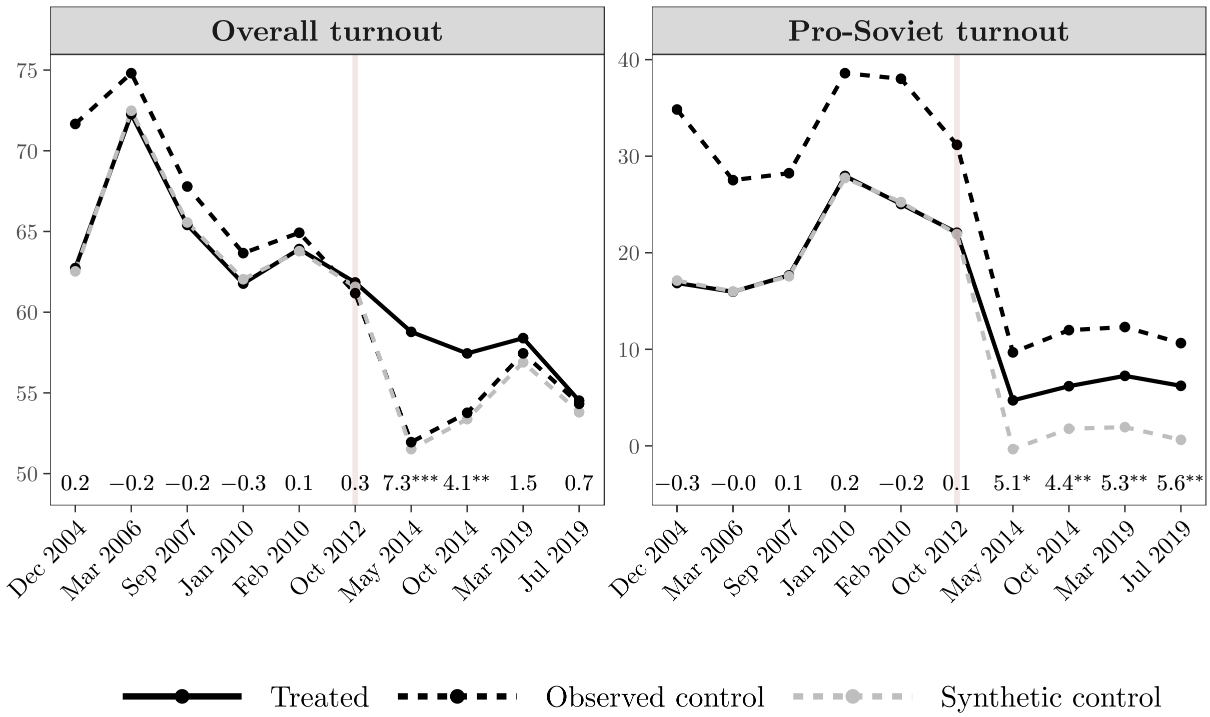
To draw inferences on the basis of more balanced comparisons, we use the generalized synthetic control method (Xu, 2017), which constructs a counterfactual control group that matches the treatment group in its pre-treatment trajectories (which are allowed to be non-linear) as well as levels using the matrix completion method. Figure 3 shows the average values of the variables in the treated precincts that saw statues removed (black solid), in the control precincts were statues existed but were not removed (grey dashed), and the synthetic control group constructed from precincts that match the treatment group prior to May 2014.[9] The figures also show the average treatment effects on the treated (ATT's), the average differences between the treated group and the synthetic control group, which represents the estimated counter-factual to the treated group.[10]

As far as the overall turnout is concerned, the observed control group is already a fairly accurate counter-factual to the treated group: they match each other closely in both levels and trajectories, in the pre-treatment period. In the case of pro-Soviet turnout, we see again (as we did in Table 3) that the observed control group had consistently higher pro-Soviet turnout, but, importantly, the trajectories of the two groups are very similar. In both cases, the matrix completion method seems to have fixed the imbalances in levels and trajectories extremely well: the treatment group and the synthetic control are virtually identical in the pre-treatment period.

Comparing the treated group with the synthetic control group, we see that there are essentially no differences between the two in the pre-treatment period, but they diverge in

[9] Turnout in presidential elections is, on average, 8% higher than in the parliamentary ones. When are arranged in time, the turnout figures show a "chain-saw" pattern causing complications in the estimation of pre-treatment trends. We "evened out" the turnout figures by subtracting 4% from all presidential elections and adding 4% to all parliamentary ones. This normalization does not bias our estimates as the same constant is added to the control and treatment units.

[10] For consistency with the DiD regressions, we weigh each observation by the number of voters.

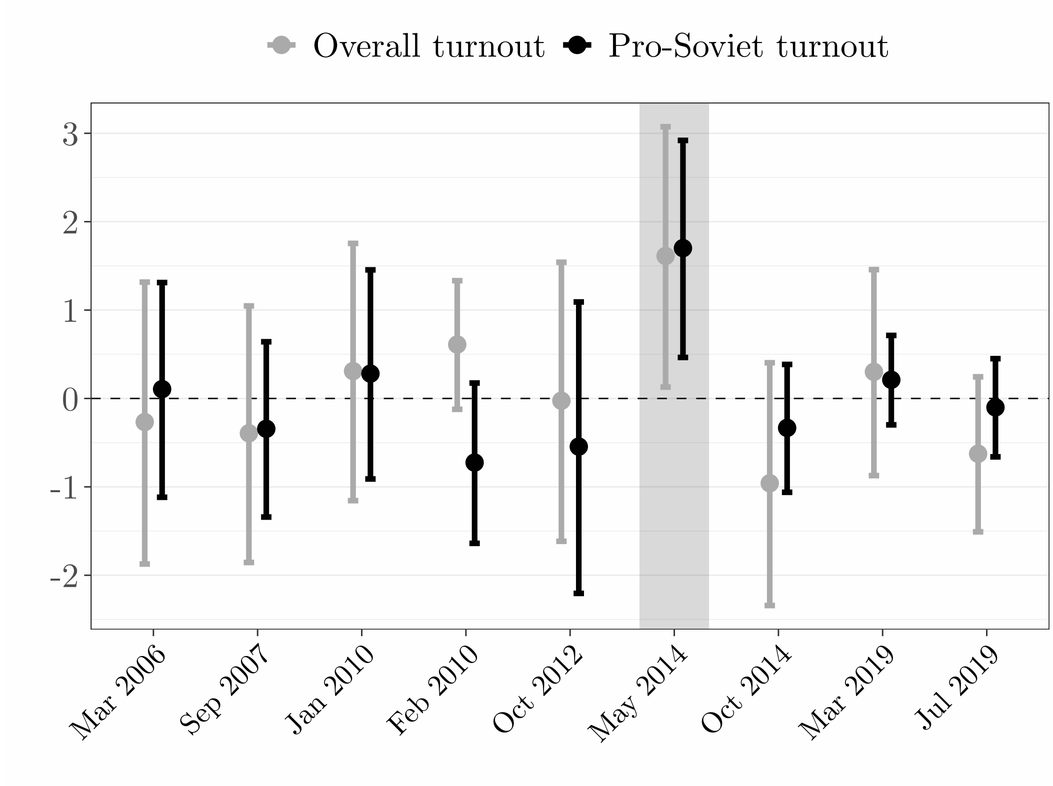


The vertical red bars separate pre- and post-treatment trajectories. The numbers at the bottom are ATTs. The standard errors were bootstrapped to account for clustering by precinct and oblast. The asterisks represent significance levels (* $p < 0.05$, ** $p < 0.01$), which are Bonferroni-corrected for multiple comparisons.

