Appendices: "Repressed Memories"

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A0. Theoretical Appendix

The following is a formalization of the theoretical argument in the main text. Suppose that there are Y_t historical markers on a city block at time t (e.g. memorial plaques to victims). The number of markers can be as low as 0 and as high as κ, the total number of terror victims who resided on that block (*severity level*). We assume there cannot be more markers than victims.

As actors petition to memorialize victims, the number of markers grows at *recognition rate* $\rho \in (0, \infty)$. Opponents of memorialization deny petitions and remove markers, at *suppression rate* $\theta \in [0, \rho]$. The following equation specifies the change in Y over time, as a function of recognition (ρ), suppression (θ), and severity (κ):

$$\frac{dY}{dt} = \rho Y_t \left(1 - \frac{Y_t}{\kappa}\right) - \theta Y_t \tag{A1}$$

This expression assumes a logistic rate of growth in markers. This rate of growth is highest where relatively few victims have been memorialized, and tapers off as this proportion rises $\left(\frac{Y_t}{\kappa} \to 1\right)$.

Over time, this process converges to one of two equilibria: one where the number of markers falls to zero ($Y_{eq} = 0$, "erasure"), and one where the number is above zero but no larger than κ ($0 < Y_{eq} \leq \kappa$, "remembrance").

Proposition 1. $\forall\ \kappa > 0$, $\exists\ Y_{eq} : Y_{eq} > 0$ *if* $\rho > \theta$ *and* $Y_{eq} = 0$ *if* $\rho = \theta$.

Proof. Define an equilibrium of equation (A1) as a fixed point satisfying $\frac{dY}{dt} = 0$. Setting equation (A1) equal to zero and solving for Y, we obtain:

$$Y_{eq} = \kappa \left(1 - \frac{\theta}{\rho}\right) \tag{A2}$$

This equilibrium exists (i.e. yields non-negative values of Y_{eq}) for all $\kappa \geq 0$, $\rho > 0$ and $0 \leq \theta < \rho$. The expression in (A2) will be equal to zero if either (a) no victims had resided on the block, $\kappa = 0$, or (b) the suppression rate matches the recognition rate, $\rho = \theta$. In order for a non-zero number of markers to remain in equilibrium ($Y_{eq} > 0$), both of the following must be true: (a) at least one victim must have resided on the block, $\kappa > 0$, and (b) the recognition rate must exceed the suppression rate, $\rho > \theta$. □

In any city block where at least one resident had been repressed, memorials to victims will become permanent ($Y_{eq} > 0$) only if the recognition rate exceeds the suppression rate ($\rho > \theta$). Otherwise, memorials — if they do exist — will be only temporary, gradually yielding to a complete erasure of victims' public memories ($Y_{eq} = 0$).

We now turn our attention to how exposure to repression (κ) affects memorialization both in equilibrium, and on the way to the equilibrium.

Predictions. *As the number of victims increases, (1) the observed number of historical markers increases, but (2) the share of markers removed by each point in time decreases.*

Proof. We first derive these results for the "remembrance" equilibrium. To show that the equilibrium number of markers is increasing in exposure, we take the derivative of (A2) with respect to κ, $\frac{dY_{eq}}{d\kappa} = 1 - \frac{\theta}{\rho}$. This expression — marginal effect of κ on Y_{eq} — is positive, increasing in ρ and decreasing in θ.

To show that this result holds at any point in time, we rearrange equation (A1) as an initial value problem:

$$Y_t = \frac{\kappa Y_0(\rho - \theta)}{\rho Y_0 - e^{-t(\rho-\theta)}(\rho Y_0 - \kappa(\rho - \theta))} \tag{A3}$$

where Y_0 is the number of historical markers at time 0. The derivative of this expression with respect to κ $\left(\frac{dY_t}{d\kappa} = \frac{\rho Y_0^2(\rho-\theta)e^{t(\rho-\theta)}\left(e^{t(\rho-\theta)}-1\right)}{\left(\theta\kappa-\rho\left(\kappa+Y_0\left(e^{t(\rho-\theta)}-1\right)\right)\right)^2}\right)$ is positive as long as $\rho > \theta \geq 0$.

To show that $\frac{dY_t}{d\kappa} > 0$ even on the path to the "erasure" equilibrium, let's consider a special case where $\theta = \rho = 1$. Equation (A1) simplifies to $\frac{dY}{dt} = -\frac{Y_t^2}{\kappa}$, and the initial value problem becomes $Y_t = \frac{\kappa Y_0}{\kappa + tY_0}$. Taking the derivative with respect to κ, we obtain $\frac{dY_t}{d\kappa} = \frac{tY_0^2}{(\kappa+tY_0)^2}$, which is positive for all $Y_0 > 0$.

To additionally show that fewer markers will be removed in places with a high number of victims, we investigate the dynamics of memorialization at different values of κ using numerical integration. In so doing, we consider the same "erasure" scenario as before ($\theta = \rho = 1$), where opponents are determined to deny or remove all markers, and where the eventual outcome is an equilibrium with zero memorials.

Figure A0.1 reports the proportion of memorials removed by an arbitrary point in time ($t = 100$), for every value of κ between 0 and 1000. Where κ is closer to zero, almost all memorials will have been removed by this time. As κ rises, the proportion declines.

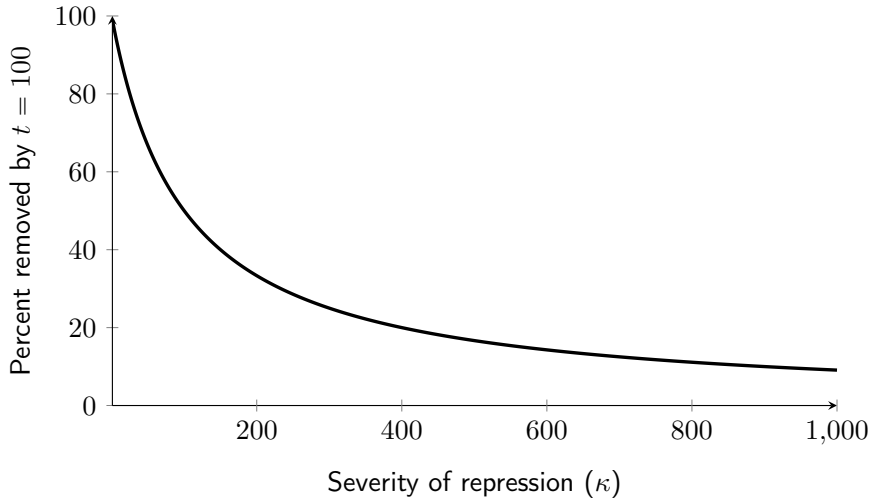
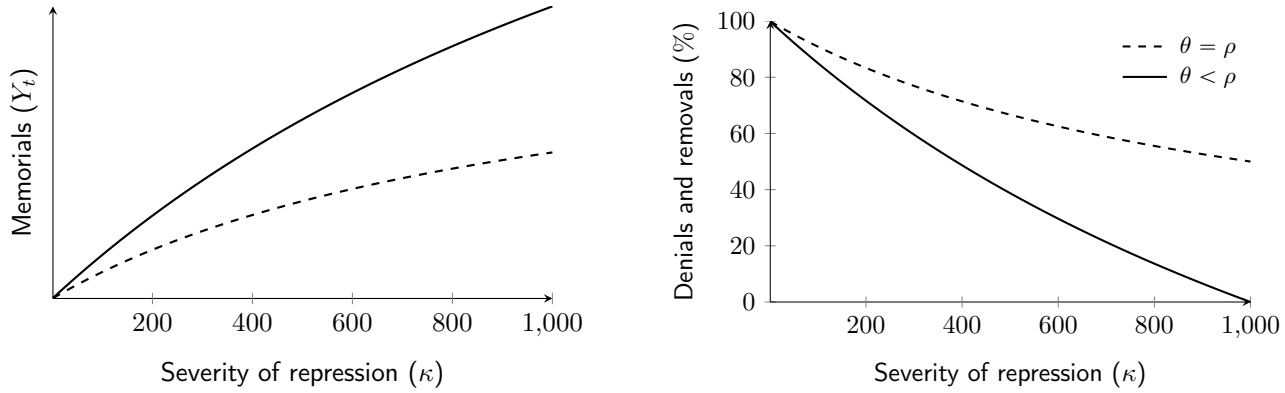


Figure A0.1: **Fewer cumulative removals where there are more victims**. Values reported are $\mathbb{E}\left[100 \cdot \left(\frac{Y_0 - Y_t}{Y_0}\right) \mid \rho = \theta = 1, Y_0 = 1, \kappa\right]$, obtained through numerical integration of differential equation (A1) over time interval $(0, 100)$, iterated across $1 \leq \kappa \leq 1000$.

Because the system proceeds toward an "erasure" equilibrium as $t \to \infty$, the curve in Figure A0.1 will gradually flatten to a horizontal line at 100%. However, convergence is slower at higher values of κ, even when $\theta = \rho$. For example, if we define "convergence" as $|\Delta Y_t| < 0.00001$, a system with $\kappa = 1$ (all else as in Figure A0.1) converges at $Y_t = 0$ at $t = 316$, but a system with $\kappa = 1000$ won't converge until $t = 9001$. □

Figure A0.2 reproduces the predictions in Figure 1 in the main text, with numerical integration details. For the "high suppression-to-recognition" case (dashed line), $\theta = \rho = 1$, as in Figure A0.1. For the "low suppression-to-recognition" case (solid line), $\theta = 0.999, \rho = 1$. All other parameters were the same as in Figure A0.1.



(a) Number of memorials at time $t = 1000$

(b) Percent denied or removed by time $t = 1000$

Figure A0.2: **Interaction between severity and the suppression-recognition ratio**. Values obtained through numerical integration of differential equation (A1) over time interval $(0, 1000)$, iterated across $1 \leq \kappa \leq 1000$. Quantities reported in panel (a) are $\mathbb{E}[Y_t | \rho = 1, \theta = 0.999, Y_0 = 1, \kappa]$ (solid line) and $\mathbb{E}[Y_t | \rho = \theta = 1, Y_0 = 1, \kappa]$ (dashed line). Panel (b) reports $\mathbb{E}\left[100 \cdot \left(\frac{Y_0 - Y_t}{Y_0}\right) | \rho = 1, \theta = 0.999, Y_0 = 1, \kappa\right]$ (solid) and $\mathbb{E}\left[100 \cdot \left(\frac{Y_0 - Y_t}{Y_0}\right) | \rho = \theta = 1, Y_0 = 1, \kappa\right]$ (dashed).