Figure 3: Generalized synthetic control analysis

the post-treatment only, which is reassuring. The effects of removals estimated on the basis of the synthetic control group are consistent with our earlier results: a removed monument produced about a 7% larger overall turnout and about a 5% larger pro-Soviet turnout in the May 2014 elections. These larger magnitudes suggest that the potential violations of the common trends assumption are likely to attenuate our baseline results. At the same time, no ex post adjustment can completely make up for the lack of balance in the raw data, and so the pre-treatment imbalance in the levels of pro-Soviet turnout remains a caveat in our analysis.

Figure 3 also suggests that the effects of removals persisted. The overall turnout stayed higher for two rounds of elections and the pro-Soviet turnout remained higher in all elections following the removals. Unpacking the causes of this persistence is outside the scope of this



DiD results for successive pairs of election where the precinct is considered as treated if it had a removal between October 2012 and May 2014. The 95% confidence intervals are Bonferroni-corrected for multiple comparisons (since we have nine point estimates for each outcome, the nominal confidence of the displayed intervals is $100 \times (1 - 0.05/9) \approx 99.4\%$).

Figure 4: A falsification test

paper, but given that removals that took place after May 2014 did not have an effect on elections, it is unlikely that the persistence was due to voters recalling the early removals in the later elections. A more plausible explanation is habitual voting (Gerber, Green and Shachar, 2003): the early wave *Leninopad* prompted pro-Soviet citizens to vote, and they continued doing so out of habit.

As a further check, we conducted a falsification test that aims to uncover short-term differential trends. We estimated two-period regressions for each successive pair of elections from December 2004 to July 2019 with the treatment variable $D_{it} = 1$ if precinct i had a monument removed between October 2012 and May 2014 and if $t = 1$ (within each pair). Under common trends, we should only see effects of removals on the May 2014 elections.

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Figure 4 shows that this was indeed the case: in all cases, except those for May 2014, the null hypotheses cannot be rejected.

The Role of Protests

Leninopad unfolded in the context of mass protests. The compounding of anti-government protests and the removals of the Soviet monuments poses an inferential challenge: can we attribute the estimated effects to *Leninopad* or should they be attributed to protests that often accompanied those removals? Additional data we collected (see below), indicate that over 90% of removals prior to May 2014 were conducted by activists, usually during protests, which underscores the problem of compound treatment.

To address this issue, we collected several types of data on Euromaidan protests from the start of Euromaidan through February 2014, the period during which most of the pre-May 2014 demolitions occurred.[11] Our first measure uses protests reported in Ukraine's mass media (see Appendix D.1 for details on data collection). Since media reports often lack information to identify the location of protests to the level of a precinct, we geo-referenced protest locations to the level of a council (*rada*), Ukraine's third-tier administrative unit.

To rule out the selective biases in the protest reporting in the media, we constructed two additional proxy measures of protests using data from Twitter, which played a crucial role in Euromaidan (Bohdanova, 2014). Our social media data consists of 2,420,807 geo-referenced tweets posted in Ukraine from December 2013 through February 2014 collected by Wilson (2017).[12] These data constitute the entire population of tweets by users with activated geo-tracking. Using the subset of these data confined to the capital city of Kyiv, Wilson (2017) found that protests could be predicted quite accurately from the volume of tweets by well-connected users. Motivated by this result, we constructed two social media-based measures of protests across Ukraine.

[11] Including protests that occurred after the removals would result in post-treatment bias.

[12] Because of Twitter's terms of use, we were not able to obtain the actual texts of the tweets, but we did have an identifier of whether a tweet mentions Euromaidan (in the text or the hashtag).

First, we calculated the total number of tweets per council that contained the word or hashtag "Euromaidan" weighted by the number of followers of the tweeting account. This measure captures the online coordination on the protest event by well-connected social media users, which arguably preceded off-line mobilization.

Second, we used machine learning to predict protest activities from the daily usage patterns of Twitter. For each council-day, we calculated the total number of tweets, the number of tweets on "Euromaidan," and both of these totals weighted by the number of followers of the respective tweets. We then used the random forest algorithm (Muchlinski et al., 2016) to predict daily protests recorded in the media from these four features of Twitter usage in the sample of councils where at least one protest was recorded by the media. The algorithm was able to predict recorded protests with 86% accuracy.[13] We then calculated the number of predicted protests per council (including out-of-sample councils with no recorded protests) as a measure of local protest activity.[14]

With these three measures of protest, we re-estimated the two-period DiD regressions by adding an interaction between a protest and the post-treatment indicator.[15] The DiD coefficient for removals should attenuate towards zero if removals were epiphenomenal to protests. In addition, we ran DiD regressions with protest as the only treatment variable in the set of councils where no monuments existed (and so none could be removed). If protests, not the removals, produced the backlash, then we should observe consistent backlash effects of protests in places without the monuments.

The results of these analyses are shown in Table 4. These two-period DiD regressions are estimated at the level of council (with council-level fixed effects) and include oblast-specific and covariate-specific trends. The first two columns show that, irrespective of the measure of protest, the coefficients for *Removals* are robust and consistent with the baseline

[13] We do not want this accuracy to be too high, because the data on which the algorithm is trained likely under-report actual protests. Of the 9,119 councils with no protests recorded in the media, the algorithm predicted protests in 3,458 of them.

[14] Appendix D.2 provides technical details.

[15] Due to skewness, all protest variables are transformed using $\ln(1+x)$ function.

	Councils with monuments N = 2,034		Councils without monuments N = 16,444	
	Overall	Pro-Soviet	Overall	Pro-Soviet
Panel A: Protests reported in the media				
Protests	0.4***	0.4*	−0.0	−0.0
	(0.1)	(0.2)	(0.2)	(0.3)
Removals	2.6***	2.4***		
	(0.5)	(0.6)		
Panel B: Tweets on "Euromaidan"				
Protests	0.3***	0.2**	0.1	0.0
	(0.0)	(0.1)	(0.1)	(0.1)
Removals	2.4**	2.5**		
	(0.7)	(0.8)		
Panel C: Protests predicted from social media				
Protests	0.2	0.2	0.6	0.8**
	(0.2)	(0.2)	(0.3)	(0.3)
Removals	3.3***	3.1***		
	(0.6)	(0.7)		

DiD regression coefficients for protests (each panel represents a different measure of protest) and monument removals. All specifications control for oblast- and covariate-specific time trends. The unit of analysis is council (*rada*). Standard errors (in parentheses) are clustered by council and oblast. Significance levels: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$.

Table 4: Protest as an alternative mechanism

estimates. There is also no consistent relationship between protests and elections in places without monuments, as shown in the last two columns of the table.[16] This suggests that the effects of the early *Leninopad* cannot be attributed to the protests which often surrounded monument removals.

When Do Symbolic Politics Matter?

We now investigate why only the first wave of monument demolitions had detectable electoral consequences. There were many differences between each round of elections, and the

[16] Similar results are born out if we use rayon as the unit of analysis (see Appendix D.3).

dynamics of *Leninopad* also varied. Any of these – or other – differences could potentially underlie the effect-heterogeneity.