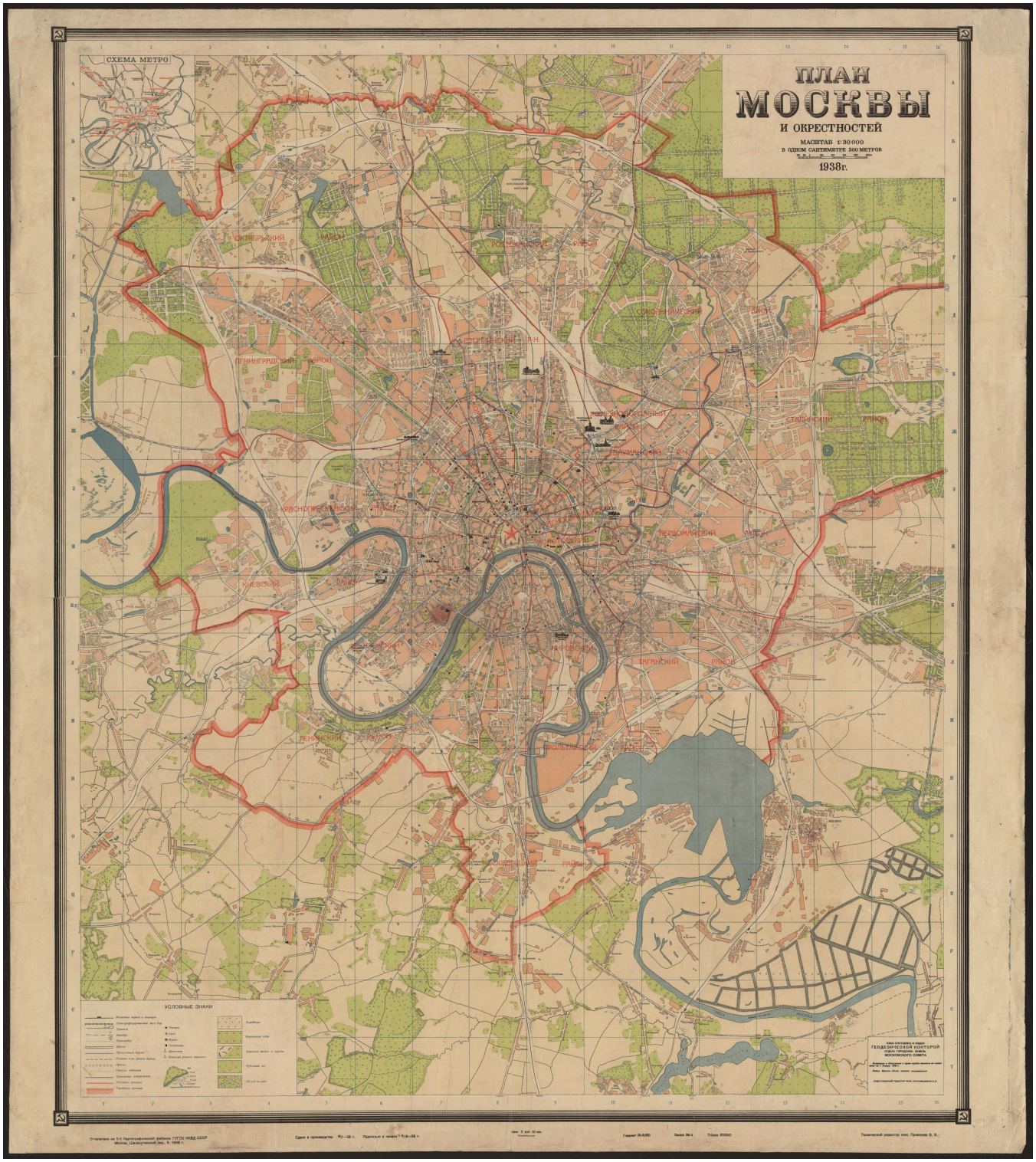
A1. Data on the Great Terror in Moscow

Figure A1.3 shows a scan of the tactical map of Moscow from the NKVD's Main Directorate for Geodesic Surveying and Cartography (Krasil'nikov, 1938).[1] The NKVD map contains detailed, street-level geometries (1:30,000 resolution, or 300 meters on Earth to one centimeter on paper), and is a primary source for our block-level data on Moscow. We supplemented this source with Memorial's *Victims of State Terror in Moscow* database (mos.memo.ru) and *Topography of Terror* (topos.memo.ru). For the former, we scraped the victims' records from the website and geocoded their residential addresses at time of arrest. For the latter, we scraped `json` geometries from the online map interface, along with relevant metadata.

We georeferenced the map image using intersections of graticule lines, and key landmarks and street intersection (Figure A1.4a). We then vectorized, through image tracing, the polygons representing city blocks. Overall, there are 5,400 city blocks in this dataset, including 1646 (30%) in neighboring parts of Pidmoskov'ya that had not yet been incorporated into the city proper. Our geocoded Memorial *Victims of State Terror in Moscow* dataset contains names, residential addresses and biographical information for 11,035 Moscow residents executed by the secret police. By overlaying these polygons with Memorial data, we can see how many people the NKVD arrested and executed from each block (dots and polygons in Figure A1.4c).

[1] For details on our Saint Petersburg data, see Section A4.

Figure A1.3: **Scan of map from** Krasil'nikov (1938).



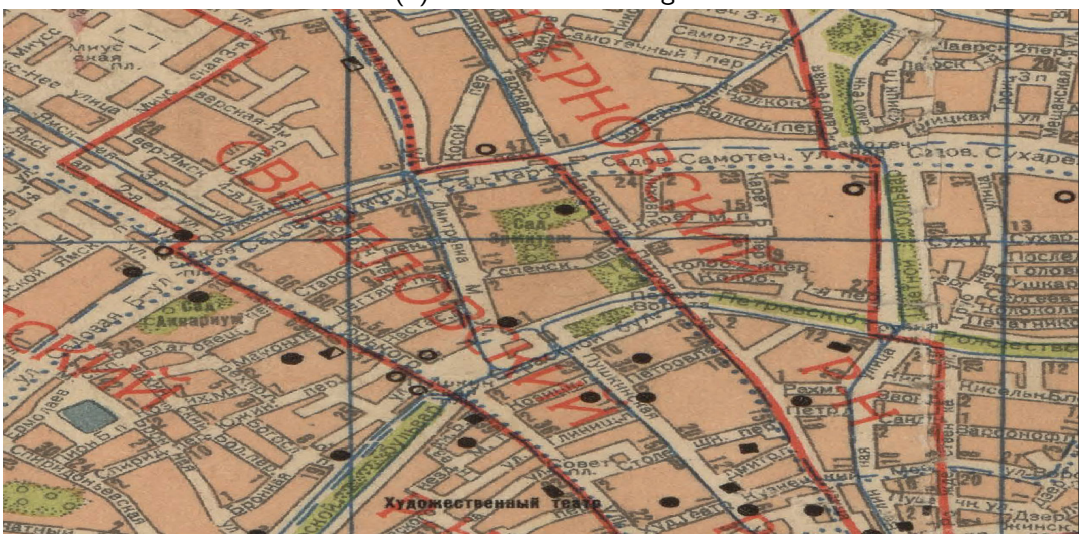
Following the same vectorization procedure, we used the NKVD map to extract the borders of Moscow's city districts as they existed in 1936-1960. In addition to exploiting border discontinuities across RO NKVD jurisdictional boundaries, this last feature allows us to link our block-level data to district-level population counts from the 1939 Soviet Census (Central Statistical Directorate of USSR, 1939). This permits us to measure NKVD

executions not only as raw counts per block, but also as a (rough) proportion of local residents. Because the 1926 census used different, older district boundaries, which were not valid after 1936, we used the 1939 census figures (but see Wheatcroft 1990). We used the district-level counts to estimate block-level population via dasymetric mapping (i.e. excluding non-residential blocks, parks, and other places where people did not live) (Mennis, 2003).

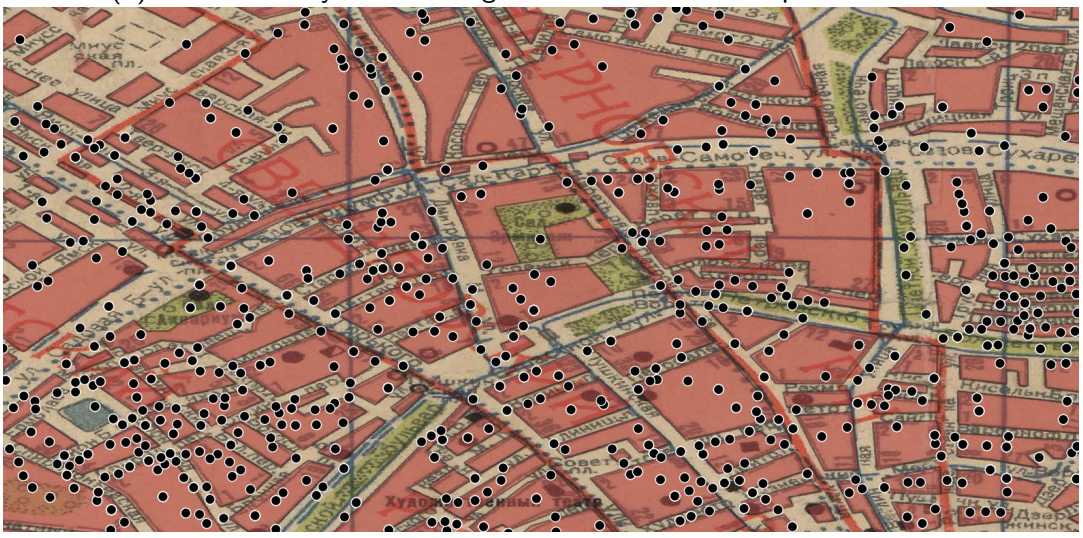
To make dasymetric mapping feasible, we classified the city blocks by zoning/land use, with information from Memorial's *Topography of Terror* (topos.memo.ru) and various supplementary sources. Zoning information allows us to (a) exclude non-residential areas from dasymetric interpolation, (b) include mixed-use zoning fixed effects for the residential blocks in our regression models, and (c) calculate measures like "intra-troika distance."

Figure A1.4: **Close-up of area around Pushkin Square**.

(a) Georeferenced image



(b) Vectorized city blocks and geocoded addresses of repression victims



A2. Robustness Tests

A2.1. Spatial Autocorrelation

To account for spatial dependence in the distribution of commemorative markers over city blocks, we extend our core model specification to accommodate a spatial random effect τ:

$$y_i = g^{-1}\left(\gamma \cdot \log(\text{Repression}_i) + \beta' \mathbf{X}_i + \text{District}_{k[i]} + \text{Zoning}_i + f(\text{Long}_i, \text{Lat}_i) + \tau_i + \epsilon_i\right) \tag{A4}$$

where $\mathbb{E}[\tau] = 0, \text{Cov}(\tau) = \sigma^2 \mathbf{R}$, and $\mathbf{R}$ is a matrix that defines the spatial dependence structure. We consider two covariance functions here. The first is a conditional autoregressive (CAR) function, which specifies $\mathbf{R}$ as:

$$\mathbf{R} = (\mathbf{I} - \rho \mathbf{W})^{-1} \mathbf{M} \tag{A5}$$

where $\mathbf{I}$ is an identity matrix, $\mathbf{W}$ is a row-standardized spatial weights matrix, and ρ is a spatial autocorrelation parameter that determines the magnitude and direction of the neighborhood effect ($\rho > 0$ indicates that neighboring observations have similar values, $\rho < 0$ indicates that neighbors have dissimilar values). We define $\mathbf{W}$ through queen contiguity, where $0 < w_{ij} \leq 1$ if blocks i and j are adjacent and $w_{ij} = 0$ otherwise, and $\sum_j w_{ij} = 1$. $\mathbf{M}$ is a symmetry condition matrix, such that $m_{ii} > 0$ and $w_{ij} m_{ji} = w_{ji} m_{ij}$.

The second specification we consider uses a simultaneous autoregressive (SAR) spatial covariance function,

$$\mathbf{R} = [(\mathbf{I} - \rho \mathbf{W})(\mathbf{I} - \rho \mathbf{W})']^{-1} \tag{A6}$$

where, unlike the symmetry requirements in equation (A5), $\mathbf{W}$ is not necessarily symmetric.

Table A2.1 reports estimates from both sets of spatial autogressive models. In the case of petitions, $\hat{\gamma}$ coefficient estimates are numerically close to those in the (non-autoregressive) main specification in Table 1 in the main text, still positive and statistically significant. Our previous specification estimated a 0.3 percentage point (pp) rise in petitions for each percentage-point increase in repression, and the CAR and SAR models both estimate this rise to be 0.26 percentage points. These results, along with the positive estimate for $\hat{\rho}$, suggest that spatial autocorrelation can account for some, although not all, of the estimated repression effect.