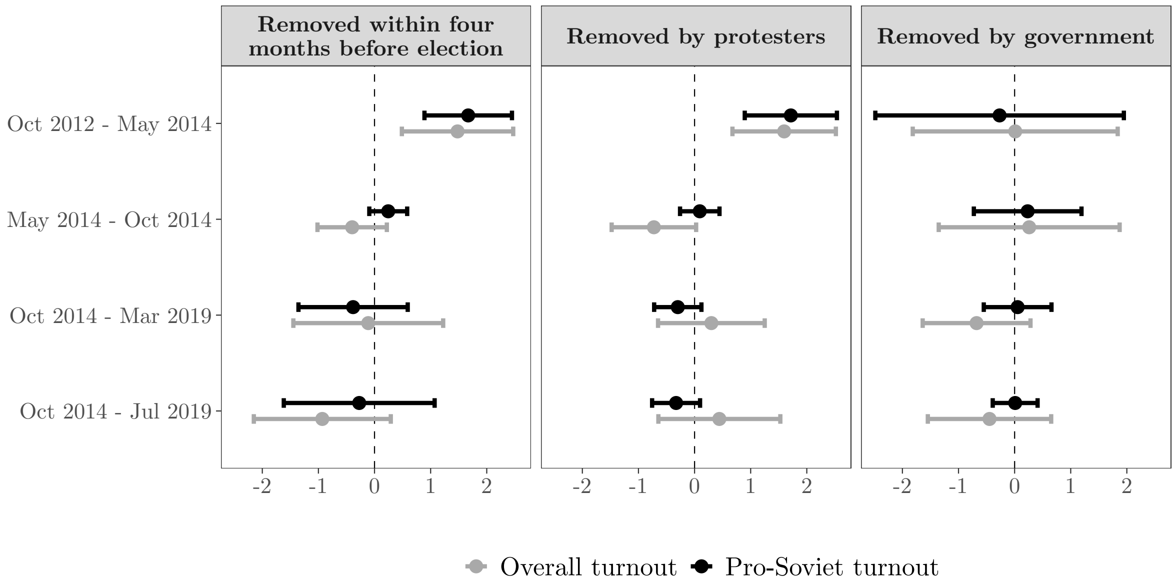
Differences in Voting Options

Voting options varied significantly across the four elections. The Communist Party of Ukraine – the most ideological Soviet legacy party – was outlawed soon after the October 2014 elections. The Party of Regions – the most successful Soviet legacy party – faced mass defections and rebranded itself into "the Opposition Block." What if *Leninopad* had no electoral impact after May 2014 simply because pro-Soviet voters had fewer viable choices?

This conjecture is questionable because the Soviet legacy parties were already ostensibly weak during the presidential election of May 2014. Many candidates from the Soviet legacy camp ran in the May 2014 elections (thereby fragmenting the pro-Soviet votes), but none of them carried the weight of its ousted leader Yanukovich. The best-performing Soviet legacy candidate in May 2014 – Serhiy Tihipko, a vice prime minister under Yanukovich – received only 5.2% of votes. If anything, with the two focal Soviet legacy parties – the Communist Party and the Opposition Block – on the ballot, pro-Soviet voters had more viable choices in October 2014 than in May 2014.

Differences in How Monuments Were Removed

As Figure 1 shows, over 90% of all removals occurred within four months of the May 2014 elections, whereas the later removals were more spread out. Could the temporal proximity of removals to elections belie the effect-heterogeneity? To answer this question, we redefine a precinct as treated if it had a monument removed within four months of an election and then re-estimate the two-period DiD regressions. The left-most graph in Figure 5 shows that even when we consider only the removals that took place close to the election, only removals prior to May 2014 had an impact on elections. The temporal distribution of removals cannot explain the effect-heterogeneity.



Two-period DiD point estimates with 95% confidence intervals for differently defined treatments (oblast- and covariate-specific trends are included).

Figure 5: Estimates for different types of removals

Another source of effect-heterogeneity could be the involvement of different actors behind the removals at different stages of *Leninopad*. Using mass media reports and publicly available videos and photos of Lenin statue demolitions, we were able to identify who was behind 87% of recorded demolitions. In the early stages, the vast majority of demolitions were done by political activists, usually during a protest: 94% before May 2014 and 73% before October 2014. But after October 2014, about 80% of removals were conducted by government authorities. Could it be that only early removals produced a backlash simply because they were conducted by protesters?

Two pieces of evidence suggest that this is not a convincing explanation. First, we did not detect electoral effects of removals in October 2014, even though protesters were behind 73% of them. Second, in Figure 5 we show the estimated effects of removals by authorities versus protesters. The removals post May 2014 had no electoral effects irrespective of whether they were conducted by protesters or government; only the removals by protesters prior to 2014 had a discernible effect. The involvement of protesters seems to be a necessary but not sufficient condition for the backlash effect.

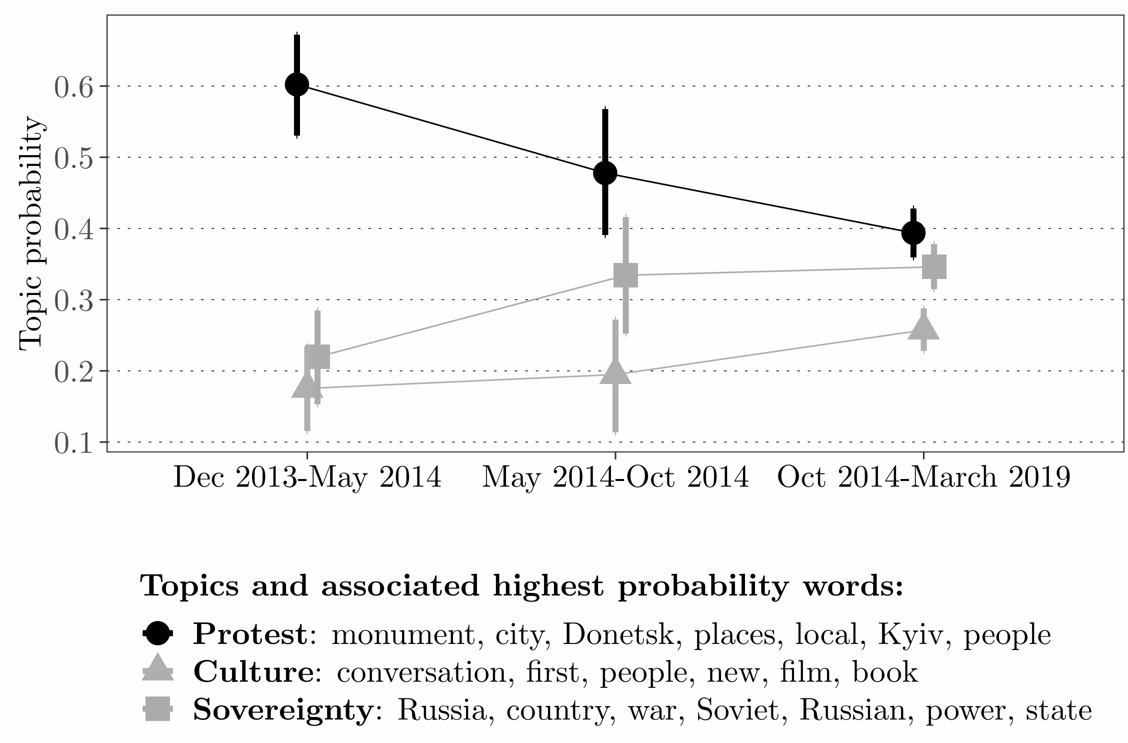
Political Deactivation of Symbols

According to our theoretical discussion, symbolic politics is likely to impact elections only when the conflicts over symbols map onto the partisan cleavages. Observers of Ukrainian politics had noted that the dominant interpretation of Soviet symbols and their removals had shifted profoundly between the start of Euromaidan and the summer of 2014. Early on, supporting *Leninopad* meant opposition towards the Communist Party and the Party of Regions and endorsement of Euromaidan, whereas speaking against *Leninopad* was a way to criticize changes wrought by Euromaidan.

The proxy war with Russia in Donbass, which escalated in the summer of 2014, perturbed this interpretation of the Soviet symbols and their removals. "The Soviet symbols and symbols of anti-Maidan as well as symbols of the regime of Yanukovich now became symbols of separatists" (Gayday and Liubarec, 2016, p. 37). Lenin and his monuments began to represent not just the persistent legacy of the Soviet past, but an assault on Ukraine's national sovereignty, an issue on which Ukrainians were united across partisan lines (Jekaterynczuk, 2015). The new cross-cutting cleavage deactivated the controversies surrounding *Leninopad*, which could explain why its electoral impacts began to dwindle following the summer of 2014.

A key empirical implication of the above argument is that the meaning of the Soviet symbols shifted after the first post-Maidan elections. To assess this claim, we assembled a corpus of news reports that mentioned the word 'Lenin' from Ukraine's daily newspapers, news websites, and one national TV station, totaling 771 articles from December 2013 until March 2019.[17] We then used the structural topic model (Roberts, Stewart and Tingley, 2019) to estimate how the topics covered in these articles have changed throughout the three inter-election periods. In particular, did the narratives surrounding Lenin shift from being

[17] The sources include pro-Ukrainian ("pravda.com.ua," "zn.ua,"), pro-Russian ("fakty.ua"), and neutral mass media ("unian.ua," "day.kyiv.ua, "24tv.ua," "glavred.info," "gazeta.ua").



The figure shows predicted probabilities of topics with 95% credible intervals, estimated by the structural topic model.

Figure 6: The meaning of Lenin

a contentious partisan topic to a consensual topic?

After pre-processing the text, we estimate a model with three topics.[18] We then labeled the topics by inspecting the most frequent words associated with them. We labeled the first topic "Protest" as it is associated with contentious events like protests ("monument," "city," "people"). The second topic, which we labeled "Culture," is about representation of Soviet history in culture ("films" and "books"). The third topic, which we labeled "Sovereignty," is distinguished by the use of terms that became central in the discussion of Ukraine's sovereignty in the context of war: "Russia," "country," "war," "power," and "state."

Figure 6 shows how the predicted proportions of these three topics changed over time.

[18]We lemmatized the text, removed stop words and words "Lenin" and "Ukraine" as they were featured in all extracted topics. We fit a low-dimensional model with three topics because, first, we do not want to risk over-fitting given that our corpus of texts is quite small, and, second, because our experimentation with more complex models did not reveal new, substantively distinct topics; the loss of topical coherence indicates redundancy of additional topics (Roberts, Stewart and Tingley, 2019).

Before May 2014, roughly 60% of news coverage related to Lenin concerned contentious protest events. However, by October 2014, the distribution of topics shifted substantially: the articles that mentioned 'Lenin' did so less in the context of protests and more in the context of national sovereignty. The prevalence of *Protest* decreased by about 13 percentage points ($p < 0.05$), whereas the prevalence of *Sovereignty* increased by about 12 percentage points ($p < 0.05$). In the period after October 2014, the prevalence of *Protest* decreased further by additional seven percentage points ($p < 0.05$). Instead, Lenin was increasingly discussed as a cultural topic: the prevalence of *Culture* increased by eight percentage points ($p < 0.05$).

During the protests of winter 2013 and spring of 2014, *Leninopad* represented the contentious issue of decommunization (Gayday, 2018). Even though most Ukrainians probably did not care whether Lenin's monuments existed or not, their demolitions activated dormant pro-Soviet sentiments, mobilizing those who explicitly opposed changes to the status quo (Kasyanov, 2019). *Leninopad* fitted neatly into the cleavage between pro-Russian and pro-Western forces, which largely defined Ukrainian politics since the Orange Revolution of 2004. Lenin's fall represented de facto empowerment of the pro-Western parties at the expense of the pro-Russian ones.

The escalating war in the summer of 2014 shifted attention towards territorial integrity, internal displacement crisis, and mass casualties. Pro-separatist organizations like *Oplot* or *Ukrainian Front*, which actively opposed *Leninopad*, employed Soviet symbols in their public relations campaigns (Barkov, 2018). These groups failed to gain meaningful support, but their use of pro-Soviet rhetoric and symbols was widely noted. The norms surrounding the Soviet symbols changed: supporting these symbols now meant approval of separatism, whereas removing these symbols now meant support for Ukraine's sovereignty (Kasyanov, 2019); subsequently, the removals of these symbols faced little opposition either from the elites or the public (Gayday and Liubarec, 2016).

The above interpretation has one important caveat: it could be that *Leninopad* would have ceased being a contentious issue naturally, even without the new cross-cutting cleavage. This is a possibility that we cannot rule out directly, but we think that at least two facts speak against it: First, a natural decline of political salience of an issue should be gradual, but we see that *Leninopad* stopped impacting elections quite abruptly, within five months after May 2014. Second, the status of the Soviet symbols continued to be discussed publicly, especially with the introduction of the Decommunization Law in May 2015, but the issue did not have the same partisan charge as it did in the spring of 2014.

Conclusion

Given that symbols and symbolic actions do not have immediate implications on the distribution of power or resources, it is remarkable how much political energy is spent on them. Why is it such a big deal if American football players kneel during the national anthem, if the national soccer team in France sings the "La Marseillaise", or if the constitution of the European Union mentions God? Why is it so important, in political terms, which historical personality is memorialized in a monument as a hero or de-memorialized as a villain?

We argued that conflicts over symbols matter because they allow competing groups to publicly test their strength. Lenin's monuments stood in Ukraine for almost a century. They might have easily gone unnoticed during the tumultuous events of 2014 as had happened during the Orange Revolution in 2004. When these memorials of Ukraine's Soviet past started being openly challenged, they became focal points of partisan contention. By removing these memorials, the Euromaidan forces were able to demonstrate the growth of their power, but that in turn agitated opponents of Euromaidan to claim back their lost status at the ballot box. *Leninopad* accrued interim benefits for Ukraine's "pro-Western" forces by invigorating the protest movement, but it also generated downstream electoral costs.

The scope conditions under which symbolic politics matter are limited in a way that makes theoretical sense. *Leninopad* sparked an electoral reaction only in its initial stage, and we argued that this was because the proxy war with Russia encumbered those who would have otherwise risen against the diminishing power-status of the Soviet legacy parties. The issue of sovereignty cut across the partisan lines along which the conflict over the Soviet symbols was fought, and *Leninopad* morphed into a routine bureaucratic operation without mobilizing charge. These scope conditions resonate well with the finding that the removals of the Confederate memorials provoke opposition only when conducted without consensus-building deliberation (Johnson, Tipler and Camarillo, 2019) as well as with the literature on how cross-cutting cleavages abate conflicts (Siroky and Hechter, 2016).

Symbols that become politically contentious often have something to do with past violence, oppression, and domination. Even long after violence and oppression end, the shadow of the past continues to mold politics. Not only are political norms shaped by history, but politics at large is often a competition between polarizing interpretations of the past (Pop-Eleches and Tucker, 2017). When such polarizing cleavages dominate politics, challenges to the artifacts that memorialize this contentious history can be perceived as a threat to the status quo distribution of political status.

We have found this to be the case even when the issue concerns something as immaterial, from the point of view of individual utility, as a monument. When the vestiges of the past concern more tangible issues, like transitional justice initiatives that threaten perpetrators of past repression (Nalepa, 2010) or economic reforms that threaten the wealth basis of past elites (Radnitz, 2010), the backlash could be more pronounced than in the case analyzed here. Without a cross-cutting cleavage that deactivates contentious historical legacies, such reforms may carry electoral costs.

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Online Appendix

Contents

A. Validating party and candidate classification

The parties were coded as 'pro-Soviet' and not 'pro-Soviet' based on the information published on the parties' official websites and Wikipedia. The coding process followed several steps. First, parties' programs were checked for references to Soviet legacy and communist ideology. Only the Communist Party of Ukraine had such references. Second, we identified whether parties' leaders and parties' representatives in the Parliament (*Verkhovna Rada*) consistently expressed pro-Soviet views, such as glorification of the USSR power and legacy, USSR nostalgia, and USSR restoration. Third, we established whether parties' members organized pro-Soviet events (for example, celebrations of Soviet holidays and Soviet monuments protection rallies). If at least one of the steps showed that a party was associated with the support of pro-Soviet views, it was coded as 'pro-Soviet'.