In the case of denials and removals, the $\hat{\gamma}$ coefficient estimates are negative, significant, and also numerically close to those in the main text. Previously, we estimated that each percentage point increase in repression yields a 10.3 pp decline in denials or removals; here, as well, the estimate is for an 12 pp decline.

Outcome	Petitions		Denied/Removed (%)	
Model	1. CAR	2. SAR	3. CAR	4. SAR
Estimate	0.26	0.26	-11.9	-11.9
Std. error	(0.01)**	(0.01)**	(1.01)**	(1.01)**
Rayon FE	✓	✓	✓	✓
Zoning FE	✓	✓	✓	✓
$\hat{\rho}$	0.55	0.57	0.52	0.01
Pseudo R^2	0.5	0.5	0.25	0.25
RMSE	0.33	0.33	26.02	26.02
AIC	2100	2098.1	10774.7	10774.7
N	3305	3305	1191	1191

Estimates from model in Equation A4 with conditional (CAR) and simultaneous autoregressive (SAR) covariance functions. Observations (blocks) weighted by population size. Significance levels (two-tailed): $^{\dagger}p < 0.1$; $^{*}p < 0.05$; $^{**}p < 0.01$.

Table A2.1: **Severity of repression and memorialization**, spatial models.

A2.2. Discontinuities Across District Borders

Our next set of analyses is motivated by the observation that RO NKVD branches — although subject to the same quotas within Moscow's city limits — had some discretion in how they implemented central orders. The junior and mid-level officers who staffed these local units were the ones who translated directives and quotas into the language of criminal investigations, assembled lists of names, detained and interrogated suspects, built the "criminal cases" against them, and — after sentencing — carried out executions. Although we cannot directly observe how zealous or cautious a given NKVD official was, we can observe some of the consequences of this discretion. For example, arrest levels (and quotas) were strongly correlated with local population size and other structural considerations, like logistics and proximity to certain government and industrial sites (Appendix A3). If local levels of repression were significantly higher or lower than these observable factors would predict, administrative discretion may help explain this variation.

To exploit variation across district borders, we implement a fuzzy regression discontinuity design (FRDD), where the forcing variable is distance from a city block to the nearest city district border. Following Rozenas, Talibova and Zhukov (2024), we first estimate how much the level of repression in each district deviated from what we would expect, given observables like population, geographic area, distance to the nearest industrial site, and the average "intra-troika" distance in the RO NKVD's jurisdiction. Our first-stage equation is:

$$\text{Repression}_k = \alpha + \beta_1 \cdot \log(\text{Population}_k) + \beta_2 \cdot \text{Area}_k + \beta_3 \cdot \text{Industry} + \beta_4 \cdot \text{Troika}_k + \epsilon_k \tag{A7}$$

where k indexes city districts. We take the residuals from this model, and select (with replacement) pairs of adjacent districts with highly divergent levels of repression that cannot be explained by these basic background characteristics (i.e. where the absolute difference in average residuals is at least one standard deviation).[2] To ensure that treated and control cases are as similar and proximate to each other as possible, we extract city blocks located within a 100 meter bandwidth of these district borders.

Figure A2.5 shows the 200 city blocks we selected for FRDD analysis. Black blocks are located in high-repression border areas; white blocks are in low-repression areas. Dotted lines represent city district boundaries. The selected blocks are all near the center of Moscow, inside the Garden Ring and (future) Third Ring roads.

We define our forcing variable, d_{ik} as the distance from block i in district k to the border of the neighboring district, such that $d_{ik} < 0$ in lower-repression districts and $d_{ik} > 0$ in higher repression ones. Figure A2.6 plots levels of repression as a function of d_{ik}. On the left are blocks in lower-repression districts ($d_{ik} < 0$), and on the right are blocks in higher-repression districts ($d_{ik} > 0$). In the middle ($d_{ik} = 0$) is a discontinuous rise in executions as one crosses the border from less to more repressive districts.[3] Covariate balance tests (Figure A2.7) suggest that repression is the only observed variable with a statistically significant discontinuity across borders.

Our FRDD estimating equations are the following:

$$\begin{aligned} \log(\text{Repression}_i) &= \alpha \cdot \mathbb{1}\{\delta_{ik} > 0\} + f_1(\delta_{ik}) + \epsilon_{1i} \\ y_i &= \gamma \cdot \log(\widehat{\text{Repression}}_i) + f_2(\delta_{ik}) + \epsilon_{2i} \end{aligned} \tag{A8}$$

where f_1 and f_2 are cubic splines of δ_{ik}, and $\mathbb{1}\{\delta_{ik} > 0\}$ is an instrument for repression.

Table A2.2 reports the FRDD estimates, which align in direction with the fixed effect estimates in Tables 1 and A3.8. According to Model 1, a one percentage point increase in repression is associated with a 1.23 pp increase in petitions, and an 11 pp decline in denials and removals. While the FRDD estimate for denials and removals loses it significance, the magnitude of the first point estimate is three times larger than earlier.[4]

Table A2.5 re-estimates our FRDD models with a per capita measure of repression, adjusting the estimating equations and weights accordingly. These additional estimates are consistent with the results reported here.

[2] We select pairs of adjacent districts (k, k') where $|\bar{\epsilon}_k - \bar{\epsilon}_{k'}| \geq \text{SD}(\epsilon_k)$. $\bar{\epsilon}_k$ is average residual for district k from Equation A7.

[3] Bias-corrected local polynomial estimate (Calonico, Cattaneo and Titiunik, 2015) is 2.09 (S.E.= 0.76).

[4] Note that the FRDD estimate represents a different quantity of interest (i.e. local average treatment effect due to proximity to district borders). This discrepancy may also reflect attenuation bias due to measurement error in the original treatment.

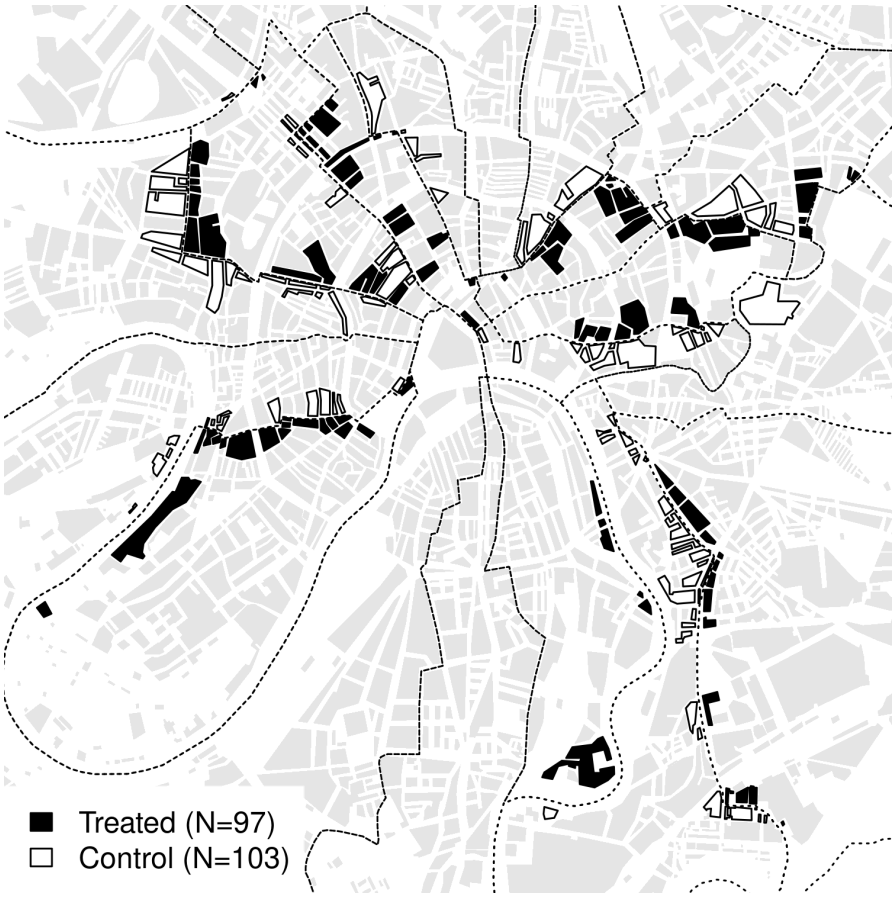


Figure A2.5: **City blocks used in RDD analyses**.

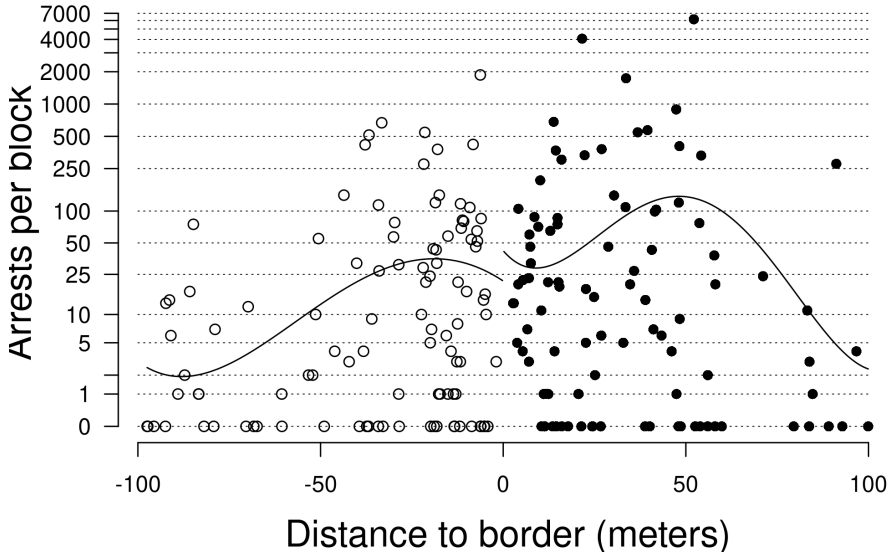


Figure A2.6: **Discontinuity at city district borders**.

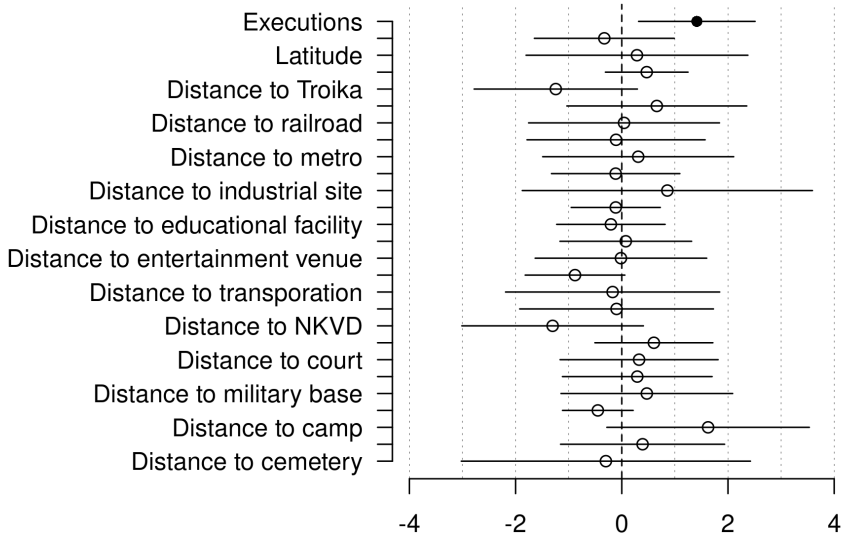


Figure A2.7: **Covariate balance at city district borders**.