The candidates were coded as 'pro-Soviet' and not 'pro-Soviet' based on their biography and election program published by the Central Election Commission of Ukraine and information on Wikipedia. Similarly to party classification, candidate classification followed several steps. First, using candidate's biography, we identified whether a candidate was affiliated with parties that were coded as 'pro-Soviet'. Second, we checked candidates' programs for references to Soviet legacy. Third, we established whether a candidate expressed aforementioned pro-Soviet views or participated in pro-Soviet events. If at least one of the steps elucidated candidate's pro-Soviet opinions and attitudes, we coded this candidate as 'pro-Soviet'. Table A.1 shows the list of parties and candidates coded as 'pro-Soviet'.

One obvious concern is whether our classification captures the relevant dimension of electoral competition. To evaluate the validity of our party and candidate codings, we conduct the following exercise. In two elections where only two candidates were running, the classification was quite straightforward. The first case is the rerun of the 2004 presidential runoff between Viktor Yanukovich and Viktor Yushchenko that followed the Orange Revolution. The two candidates clearly disagreed on the preferable geo-political orientation of Ukraine, with Yushchenko campaigning on pro-Western line and Yanukovich trying to defend the pro-Russian economic and political status quo ante. The candidates also showed clear distinction in their interpretation of the Soviet past. For example, Viktor Yanukovich and Viktor Yushchenko had contradicting views on the Holodomor (the Great Famine which took place in Ukraine in 1932-1933). While Viktor Yanukovich denied the genocide status of Holodomor (Kommersant, April 2010), Yushchenko systematically emphasised that Holodomor famine was the genocide of the Ukrainian people by the Soviet government (Interfax, November 2008). The same binary opposition emerged in the second round of 2010 presidential election where Viktor Yanukovich competed against Timoshenko. Similarly to

Table A.1: Pro-Soviet candidates and parties which participated in Ukrainian Elections, 2012-2019

Election	Pro-Soviet Candidates/ Parties
Presidential election 2004 (first round)	Oleksandr Bazyliuk, Anatolii Kinakh, Vlasdyslav Kryvobokov, Oleksandr Moroz, Petro Symonenko, Natalia Vitrenko, Oleksandr Yakovenko, Viktor Yanukovich
Presidential election 2004 (second round)	Viktor Yanukovich
Presidential election 2004 (revote)	Viktor Yanukovich
Parliamentary election 2006	Political Party of Ukraine "Party of Putin's Politics," Communist Party of Ukraine, Party Viche, Party Vidrodzhennia, Electoral Political Party Bloc "Za Soyuz!", Party of Regions, Electoral Bloc "Derzhava - Trudovyy Soyuz," Socialist Party of Ukraine, Natalia Vitrenko's Bloc "Narodna Opozytsiia," Electoral Bloc "Vlada Narodu," Ukraina-Vpered!, Opposition Bloc "Ne Tak!", Trudova Ukraina
Parliamentary election 2007	Communist Party of Ukraine (renewed), Party of Regions, Socialist Party of Ukraine, Progressive Socialist Party of Ukraine, Communist Party of Ukraine, Electoral Bloc of Political Parties "Kuchma"
Presidential election 2010 (first round)	Inna Bogoslovska, Oleksandr Moroz, Petro Symonenko, Serhiy Tihipko, Viktor Yanukovich
Presidential election 2010 (second round)	Viktor Yanukovich
Parliamentary election 2012	Party of Regions, Communist Party of Ukraine, Ukraina-Vpered!, Socialist Party of Ukraine, Rysky Block, Narodno-Trudovyy Soyuz Ukrainy, Nova Polityka, Party Soyuz
Presindential election 2014	Yuriy Boiko, Mykhailo Dobkin, Valeriy Konovalyuk, Vadym Rabinovych, Petro Symonenko, Serhiy Tihipko, Vasyl Tsushko
Parliamentary election 2014	Opposition Block (Oppozytsiynyy Block), Vidrodzhennia, Nova Politika, Communist Party of Ukraine, Sylna Ukraina
Presidential election 2019	Inna Bogoslovska, Yuriy Boiko, Viktor Bondar, Oleksandr Vilkul, Illia Kyva, Volodymyr Zelensky
Parliamentary election 2019	Opposition Block (Oppozytsiynyy Block), Oppozytsiyna Platforma - Za Zhyttia, Sluga Narodu, Partia Shariya, Nezalezhnist

Yushchenko, Timoshenko argued that "Holodomor of 1932-1933 was the true genocide of the Ukrainian people. It was designed to destroy the freedom-loving spirit of the Ukrainians, to put the weakened people to their knees in humble service to the totalitarian system"

(Svoboda, November 2009). Debates regarding the legacy of the USSR were not limited to interpretation and denial of political repressions. According to Viktor Yanukovich, the Soviet Union helped Ukraine lay "the foundations of economic and cultural power", without which independence would be unthinkable (Izvestiya, July 2010). In contrast, Viktor Yushchenko supported de-Sovietization long before Leninopad (Izvestiya, July 2010) and blamed the USSR for Ukraine's inability to integrate to the EU (Pravda, May 2005).

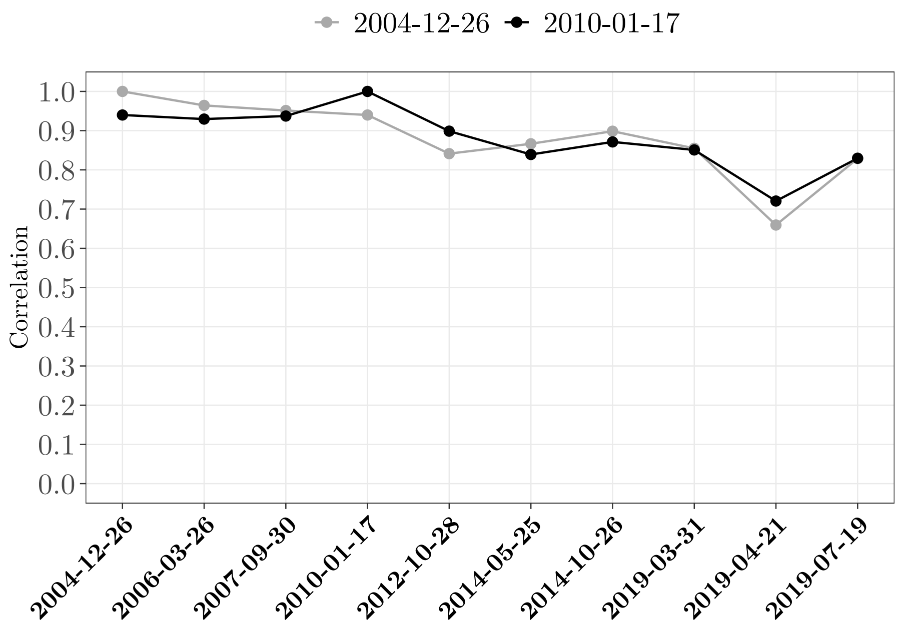


Figure 1: Precinct-level bivariate correlations between 'pro-Russian' votes based on our manual codings across elections: grey line shows correlations with the third round of 2004 presidential election (2004-12-26) and black line shows correlations with the second round of 2010 presidential election (2010-01-07).