Outcome	Petitions	Denied/Removed (%)
Model	1. FRDD	2. FRDD
Estimate	1.23	-11.37
Std. error	(0.49)*	(19.52)
First stage $\mathcal{F}$ score	3.05†	4.75*
Wu-Hausman	5.61*	0
Adj. R^2	0.28	0.18
RMSE	56.54	1927.75
N	200	147

Estimates from fuzzy regression discontinuity design. Treatment is number of city block residents executed (logged). Outcome is log-transformed. Robust standard errors in parentheses, clustered by rayon. Observations (blocks) weighted by population size. Significance levels (two-tailed): $^{\dagger}p < 0.1$; $^{*}p < 0.05$; $^{**}p < 0.01$.

Table A2.2: **Severity of repression and memorialization**, FRDD estimates.

A2.3. Per Capita Repression

While our main specifications measure exposure to repression as the absolute number of executions per block, we now consider a per capita measure, where repression is the percent of block residents whom the NKVD executed. The denominator is the block-level population estimate we obtained via dasymetric interpolation from the 1939 Soviet census (Appendix A1), and the same measure that we use as weights for our main models in Table 1.

Table A2.3 re-estimates the linear and binomial models in Table 1 with the per capita treatment variable. Table A2.4 re-estimates the CAR and SAR models from Table A2.1 in the previous section. Table A2.5 does the same for our FRDD models from A2.2. Due to re-scaling, these estimates differ from the originals in their numerical magnitude, but not in sign or significance (except Table A2.5, where one estimate regains significance).

Outcome	Petitions	Denied/Removed (%)	
Model	1. Linear	2. Linear	3. Binomial
Estimate	1.13	-21.97	-1.22
Std. error	(0.09)**	(5.64)**	(0.4)**
Rayon FE	✓	✓	✓
Zoning FE	✓	✓	✓
Adj. R^2	0.53	0.25	
Pseudo R^2			0.34
RMSE	17.09	1381.07	0.29
N	3305	1191	1191

Estimates from Linear and Binomial fixed effect regression models. Treatment is percent of city block residents executed (logged). Outcome is log-transformed in Linear model, rescaled as proportion between 0 and 1 in Binomial model. Robust standard errors in parentheses, clustered by rayon. All models include spatial spline and block-level covariates. Observations (blocks) weighted by population size. Significance levels (two-tailed): $^{\dagger}p < 0.1$; $^{*}p < 0.05$; $^{**}p < 0.01$.

Table A2.3: **Per capita repression and memorialization**.

Outcome	Petitions		Denied/Removed (%)	
Model	1. CAR	2. SAR	3. CAR	4. SAR
Estimate	0.49	0.49	-8.14	-8.14
Std. error	(0.02)**	(0.02)**	(2.21)**	(2.21)**
Rayon FE	✓	✓	✓	✓
Zoning FE	✓	✓	✓	✓
$\hat{\rho}$	0.95	0.56	0.02	0.02
Pseudo R^2	0.4	0.4	0.16	0.16
RMSE	0.36	0.36	27.4	27.4
AIC	2663.7	2664.7	10890.3	10890.3
N	3305	3305	1191	1191

Treatment is percent of city block residents executed (logged). See note under Table A2.1 for details.

Table A2.4: **Per capita repression and memorialization**, spatial models.

Outcome	Petitions	Denied/Removed (%)
Model	1. FRDD	2. FRDD
Estimate	4.22	-40.91
Std. error	(1.97)*	(74.92)
First stage $\mathcal{F}$ score	3.88†	3.89†
Wu-Hausman	4.79*	0.06
Adj. R^2	0.36	0.11
RMSE	58.29	2003.05
N	200	147

Estimates from fuzzy regression discontinuity design. Treatment is percent of city block residents executed (logged). Outcome is log-transformed. Robust standard errors in parentheses, clustered by rayon. Observations (blocks) weighted by population size. Significance levels (two-tailed): $^{\dagger}p < 0.1$; $^{*}p < 0.05$; $^{**}p < 0.01$.

Table A2.5: **Per capita repression and memorialization**, FRDD estimates.

A3. Additional Analyses

A3.1. Predictors of Repression

Our FRDD analyses exploit differences in repression across city district lines, net of observable predictors of NKVD activity. To establish what some of these observables might have been, we use Bayesian Model Averaging (BMA) (Madigan and Raftery, 1994; Raftery et al., 2022). This approach computes posterior probabilities over models with all possible combinations of relevant covariates, and constructs a weighted average over the model space. Our quantities of interest are model-weighted posterior distributions for coefficients:

$$P(\beta|\text{Repression}, X) = \sum_{m}^{2^K} P(\beta|M_m, \text{Repression}, X)P(M_m|\text{Repression}, X) \tag{A9}$$

where M_m denotes the m-th model, and $P(M_m|\text{Repression}, X)$ are posterior model probabilities (model weights):

$$P(M_m|\text{Repression}, X) = \frac{P(\text{Repression}|M_m, X)P(M_m)}{\sum_{s}^{2^K} P(\text{Repression}|M_s, X)P(M_s)} \tag{A10}$$

where $P(M_m)$ is the prior probability of model m (we use a uniform prior, $P(M_m) = \frac{1}{2^K}$) and $P(M_m|\text{Repression}, X)$ is the marginal likelihood of model m.[5] Our core model specification is the following:

$$\text{Repression}_i = g^{-1}\left(\beta'\mathbf{X}_i + \text{District}_{k[i]} + \epsilon_i\right) \tag{A11}$$

where $g^{-1}(\cdot)$ is an inverse link function. We consider two sets of models: (1) with a Gaussian link function and logged outcome, $\log(\text{Repression}_i)$, and (2) with a quasi-Poisson link function and the outcome on a natural scale. The vector X may contain any combination of: (a) block population (logged), to account for the number of potential targets, (b) intra-troika distance, to account for the logistical cost of repression, (c) distance to the nearest industrial site, to account for ease of targeting by factory lists, (d) longitude and latitude, to account for spatial trends, (e) geographic area, to account for the size of zones of operation, and (f) district fixed effects. The model space includes $K = 28$ covariates and $2^{28} = 268{,}435{,}456$ potential model specifications.

Table A3.6 reports inclusion probabilities and posterior means and standard deviations for the BMA analysis. The strongest predictors of repression are population size, intra-troika distance, distance to industrial site and, to a lesser extent, area. These are the covariates we include in the first-stage FRDD specification (Equation A7).

[5] We use a BIC approximation, $P(\beta_1 \neq 0|\text{Repression}, X) = \sum_{j:\beta_1 \in M_j} \frac{\exp(BIC_j/2)}{\sum_i^K \exp(BIC_i/2)}$, for inclusion probability priors.

Variable	(1) Gaussian $P(\hat{\beta} \neq 0)$	(1) Gaussian Post. Mean	(2) Quasi-Poisson $P(\hat{\beta} \neq 0)$	(2) Quasi-Poisson Post. Mean
Intercept	100	-175.9 (62.2)	100	-179.8 (130.3)
Population (log)	100	0.2 (0.02)	100	0.8 (0.1)
Distance to Troika	100	-0.2 (0.02)	100	-0.9 (0.1)
Distance to industrial site	100	-0.1 (0.02)	99.5	-0.3 (0.1)
Longitude	100	4.1 (0.4)	87.3	5.9 (2.6)
Latitude	18.1	0.4 (1)	18.4	-0.8 (2)
Area	95.6	3.1 (1.1)	75	-4.9 (3.7)
Dzerzhinskiy	1.2	0.0003 (0.01)	29.3	0.2 (0.4)
Frunzenskiy	100	0.4 (0.1)	17.6	0.1 (0.3)
Kievskiy	5.8	0.003 (0.04)	11.2	0.1 (0.2)
Kirovskiy	6	-0.01 (0.05)	78.1	-0.7 (0.5)
Kominternovskiy	95.7	0.5 (0.2)	3.5	-0.0003 (0.1)
Krasnogvardeyskiy	99.9	0.7 (0.2)	8.9	0.04 (0.2)
Krasnopresenskiy	15.2	0.03 (0.1)	75.2	0.4 (0.4)
Kuybyshevskiy	100	1.4 (0.2)	92.3	0.6 (0.3)
Leningradskiy	3.5	-0.004 (0.02)	6.2	0.01 (0.2)
Leninskiy	16.4	0.05 (0.1)	39.6	0.3 (0.4)
Molotovskiy	13.1	-0.04 (0.1)	34.2	-0.3 (0.4)
Moskvoretskiy	96.6	-0.4 (0.1)	80.6	-0.8 (0.4)
Oktyabrskiy	3.7	0.003 (0.02)	10.9	0.1 (0.3)
Pervomayskiy	100	-0.7 (0.1)	78.3	-1.1 (0.7)
Proletarskiy	100	-0.7 (0.1)	99.4	-1.6 (0.5)
Rostokinskiy	100	-0.4 (0.1)	23.3	0.2 (0.3)
Sokolnicheskiy	100	-0.8 (0.1)	78.6	-1.1 (0.6)
Sovetskiy	100	0.7 (0.1)	14.3	0.1 (0.2)
Stalinskiy	100	-0.7 (0.1)	78	-1.1 (0.6)
Sverdlovskiy	100	1.5 (0.2)	16.2	-0.1 (0.2)
Taganskiy	100	-0.6 (0.1)	75.1	-0.7 (0.5)
Zheleznodorozhnyy	12.6	-0.03 (0.1)	68.8	-0.5 (0.4)

$P(\hat{\beta} \neq 0)$ are posterior inclusion probabilities, scaled 0 to 100. Quantities reported under "Post. Mean" are means (standard deviations) of coefficient estimates' posterior distributions. 132 Gaussian models, 1018 quasi-Poisson models selected (28 covariates).

Table A3.6: **Predictors of Repression**, Bayesian Model Averaging

A3.2. Correlates of Rehabilitation

After Stalin's death in 1953, the Soviet Union began to (posthumously) rehabilitate some repressed individuals, clearing them of crimes and providing benefits for relatives (e.g., restoration of property rights, pensions, removal of the stigma of association with "enemies of the people"). This process gained steam after Nikita Khrushchev's secret speech denouncing Stalin's cult of personality at the 20th Party Congress in 1956, and accelerated under Perestroika and following the Soviet collapse. Authorities excluded those accused of serious political crimes from rehabilitation (e.g. Nazi collaboration, insurgency), but the sheer scale of Stalin's repression created practical challenges for sorting through the millions of other cases.

Because only rehabilitated individuals are eligible for *Last Address* petitions, it is worth considering how rehabilitated repression victims differ from the non-rehabilitated. To this end, we analyzed the demographic differences across the 2.85 million individuals included in Memorial (2014)'s *Victims of Political Terror in the USSR* database. Table A3.7 reports coefficient estimates from this model:

$$\text{Rehabilitation}_i = g^{-1}\left(\theta' \mathbf{X}_i + \epsilon_i\right) \tag{A12}$$

where $\mathbf{X}_i$ is a series of biographical attributes, including education, industry of employment, birth year, professional status, and republic of birth. Table A3.7 suggests that ethnic Russians, government workers, high-school graduates, managers and military personnel were the most likely to be rehabilitated.

Table A3.7: **Who was most likely to receive rehabilitation?** Sample includes all repression victims in Memorial's 'Victims of Stalinist Terror' database. Reference categories for education, ethnicity, industry and republic are 'secondary,' 'Russian,' 'government' and 'RSFSR.'