Given the unambiguous classification of candidates in the elections in 2004 and 2010, we can validate our classification scheme in the remaining elections by checking how well the aggregate 'pro-Russian' votes in those elections correlate with the vote-share for Viktor Yanukovich in 2004 and 2010 elections. Figure 1 shows that, at least by this measure, our codings appear to be valid: 'pro-Russian' votes (as classified by us) across most elections very strongly correlate with votes for Viktor Yanukovich in 2004 and 2010. For example, the total share of votes by 'pro-Russian' candidates in the 2014 elections is correlated with prior votes for Yanukovich at the level of 0.85. Overall, the bivariate correlations are always above 0.8, with the exception of the second round of 2019 presidential election where the correlations hover around 0.7, and this is one reason we did not include this election in our analysis.

B. Robustness analyses

B.1. Multi-period DiD with flexible time trends

Estimates in Table B.2 use linear oblast- and covariate-specific trends. The linearity assumption is what permits us to exploit data prior to the 2012 elections in the estimation of these trends. The downside, of course, is that the linearity assumption might be too demanding. The table below shows estimates from the regression where oblasts and the covariates are interacted with election period (time) treated as a factor. The point estimates are either very similar to the ones reported in the paper or larger in magnitude, suggesting that the linearity assumption produces more conservative estimates.

Table B.2: Generalized DiD with flexible time trends

	(1)	(2)	(3)	(4)
Effect on turnout	3.6***	3.5***	3.4***	4.5***
	(0.6)	(0.6)	(0.7)	(0.9)
Effect on pro-Soviet turnout	2.4***	1.9***	1.8***	2.3***
	(0.5)	(0.4)	(0.4)	(0.5)
Precincts FE	✓	✓	✓	✓
Election FE	✓	✓	✓	✓
Oblast FE × time		✓	✓	
Covariates × time			✓	
Precincts FE × time				✓
N	11,860	11,860	11,860	11,860
Adjusted R^2	0.8	0.8	0.8	0.8

B.2. Alternative specifications

Table 2 in the main text reports DiD estimates using the full specification (precinct and election fixed effects, oblast-level trends, and the covariates). The table below reports DiD coefficients for two simpler models. We see that, irrespective of specification, only the estimates for May 2014 elections are sizable and significant, and the magnitudes of the coefficients for May 2014 elections are larger than the ones reported in the paper.

Table B.3: DiD estimates for each election.

	Overall turnout	Pro-Soviet turnout	Precincts
Model 1: precint and time fixed effects			
Oct 2012 - May 2014	6.4 (1.3)***	4.4 (1.0)***	1,296
May 2014 - Oct 2014	−0.8 (0.6)	0.4 (0.5)	887
Oct 2014 - Mar 2019	−0.9 (0.9)	−0.9 (0.8)	792
Oct 2014 - Jul 2019	0.3 (1.2)	−1.1 (0.8)	792
Model 2: precint and time fixed effects and oblast-level trends			
Oct 2012 - May 2014	2.5 (0.4)***	3.3 (0.4)***	1,296
May 2014 - Oct 2014	−0.3 (0.4)	0.3 (0.2)	887
Oct 2014 - Mar 2019	−1.3 (0.8)	−0.9 (0.8)	792
Oct 2014 - Jul 2019	0.0 (0.7)	−0.9 (0.7)	792

B.3. Alternative definitions of the treatment

Table B.4: DiD estimates for different definitions of treatment.

	Turnout	Pro-Soviet
Model 1: all monuments removed		
All monuments removed	1.5**	1.5**
	(0.5)	(0.4)
Model 2: number of removals (linear)		
Number of removed monuments	1.4**	1.4***
	(0.4)	(0.3)
Model 3: number of removals (factor)		
One monument removed	1.6**	1.7***
	(0.5)	(0.4)
Two monuments removed	1.9	1.5
	(0.9)	(0.7)
Model 4: percentage of removals		
Percentage of monuments removed	1.6**	1.7***
	(0.5)	(0.4)

B.4. Regressions without weights

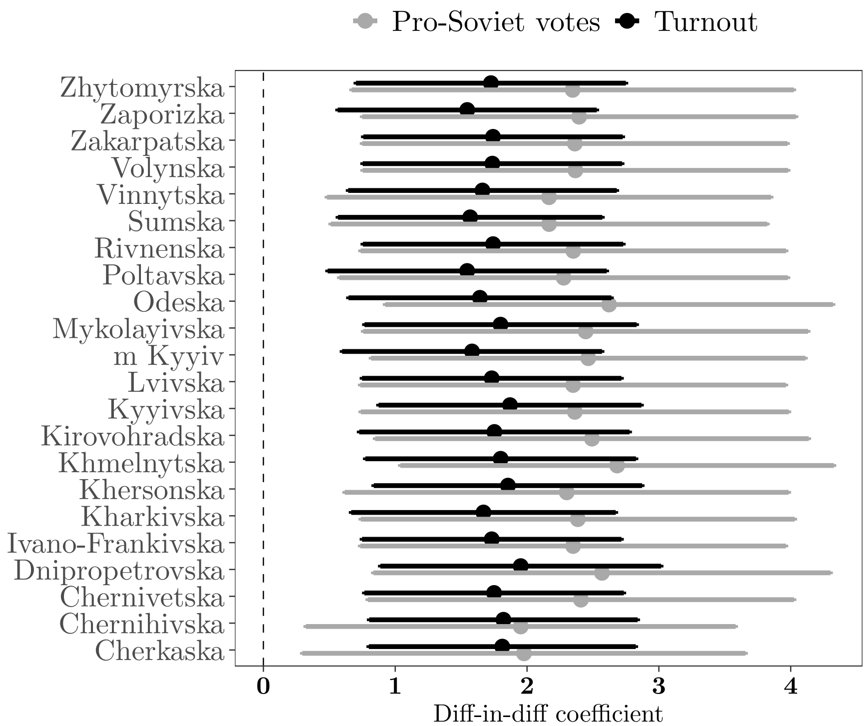
The table below shows regression results where all precincts are weighted equally.

Table B.5: DiD estimates for each election.

	Overall turnout	Pro-Soviet turnout	Precincts
Model 1: precint and time fixed effects			
Oct 2012 - May 2014	6.1 (1.2)***	4.8 (0.9)***	1,296
May 2014 - Oct 2014	−1.0 (0.6)	0.3 (0.5)	887
Oct 2014 - Mar 2019	−1.4 (1.1)	−1.1 (0.8)	792
Oct 2014 - Jul 2019	−0.3 (1.4)	−1.1 (0.7)	792
Model 2: precint and time fixed effects and oblast-level trends			
Oct 2012 - May 2014	2.7 (0.3)***	3.8 (0.4)***	1,296
May 2014 - Oct 2014	−0.6 (0.5)	0.4 (0.3)	887
Oct 2014 - Mar 2019	−1.0 (1.0)	−1.0 (0.8)	792
Oct 2014 - Jul 2019	0.2 (1.2)	−1.0 (0.7)	792
Model 3: precint and time fixed effects, oblast-level trends, and covariates			
Oct 2012 - May 2014	1.7 (0.4)***	1.7 (0.5)**	1,296
May 2014 - Oct 2014	−0.6 (0.4)	0.2 (0.2)	887
Oct 2014 - Mar 2019	−0.8 (0.8)	−0.6 (0.8)	792
Oct 2014 - Jul 2019	0.1 (1.1)	−0.8 (0.7)	792

B.5. Sensitivity to exclusion of oblasts

The figure below shows regression coefficients for 2014 May elections when each oblast is excluded one-by-one from the regression.



Regression coefficients with 95% confidence intervals for 2014 May elections excluding oblasts one-by-one. All models include interactions between treatment period and distance from Kyiv, longitude, latitude, interaction between longitude and latitude, and precinct size. The confidence intervals account for clustering by precinct.