Dependent Variable:	Rehabilitated
Model:	(1)
	Logit
Variables	
Education = Higher	-0.37*** (0.08)
Education = Illiterate	-0.02 (0.34)
Education = Primary	-0.07 (0.50)
Education = Unknown	-1.1*** (0.14)
Ethnicity = Armenian	-0.62*** (0.13)
Ethnicity = Belarusian	-0.27 (0.52)
Ethnicity = Chechen	0.17 (0.30)
Ethnicity = Chinese	-0.47* (0.23)
Ethnicity = Estonian	-0.64*** (0.04)
Ethnicity = German	-0.20 (0.24)
Ethnicity = Greek	-0.65*** (0.05)
Ethnicity = Jewish	-1.6*** (0.38)
Ethnicity = Kabardin	-0.36*** (0.03)
Ethnicity = Kalmyk	-0.64*** (0.03)
Ethnicity = Korean	-0.36 (0.39)
Ethnicity = Latvian	-0.49*** (0.08)
Ethnicity = Lithianian	-0.61*** (0.16)
Ethnicity = Ossetian	-0.09 (0.14)
Ethnicity = Polish	-1.2*** (0.30)
Ethnicity = Tatar	0.20** (0.07)
Ethnicity = Ukrainian	-0.36** (0.13)
Industry = Agriculture	-0.87*** (0.15)
Industry = Commerce	-0.51** (0.19)
Industry = Construction	-0.57*** (0.05)
Industry = Culture/Arts	-0.35*** (0.09)
Industry = Econ/Finance	-0.65*** (0.12)
Industry = Education	-0.53*** (0.07)
Industry = Foreign	-1.1*** (0.16)
Industry = Forestry	-0.26* (0.11)
Industry = Health	-0.37*** (0.09)
Industry = Heavyindustry	-0.45*** (0.08)
Industry = Information/Accounting	-0.20* (0.09)
Industry = Logistics	-0.39*** (0.06)
Industry = Other	-0.47** (0.16)
Industry = Procurement	-0.39** (0.13)
Industry = RealEstate	-0.20 (0.17)
Industry = Residential	-0.70*** (0.16)
Industry = Retail/Food	-0.30*** (0.09)
Industry = Science	-0.60*** (0.03)
Industry = Service	-0.55** (0.17)
Industry = SocialOrganizations	-0.12 (0.25)
Industry = Transport/Communications	-0.55*** (0.08)
Industry = Unemployed	-0.88*** (0.21)
Industry = Unknown	-0.79*** (0.08)
Manager	0.11* (0.05)
Clergy	-0.03 (0.06)
Military	0.15*** (0.03)
Birth year	0.002 (0.006)
Fixed-effects	
Republic of birth	Yes
Fit statistics	
Observations	2,851,928
BIC	3,530,298.6

Clustered (Republic of birth) standard-errors in parentheses
*Signif. Codes: ***: 0.001, **: 0.01, *: 0.05, .: 0.1*

A3.3. Individual-Level Coefficient Estimates

Tables A3.8 and A3.9 report individual-level coefficient estimates, regressing petition (Models 1 and 2) and denial/removal (3 and 4) on the severity of repression and other predictors in Equation 2. Table A3.8 reports

estimates for "repression at home" and Table A3.9 "repression at work." The outcomes are log-transformed for columns 1 and 3 ($g(\cdot)$ is identity link), and binary in the Binomial models in columns 2 and 4 ($g(\cdot)$ is logit link). The predicted probabilities in Figures 4 and 5 in the main text are based on Models 2 and 4.

Outcome	Petition		Denied/Removed	
Model	1. Linear	2. Binomial	3. Linear	4. Binomial
Estimate	0.01	0.21	-0.08	-0.6
Std. error	(0.004)**	(0.07)**	(0.02)**	(0.15)**
Rayon FE	✓	✓	✓	✓
Zoning FE	✓	✓	✓	✓
Ethnicity FE	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓
Adj. R^2	0.03		0.17	
Pseudo R^2		0.06		0.19
RMSE	0.19	0.28	0.3	0.44
AIC	-4627.3	5679.2	564.2	1094.4
N	10121	9699	868	824

Treatment is number of residents from same street address executed (logged). Robust standard errors in parentheses, clustered by rayon. Model specification in Equation 2. Significance levels (two-tailed): $^{\dagger}p < 0.1$; $^{*}p < 0.05$; $^{**}p < 0.01$.

Table A3.8: **Severity of repression vs. neighbors and memorialization**, individual-level.

Outcome	Petition		Denied/Removed	
Model	1. Linear	2. Binomial	3. Linear	4. Binomial
Estimate	0.03	0.49	-0.02	-0.2
Std. error	(0.003)**	(0.03)**	(0.01)*	(0.07)**
Rayon FE	✓	✓	✓	✓
Zoning FE	✓	✓	✓	✓
Ethnicity FE	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓
Adj. R^2	0.06		0.14	
Pseudo R^2		0.12		0.19
RMSE	0.18	0.27	0.29	0.44
AIC	-4215	4037.4	453.2	822.6
N	7849	7448	636	594

Treatment is number of repression with same employer as victim (logged). See note under Table A3.8 for details.

Table A3.9: **Severity of repression vs. co-workers and memorialization**, individual-level.

A3.4. More Obstacles to Memorialization

The main text examined how several individual and block-level attributes — including victim's identity, political affiliation, social status, and local political opportunity structures — might moderate the relationship between the severity of repression and memorialization. We now present results for alternative measures of these attributes.

First, we consider whether patters for foreign-born victims are similar to those for non-Russian victims. We

expanded individual-level model (2) with interaction term $\log(\text{Repression}_j) \times \text{Foreign-born}_j$, where Foreign-born$_j$ is equal to 1 if j was born outside the original 1922 borders of the USSR, and 0 otherwise. Figure A3.8 reports predicted probabilities for native-born (solid) and foreign-born victims (dashed). The probability of a petition is significantly lower for the latter group, hovering around 0.04, irrespective of the severity of repression. By contrast, native-born victims' probability of petition rises from 0.06 (solitary) to 0.18 (maximum). The probability of denial or removal is consistently higher for foreign-born victims, but the difference is not statistically significant.

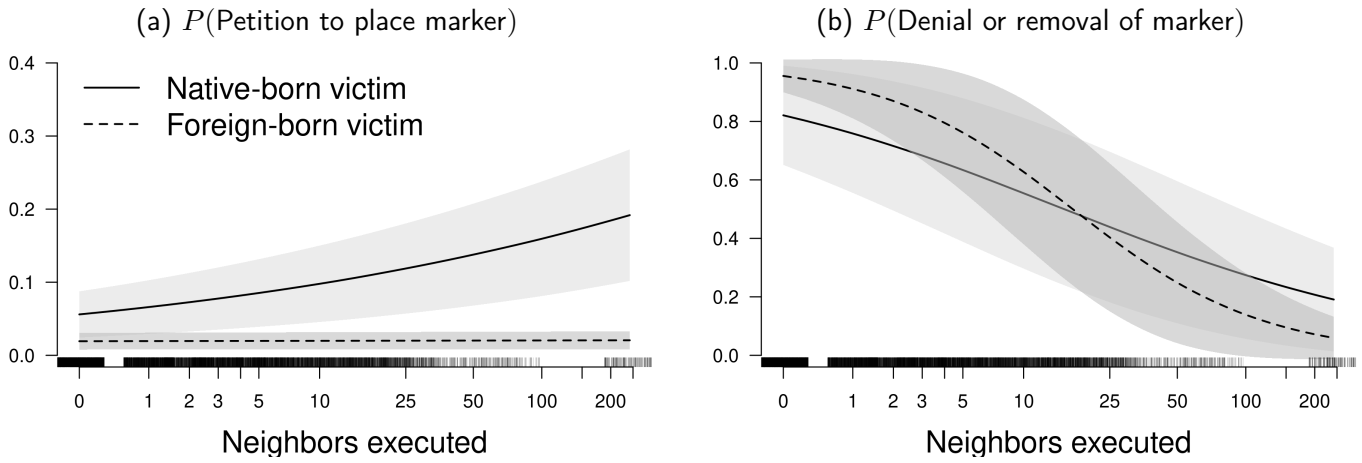


Figure A3.8: **Foreign-born victims' probability of memorialization**. Solid and dashed lines represent point estimates for victims born inside and outside of the USSR's 1922 borders; grey regions are bootstrapped 95% confidence intervals from 1000 simulations.

Second, we consider alternative measures of political affiliation with the Soviet regime. Figure A3.9 reports simulation results from another individual-level interactive model, examining rank-and-file party membership. Formally, the interaction term is $\log(\text{Repression}_j) \times \text{Party}_j$, where Party$_j$ is equal to 1 if j was a VKP(b) member at the time of arrest, and 0 otherwise. Party members' probability of petition is generally lower and less responsive to the local severity of repression, rising from 0.06 (solitary victims) to 0.09 (maximum), compared to 0.04 to 0.25 for non-members. The predicted probability of denial or removal for VKP(b) members is also less sensitive to repression severity — ranging from 0.81 to 0.29, compared to 0.87 to 0.05 for non-members.

We can further expand this analysis to include not only VKP(b) members (43% of victims), but also candidates (0.9%) and youth wing affiliates (0.3%). The results, in Figure A3.10, are nearly identical to Figure A3.9.

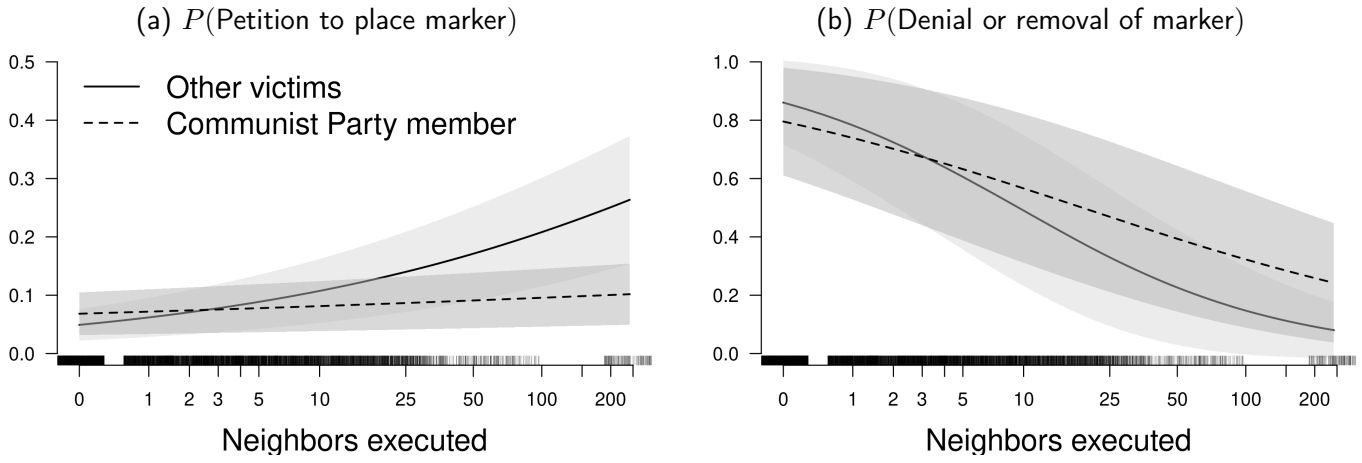


Figure A3.9: **Party membership and memorialization**. See note under Figure A3.8 for details.

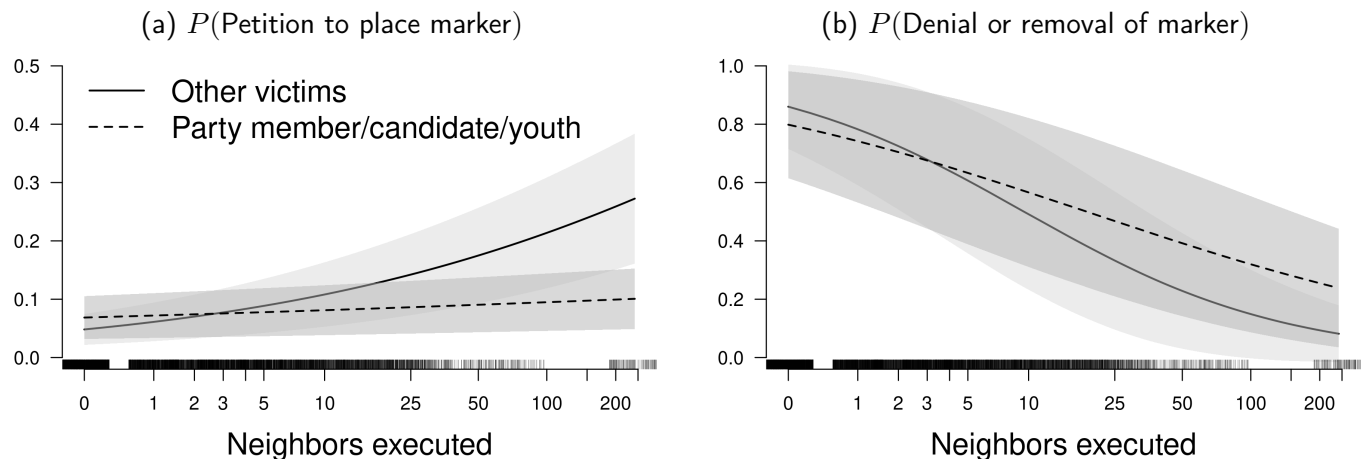


Figure A3.10: **Party membership (expanded) and memorialization**. See note under Figure A3.8 for details.

Figure A3.11 repeats this analysis for NKVD officers.[6] The patterns here are similar to those for the *nomenklatura*. Where they were the sole victims, purged NKVD personnel (dashed) were *more* likely to receive a petition than civilians (solid) (0.12 vs. 0.06), and *less* likely to have plaques denied or removed (0.16 vs. 0.86). These relationships flip as the local severity of repression rises. With 10 repressed neighbors, the predicted probabilities of petition are 0.05 (NKVD) vs. 0.09 (non-NKVD); and probabilities of denial or removal are 0.99 vs. 0.51.

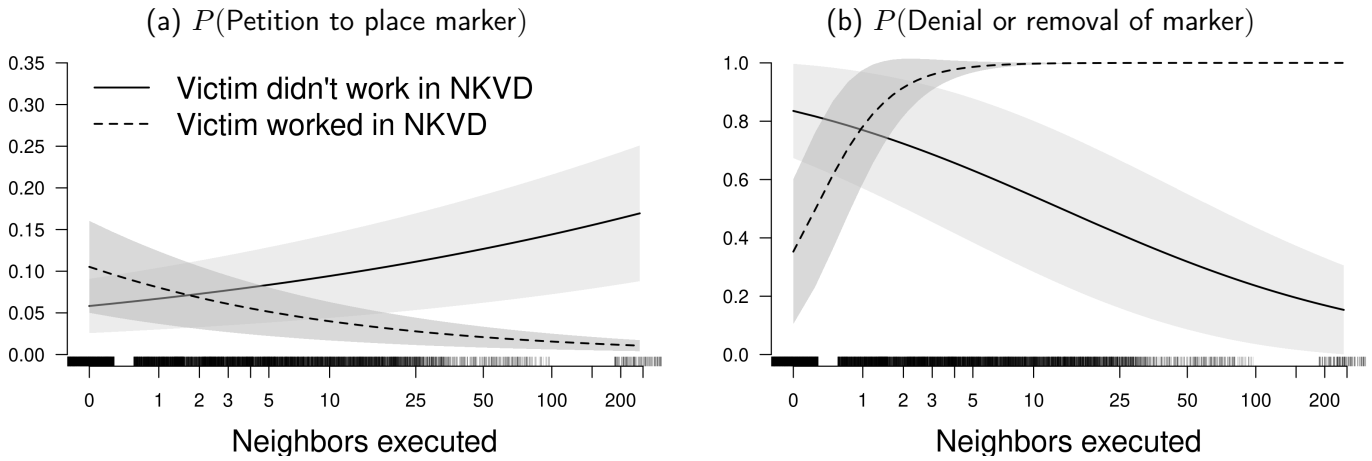


Figure A3.11: **Purged NKVD officers and memorialization**. See note under Figure A3.8 for details.

Third, we consider an alternative measure of social status: whether one belonged to the Soviet professional-managerial class prior to repression. This category includes people with technical expertise and administrative responsibility, who adapted to the Soviet system and achieved a privileged socio-economic position. Professional-managerial positions existed across several organizational layers, including upper management (factory directors, institutional managers), middle management (department heads, workshop managers, section chiefs), and technical specialists (senior engineers, skilled supervisors). These positions required specialized education or technical training, and provided material benefits, like above-average salaries, better housing assignments, and access to special stores and services. Figure A3.12 reports simulation results from these analyses, which align with those for education in Figure 8: the differences appear to be in the expected direction, but are statistically insignificant.

[6] We identified purged NKVD officers by linking our data to Memorial's archive of service histories for NKVD officers (Rachinskiy, 2017), using officers' full names and service locations at the time of the purges (Moscow, Leningrad).

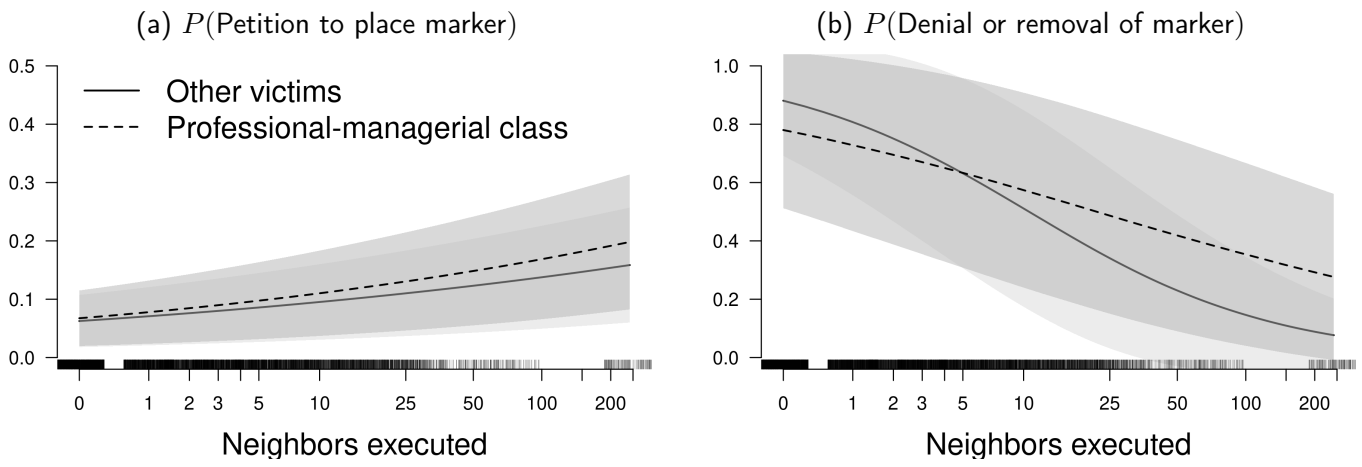


Figure A3.12: **Soviet professional-managerial class and memorialization**. See note under Figure A3.8.

Fourth, we expanded our definition of state security presence to include judicial and defense-related entities. The simulation results, in Figure A3.13, align with to those in Figure 9 in the main text, which includes only public safety and order institutions like the FSB and law enforcement.

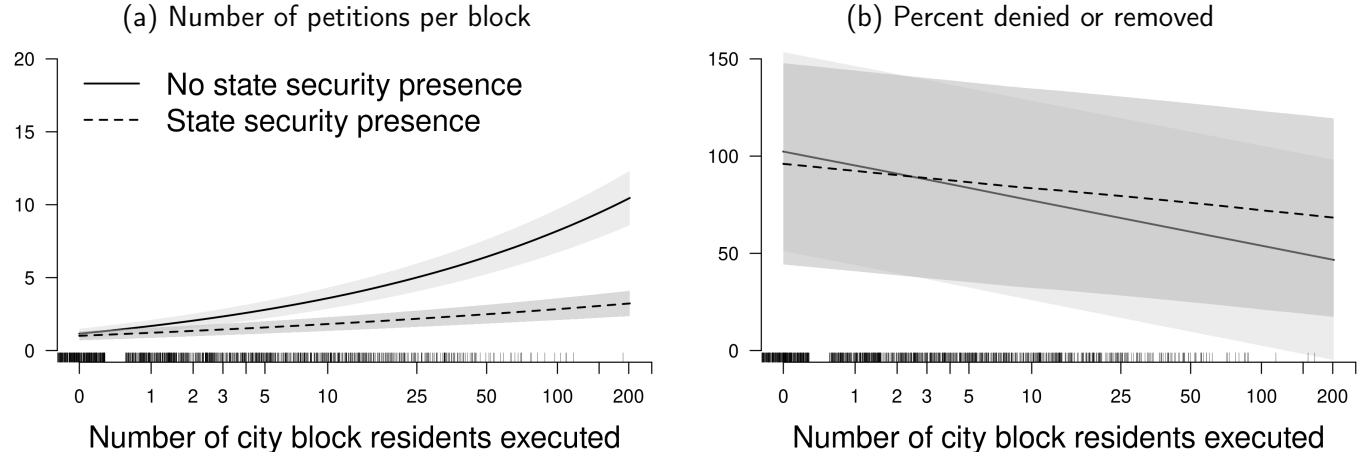


Figure A3.13: **State security presence (expanded) and memorialization**. Block-level estimation.

Fifth, we investigated an additional obstacle to memorialization: the coordination costs associated with securing petition approval. Russian Housing Code gives building owners ultimate approval authority, but the process varies by zoning. In primarily residential buildings, consent from all tenant-owners is required to install markers, increasing the administrative and legal costs of each petition. In non-residential buildings, there are generally fewer owners and veto players, but costs may be higher in buildings owned by larger corporate entities — where multi-level approval by regional management, legal departments and boards of directors may delay the process. Commercial tenants also play a role, if lease agreements include provisions on changes to exteriors.

We used Bureau van Dijk's Orbis database to measure (a) whether a city block hosts primarily residential property, and (b) whether the average enterprises on the block are independently-owned or subsidiaries of larger corporate entities.[7] We expect the suppression-to-recognition ratio to be higher — and the severity effect to be weaker — on residential city blocks and blocks with larger corporate owners. Figures A3.14 and A3.15 report simulation results from block-level models interacting these variables with repression. As expected, the severity effect for petitions is weaker in residential buildings (Figure A3.14a). No other interactions are significant.

[7]The residential category includes some mixed-use buildings, as long as the local businesses are in the service (e.g. retail) or informational sector. 35% of the historical Moscow city blocks in our sample fall in this category. We define "independently owned" as an enterprise that is not part of a corporation with other co-owned businesses. 50% of Moscow city blocks fall into this category.