Figure 2: Robustness to exclusion of oblasts

B.6. Floor effects

To evaluate the possibility that the results on the effects of removals on pro-Soviet votes are driven by floor effects, we estimate regression models by excluding precincts with small percentages of pro-Soviet votes in May 2014 elections. This way, if we observe comparable effects of removals in the precincts that are reasonably high "above the floor," the concern would be mitigated.

	Coeff (Cluster S.E.)	Precincts
All precincts	1.6 (0.5)**	1,296
Pro-Soviet turnout above 2.8 % (25th percentile)	1.6 (0.6)**	973
Pro-Soviet turnout above 6.1 % (50th percentile)	1.5 (0.7)	648

Table B.6: DiD coefficients for the effect of removals on pro-Soviet votes in May 2014 elections in truncated samples.

The results are shown in Table B.6. We use the same specification as in the main regressions of the paper. The first row shows the results in the full dataset (without truncation), for comparison. The second row shows the coefficient estimate when we truncate the dataset to include only precincts where pro-Soviet candidates received at least 5% of votes in the May 2014 elections. We see that the coefficient is very similar in magnitude to the baseline estimate and remains significant at 5% level. In the third row, we include only precincts where pro-Soviet parties received at least 10% of votes (the 50th percentile). Again, the coefficient remains very close to the original estimate; only standard errors increase due to this truncation. Had the estimates been driven by floor effects, we would see substantial attenuation of the baseline effect with each increasing truncation of the dataset, but that does not appear to be the case.

C. Mobilization or party-switching?

C.1. Correlation between turnout and pro-Soviet support

In the main text, we argue that the similarity in the coefficients for the overall turnout and pro-Soviet turnout is indicative of *Leninopad* leading to pro-Soviet mobilization: voters sympathetic to pro-Soviet parties who would have abstained otherwise, turned out in elections if Lenin's monuments were removed in their neighborhoods. The figure below provides additional evidence corroborating this conclusion as it suggests that higher turn out in May 2014 benefited pro-Soviet parties, on average.

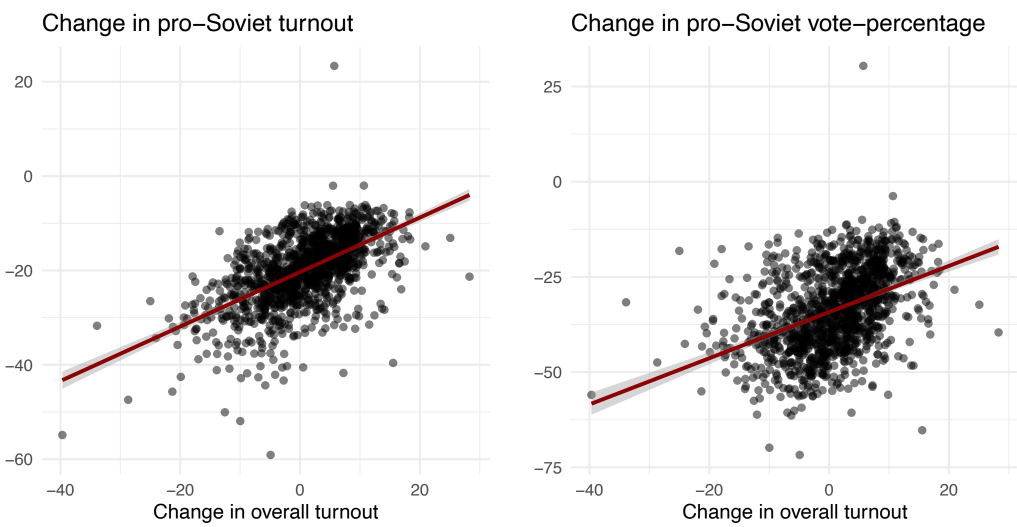


Figure 3: Changes in election outcomes between October 2012 and May 2014

On the x-axes, we plot the change in turnout between October 2012 and May 2014. The y-axis in the left figure shows the change in pro-Soviet turnout between the two elections. We see very strong correlation between the two outcomes suggesting that in places where turnout increased more, we also saw higher turnout for pro-Soviet parties. This, of course, could be partly mechanical because both outcomes share a common denominator – the number of eligible voters. So, in the right figure we plot the change in the overall turnout against the percentage of votes cast (instead of eligible voters) for the pro-Soviet parties, but we see that the correlation remains positive, albeit weaker.

C.2. Effects on centrist and nationalist parties

Here we analyze the impact of the removals on parties other than the Soviet legacy parties. First, we identify parties and candidates from October 2012 and May 2014 elections that can be considered as "nationalist," that is, if they state that they support nationalist, conservative, or right wing ideology, as well as such issues as OUN-UPA recognition or prohibition of Russian language. Based on this scheme, the following parties and candidates were identified as "nationalist":

Election	Nationalist Candidates/ Parties
Parliamentary election 2012	Ukrainian Platform "Sobor," Ukrainian National Assembly, Svoboda
Presidential election 2014	Vasyl Kuibida, Oleg Tiagnybok, Dmytro Yarosh, Anatoliy Hrytsenko

Table C.7: Nationalist candidates and parties which participated in Ukrainian Elections, 2012-2014

Then, the parties and candidates that were not identified as either "nationalist" or "pro-Soviet" were coded as centrists. Accordingly, we then created two new dependent variables, one measuring turnout for centrist parties and another measuring turnout for nationalist parties. Finally, we replicated our baseline two-period DiD regressions (with oblast- and covariate-specific trends) on these two outcomes. The table below shows coefficients for the removal indicator. The point estimate for the effect of a removal on centrist turnout is positive but not significant and the point estimate for the effect of a removal on nationalist turnout is negative, and although it is small in magnitude it is nonetheless significant at 95 percent confidence level.

Outcome	Coefficient (clustered S.E.)
Centrist turnout	0.4 (0.4)
Nationalist turnout	-0.5 $(0.2)^{*}$

Table C.8: Effects on centrist and nationalist parties

D. The Role of Protests

D.1. *Identifying protests from media*

In order to collect the data on Euromaidan protests in Ukraine, we used the crowdsourced list of Euromaidan events, Google News search, and Google Maps. First, we used the user-generated Wikipedia Commons list of Euromaidan protests (Wikipedia, 2021). This list of events allowed us to identify the locations of protests in November 2013 - March 2014, their size, dates, and protest-related keywords. Second, keywords were used to search for protest events in Google News archive. In this step, we checked for potentially missing events and verified the start and ending dates of protests in each location, as well as the number of participants. We generated a list of 136 protest locations which experienced protests in November 2013 - March 2014. Third, we used Google maps to collect data on the coordinates of each protest, based on information from news articles found in Google News archive. In most cases, the location of protest events coincided with the towns' central squares (*maidan*). These are shown in the figure below:

Figure 4: Locations of protests recorded in the mass media between Dec, 2013 and Feb, 2014

D.2. Predicting protests from social media

Figure below shows the spatial distribution of all geo-coded tweets as well as the tweets that mention Euromaidan from December 2013 through February 2014. We now provide details of how we used these data together with the data on protests recorded in the standard mass media sources to predict protest activities at a more granular level.