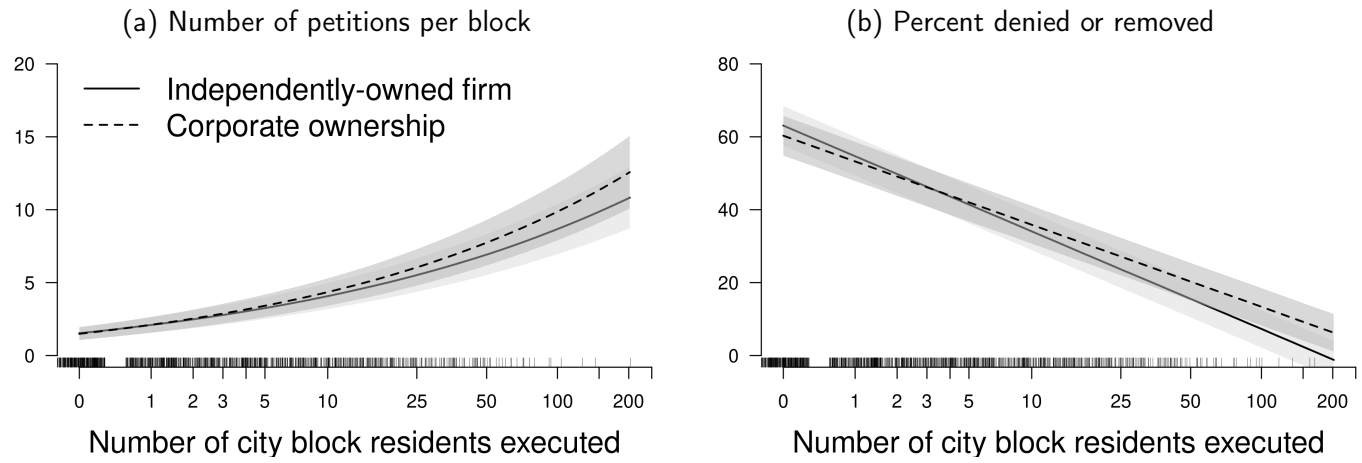


Figure A3.14: **Residential blocks and memorialization**. Lines represent point estimates for city blocks that are currently residential (dashed) or non-residential (solid); grey regions are bootstrapped 95% confidence intervals.

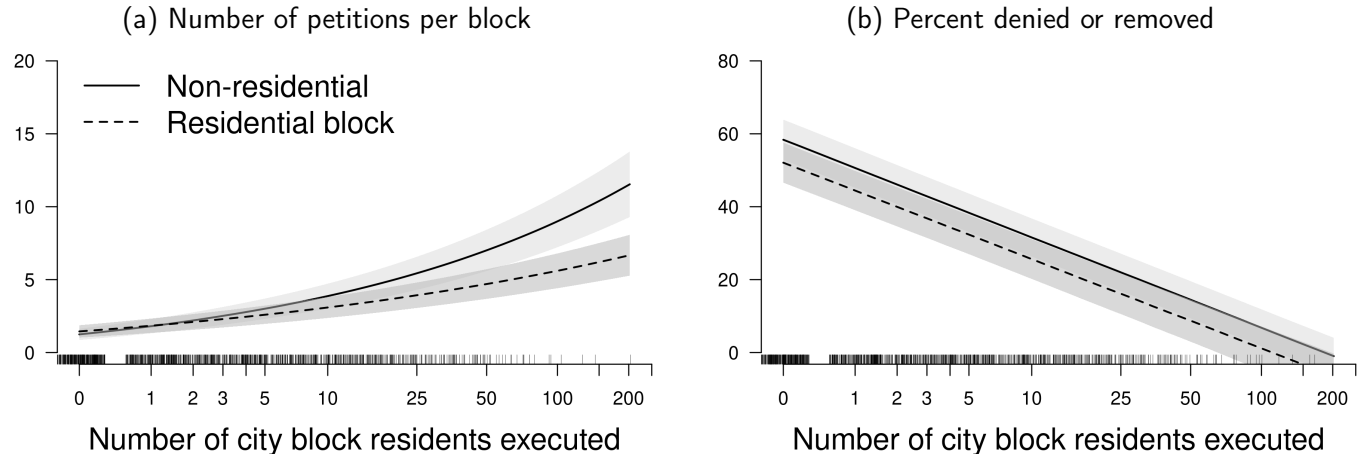


Figure A3.15: **Commercially-owned buildings and memorialization**. See note under Figure A3.14.

A4. External Validation Data and Test: Saint Petersburg

To replicate our analyses in a second Soviet city, we collected block-level and individual data on the Great Terror and *Last Address* memorials in Saint Petersburg.

A4.1. Data Sources

Table A4.10 summarizes differences between the data sources we used for the two cities. Notably, we used a different historical map to construct the block-level data (Figure A4.16), and a different Memorial database to construct the sample of repression victims. Because we could not locate an NKVD map for Leningrad, we used a map of similar scale (1:25,000) from municipal authorities (Russ, 1935). Given the lack of curated Memorial data for Saint Petersburg on rehabilitated repression victims (like *Victims of State Terror in Moscow*) or NKVD infrastructure (like *Topography of Terror*), we used Memorial's much larger *Victims of Political Terror in the USSR* database (lists.memo.ru) to extract repression victims whose residential locations were (a) recoverable with street-address level geoprecision, and (b) within the borders of 1936 Leningrad. We followed the same geoprocessing procedures as those we used for Moscow (e.g. georeferencing, vectorization, dasymetric mapping), and used the same ancillary data sources for key covariates (e.g. 1939 Soviet census, Orbis).

Figure A4.16: **Scan of map from** Russ (1935).

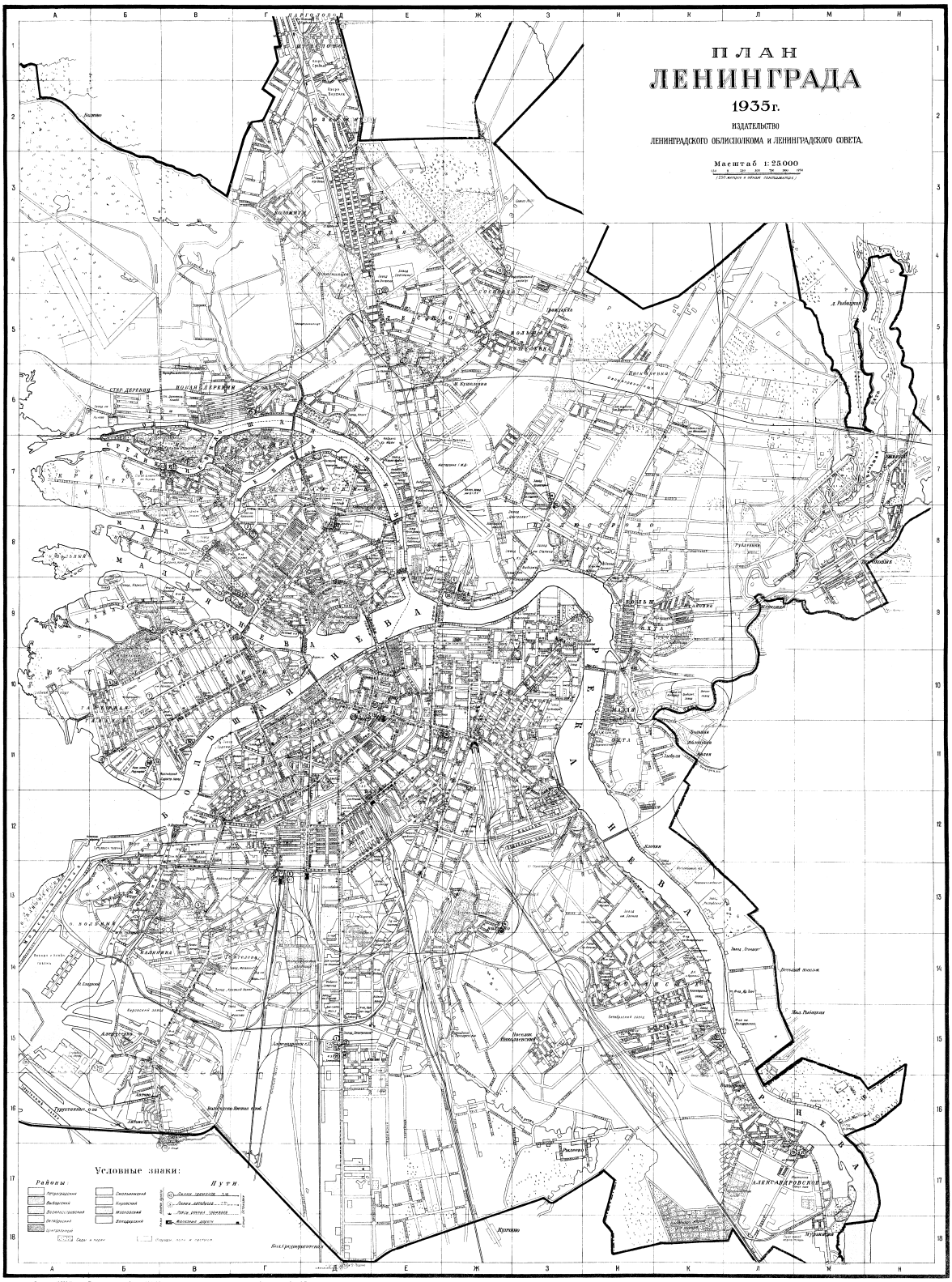
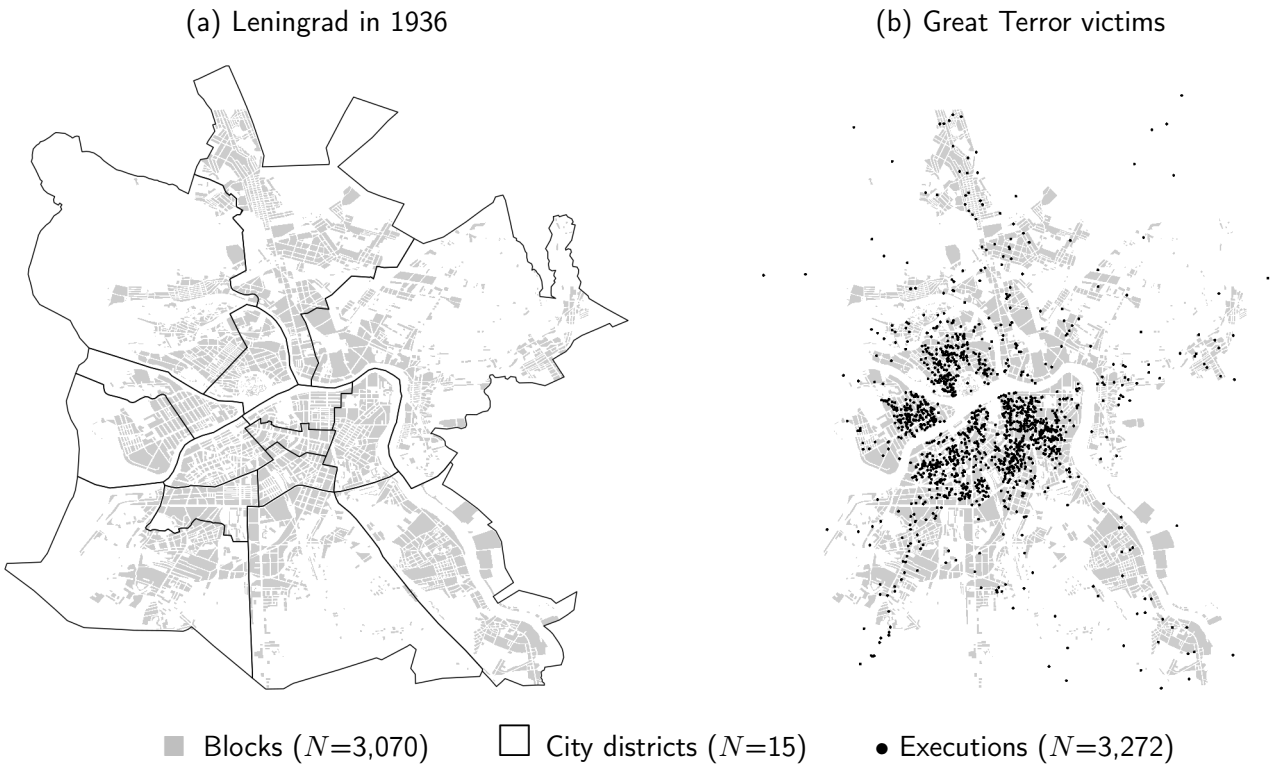


Table A4.10: **Summary of data sources**. Sample sizes reflect individuals and plaques whose locations (a) we could geocode to specific street addresses, and (b) are within the boundaries of 1938 Moscow, 1936 Leningrad.