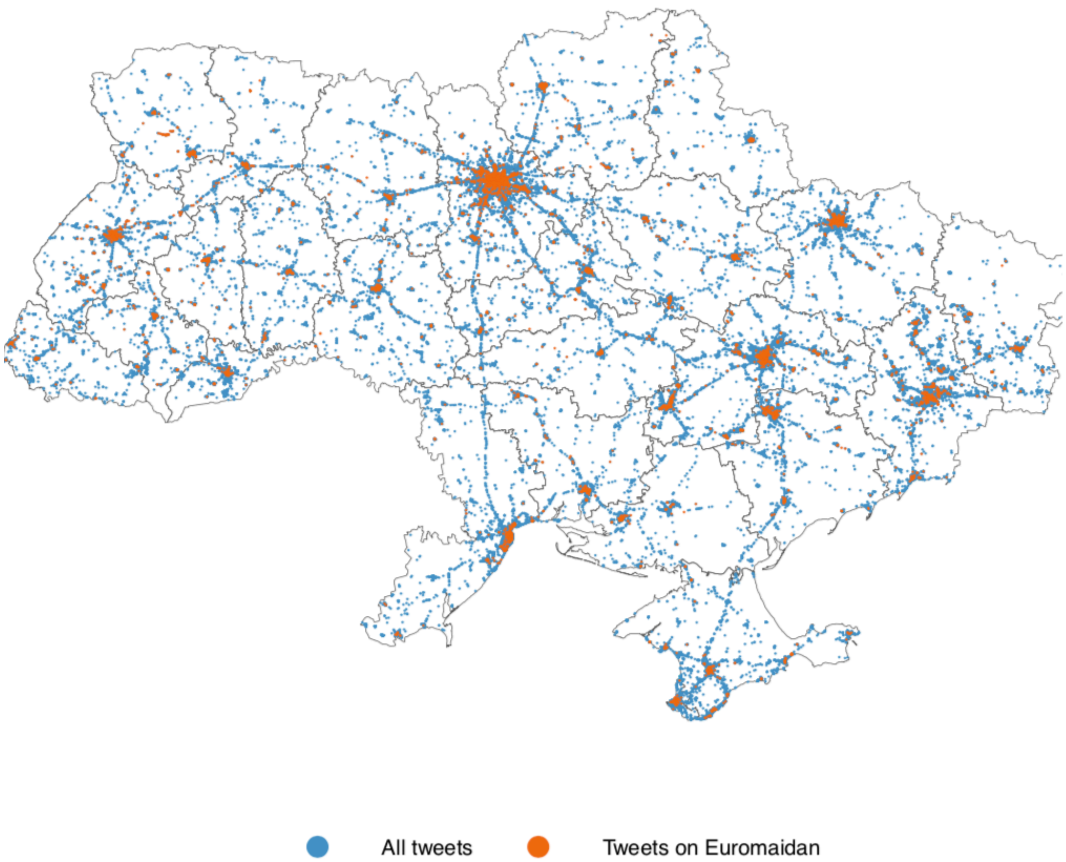


Figure 5: Spatial distribution of geo-coded tweets and tweets mentioning Euromaidan between Dec, 2013 and Feb, 2014

1. We first map each tweet and each protest to council polygons. Let $protest_{it}$ denote a protest in a council i on day t. For each council-day, we calculate the total number of tweets ($tweets\_all_{it}$), the total number of tweets on Euromaidan ($tweets\_maidan_{it}$), the number of tweets with each tweet weighted by the number of followers ($tweets\_followers\_all_{it}$), and the number of tweets on Euromaidan with each tweet weighted by the number of followers ($tweets\_followers\_maidan_{it}$).

2. We then use the random forest algorithm with the binary outcome variable $protest_{it}$ and the four council-day measures of Twitter activity as predictors. Since protest

events are rare, we over-sample council-days with recorded protests to improve the predictive accuracy (Muchlinski et al., 2016). For each council day, this procedure generates a predicted probability of protest, π_{it}.

3. For each council i, we calculate the number of predicted protests by adding the number of days in that council where the predicted probability of protest exceeded 50%, that is, $protest_i = \sum_t \mathbb{1}\{\pi_{it} > 0.5\}$.

The figure below plots the value of each of the four social media features against the predicted number protests. These patterns make intuitive sense: more protests are predicted in locations with higher overall Twitter activity and the activity of well-connected users of Twitter. This is consistent with the existing literature on measuring protests via Twitter (Wilson, 2017).

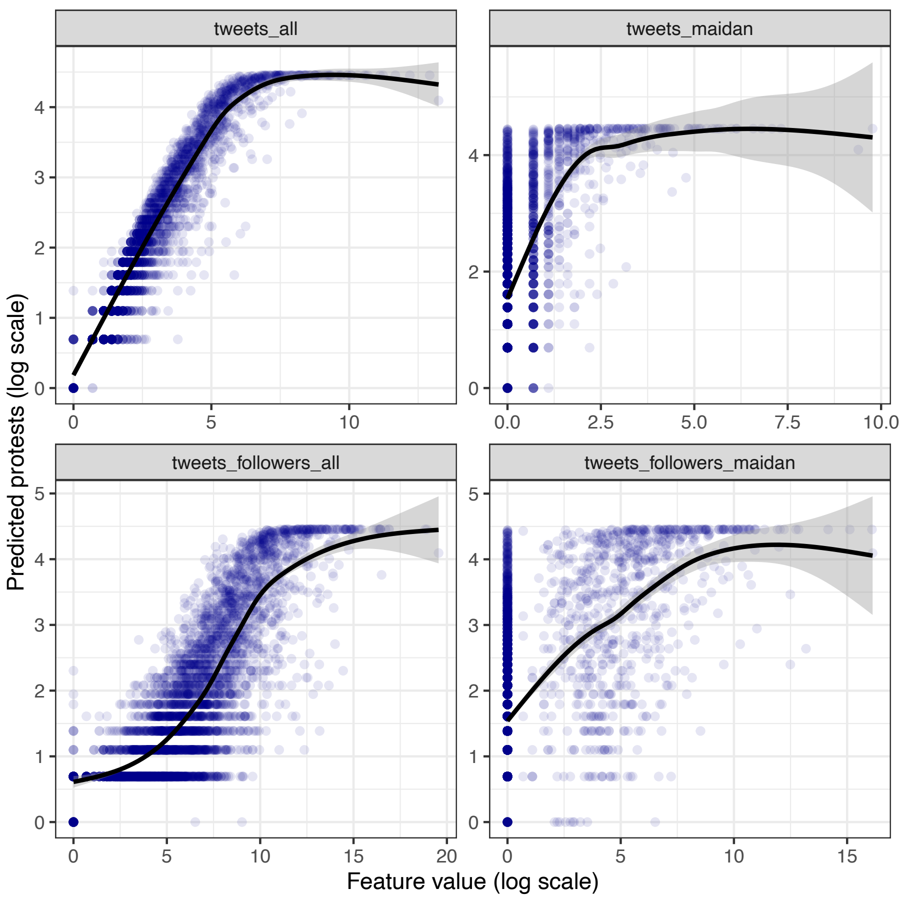


Figure 6: Value of four social media features and the predicted number protests.

D.3. Rayon-level analysis of protests

The table below shows estimates for regressions that account for pre-removal protests conducted at the level of municipality (*rayon*). We see that the effects of removals remain positive, large, and significant even at highly conservative levels in all three panels, whereas protest variables in rayons without monuments are not significant in all three panels. The reported results on removals are, therefore, robust to the level of aggregation, whereas the results on protests are not.

	Rayons with monuments N = 806		Rayons without monuments N = 314	
	Overall	Pro-Soviet	Overall	Pro-Soviet
Panel A: Protests reported in the media				
Protests	0.4*	0.3	0.1	0.3
	(0.1)	(0.2)	(0.1)	(0.1)
Removals	2.3***	2.3***		
	(0.5)	(0.4)		
Panel B: Tweets on "Euromaidan"				
Protests	0.3***	0.3***	0.0	−0.1
	(0.0)	(0.0)	(0.1)	(0.2)
Removals	2.3***	2.3***		
	(0.5)	(0.4)		
Panel C: Protests predicted from social media				
Protests	0.6***	0.9***	0.4	0.2
	(0.1)	(0.2)	(0.4)	(0.5)
Removals	2.5***	2.5***		
	(0.5)	(0.4)		

Table D.9: Protest as an alternative mechanism (rayon level analysis).

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