	Moscow	**Saint Petersburg**
City blocks	Map: NKVD (Krasil'nikov, 1938) Supplement: *Topography of Terror* (Memorial) N: 5,400 blocks (3,305 residential)	Map: Leningrad Soviet (Russ, 1935) Supplement: N/A N: 3,070 blocks (2,689 residential)
Repression	List: *Victims of State Terror in Moscow* N: 10,122 executed, rehabilitated victims	List: *Victims of Political Terror in the USSR* N: 3,272 executed, rehabilitated victims
Memorials	List: *Last Address* N: 868 petitions Soviet-era memorials: Kukina (2018) N: 1221 plaques	List: *Last Address* N: 686 petitions Soviet-era memorials: N/A

Figure A4.17: **Spatial distribution of Saint Petersburg data**. Each polygon in (a) represents a city block. Each point in (b) represents the last known address of a citizen executed by NKVD.



A4.2. Replication of Moscow Analyses

We re-estimated all statistical tests reported in the main text, with four exceptions. First, because Krasil'nikov (1938) and *Topography of Terror* were critical sources for intra-troika distance, and are unavailable here, we omit this covariate from our Saint Petersburg analyses. Second, we lack sufficiently-detailed employment data to analyze the impact of repression against co-workers in Saint Petersburg. Third, we lack sufficient data on party and NKVD membership in Saint Petersburg to re-estimate the interactive analyses with victims' political affiliation. Fourth, we have no data (and no results to report) on Soviet-era building plaques in Saint Petersburg.

In the following, Figure A4.17 corresponds to Figure 3, Table A4.11 corresponds to Table 1, Figure A4.18 corresponds to Figure 4, and Figures A4.19, A4.20 and A4.21 correspond to Figures 6, 8 and 9.

Outcome	Petitions	Denied/Removed (%)	
Model	1. Linear	2. Linear	3. Binomial
Estimate	0.42	-17.01	-0.83
Std. error	(0.04)**	(2.9)**	(0.17)**
Rayon FE	✓	✓	✓
Zoning FE	✓	✓	✓
Adj. R^2	0.59	0.17	
Pseudo R^2			0.31
RMSE	13.1	1837.03	0.37
N	5378	1352	1352

Estimates from Linear and Binomial fixed effect regression models. Treatment is number of city block residents executed (logged). Outcome is log-transformed in Linear model, rescaled as proportion between 0 and 1 in Binomial model. Robust standard errors in parentheses, clustered by rayon. All models include spatial spline and block-level covariates. Observations (blocks) weighted by population size. Significance levels (two-tailed): $^{\dagger}p < 0.1$; $^{*}p < 0.05$; $^{**}p < 0.01$.

Table A4.11: **Severity of repression and memorialization** (Saint Petersburg).

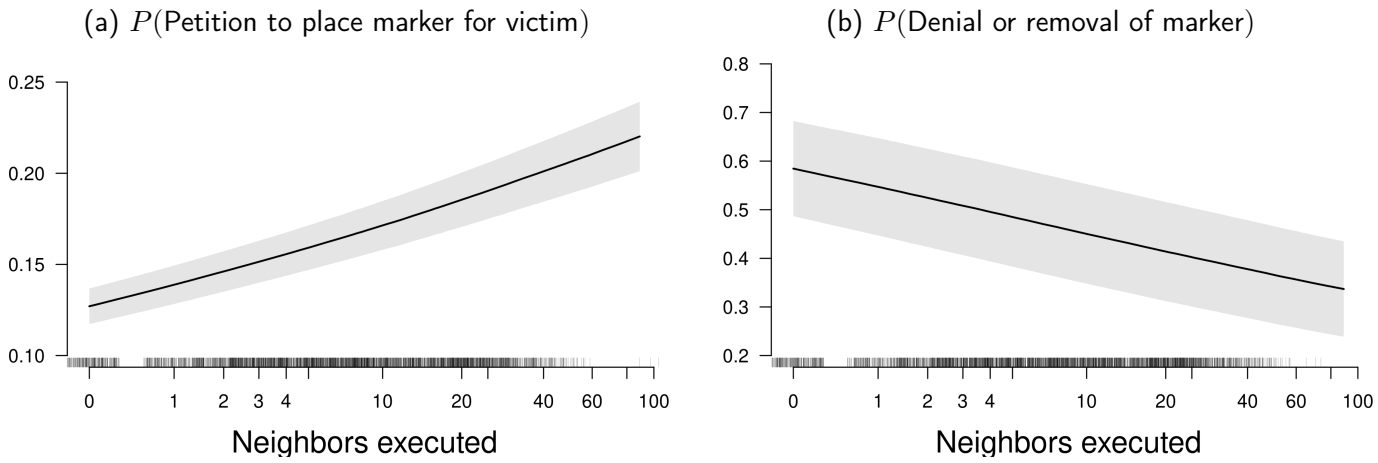


Figure A4.18: **Repression at home and victim's memorialization** (Saint Petersburg). Black lines are predicted probabilities from individual-level model in Equation 2. Grey regions are bootstrapped 95% confidence intervals.

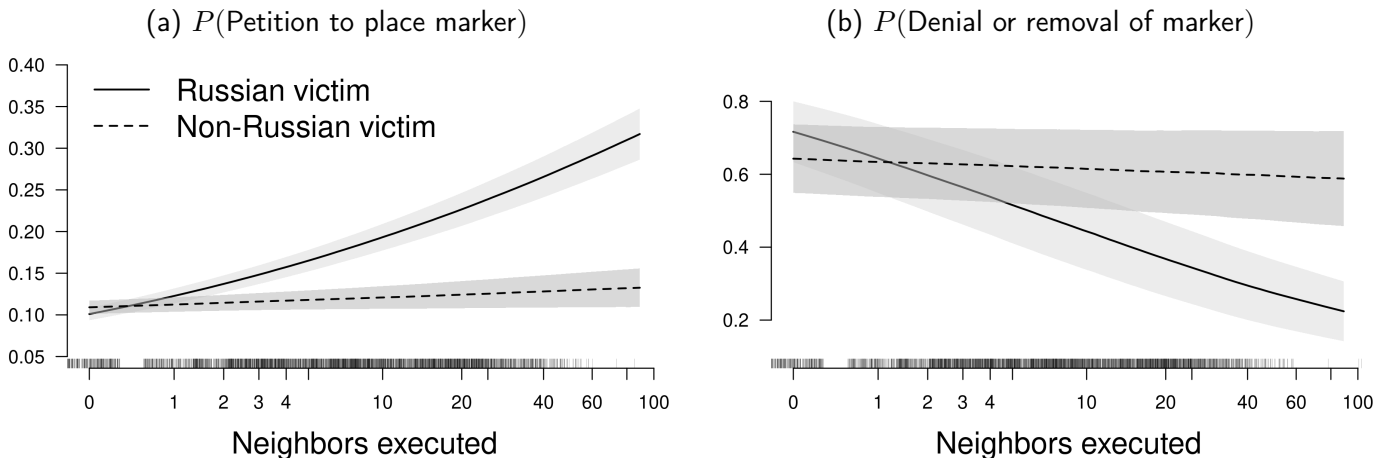


Figure A4.19: **Ethnicity and probability of memorialization** (Saint Petersburg). See note under Figure 6.

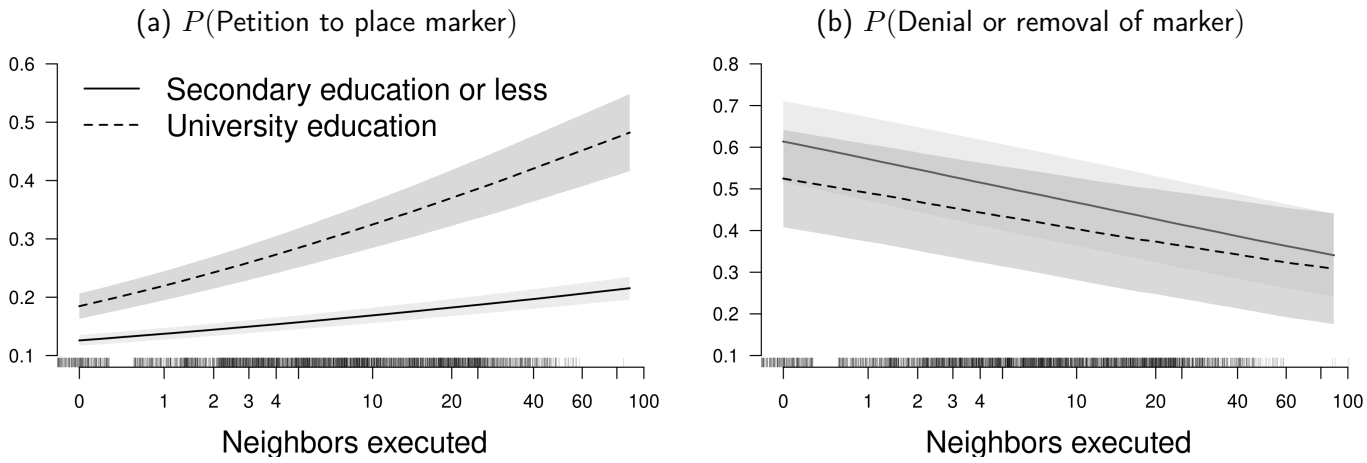


Figure A4.20: **Education and probability of memorialization** (Saint Petersburg). See note under Figure 8.

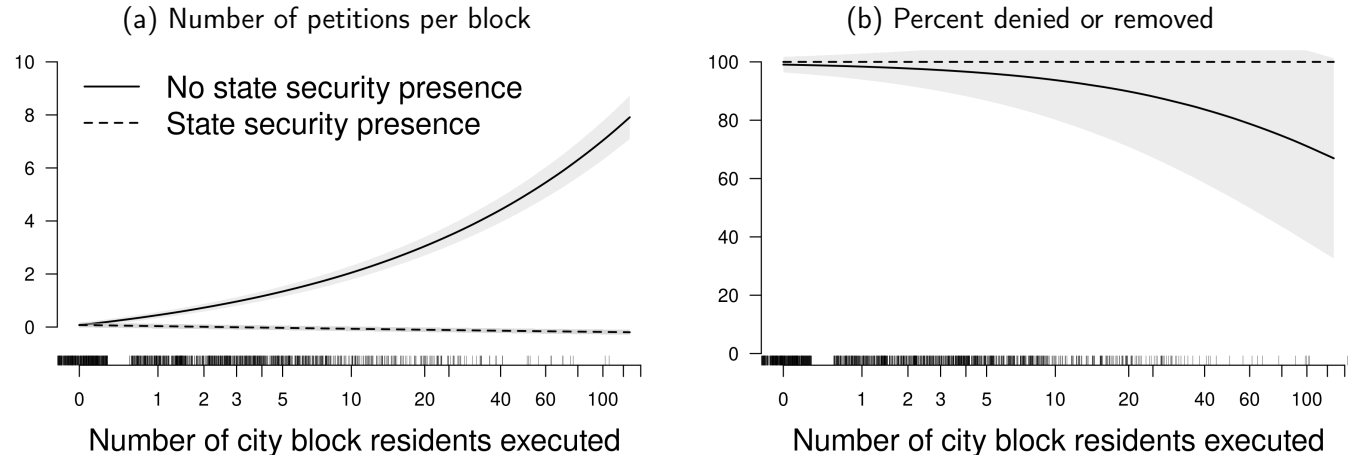


Figure A4.21: **State security presence and memorialization** (Saint Petersburg). See note under Figure 9.

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