One-Sided Violence

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Abstract

In contested territories, armed groups competing for civilian loyalty can diverge sharply in their use of force: one side sustains violence unilaterally while the other restrains. What explains this asymmetry? This question has bearing on whether coercion succeeds or backfires, how conflicts endure, and the costs that civilians must bear. Existing accounts attribute one-sided violence to deficits and asymmetries in information, resources, or organizational culture. We argue instead that sustained unilateral punishment follows surpluses: of targeting capacity, of outside options, or both. Combatants commit to sustained unilateral punishment (what we call "coercive persistence") when their violence is sufficiently selective to extract compliance, or when outside options (e.g., external recruits, lootable resources, expeditionary forces) make civilian cooperation strategically dispensable. We derive a scalar measure of coercive persistence, estimable from any dyadic conflict panel data. We test our claims with secret police records on Soviet counterinsurgency in western Ukraine (1944-1950) and cross-national data spanning dozens of modern armed conflicts. Sustained one-sided violence reflects surpluses of information and resources, not deficits.

In contested territories, armed groups competing for the same civilian population often behave as though they have reached opposite conclusions about how coercive violence works.[1] One side sustains high levels of violence unilaterally, as if confident that enough force will compel civilian cooperation. The other restrains, as if expecting violence to drive civilians away. What explains this asymmetry? One-sided violence is among the most common structural features of armed conflict, with direct bearing on how wars unfold, and who pays their costs: combatants or civilians. Why, when both sides face the same population, does one find sustained unilateral violence worthwhile and the other does not?

The phenomenon we study occupies a specific position in the landscape of political violence. State repression (i.e., a government using violence and intimidation against its citizens to maintain power) shares surface features with one-sided violence but differs in a critical respect: the repressor faces no organized armed rival competing for the same civilians. Our framework requires that rivalry. Terrorism and counterterrorism, insurgency and counterinsurgency, civil war and military occupation all qualify, because in each case two organized armed groups simultaneously claim authority over a civilian population and direct violence toward it. What distinguishes our question from most of this literature is that we do not treat one-sided violence as a defining feature of these conflicts. The same conflict can exhibit mutual restraint in some localities and mutual escalation in others, with pockets of one-sided violence by either side scattered across the same theater and time period. We ask where, when, and why sustained one-sided violence emerges, and by which side, rather than assuming it as a background condition.

Potential explanations of one-sided violence in two-sided armed conflicts include informational deficits (combatants escalate to compensate for targeting inaccuracy or impre-

[1] *Contested territories* refer to any areas where two or more organized armed groups simultaneously claim authority over a civilian population, and neither holds a monopoly on the legitimate use of force. The category encompasses insurgencies, civil wars, military occupations, and expeditionary conflicts, and excludes settings in which one side has effectively consolidated control.

cision; Kalyvas 2006, 146-172, Schutte 2017; Zhukov 2023), resource imbalances (weaker parties escalate to signal resolve, stronger parties escalate because they can; Mack, 1975; Fearon, 1997; Arreguin-Toft, 2001), organizational asymmetries (differences in command cohesion and monitoring capacity enable one side to better sustain violence; Tyson, 2018; Bueno de Mesquita et al., 2024), and normative constraints (some regimes face higher costs of one-sided violence, or more restrictive rules of engagement; Merom, 2003; Lyall, 2010). A parallel literature examines why state repression occurs and how it shapes civilian compliance (Shadmehr and Bernhardt, 2011; Shadmehr and Boleslavsky, 2015; Gibilisco, 2021; Ritter et al., 2025; Sun, 2024), but in the context of a one-sided coercive relationship in which the repressor already holds a monopoly on legitimate force.

We build on past research by examining a competitive dynamic that these accounts leave undertheorized: not why armed actors punish, but why one side sustains unilateral punishment while the other does not. We call this pattern *coercive persistence*: a combatant's behavioral commitment to sustained one-sided violence. We conceptualize the strategic interaction between two armed groups as a stochastic game between two armed groups, in which each side's dominant punishment strategy depends on the selectivity of its violence, and on the degree to which outside options insulate it from the loss of civilian cooperation. A combatant sustains unilateral punishment when its violence is precise enough to extract cooperation, or when its outside options are sufficient to make local civilian support strategically dispensable. From this framework we derive a scalar measure of coercive persistence, estimable from any dyadic conflict panel data, that locates each combatant within our theoretical model's equilibrium structure.

How a combatant delivers punishment determines whether one-sided violence succeeds. When a combatant strikes selectively, targeting enemy collaborators and sparing bystanders, civilians protect themselves by cooperating with the punishing side: submission. When a combatant strikes indiscriminately, civilians absorb harm regardless of their loyalties, and cooperation with the punishing side offers no protection: defiance. Indiscriminate violence can still degrade the opponent's support base by chance, however, and combatants with robust outside options (e.g., external recruitment, lootable resources, forces drawn from outside the locality) can afford to absorb the civilian backlash it provokes. A combatant turns to one-sided violence, then, either because it expects escalation to make civilians submit, or because it does not care if they defy.

The empirical challenge is that we almost never observe civilian cooperation directly. We can, however, treat observed patterns of escalation and restraint as revealing combatants' beliefs about how civilians might respond to violence. Our empirical analysis proceeds in two stages. First, we estimate coercive persistence for a single, well-documented armed conflict, whose archival record is relatively complete: the Soviet campaign against the Ukrainian Insurgent Army (1944-1950). Using micro-level data from declassified secret police archives, we show that the Soviet side had a greater commitment to sustained one-sided violence throughout the conflict, and this coercive persistence rose monotonically with targeting selectivity. Second, we extend the analysis to a cross-national sample of armed conflicts, spanning civil wars, counterinsurgencies, occupations, and expeditionary wars. We show that our theoretical model's predictions about one-sided violence hold across conflict types, and are not an artifact of a single idiosyncratic case.

Prior accounts explain why violence happens; our contribution is to explain why it sometimes persists mainly on one side. Existing theories locate the cause of one-sided violence in deficits: of information, resources, organizational coherence, or political accountability. We locate it instead in surpluses: a combatant sustains unilateral punishment when it has enough targeting precision to make civilians submit, or enough outside options to make their defection irrelevant. One-sided violence, in this view, is not a sign of desperation or failure of restraint. It is a rational response to informational and material advantage.

1 Theory of coercive persistence

Our theory applies to armed conflicts in which two organized combatants compete for the loyalty of a civilian population that neither side fully controls. The combatants may be states or non-state actors; the conflict may be an insurgency, civil war, military occupation, or colonial counterinsurgency. The framework requires contested sovereignty, where neither combatant holds a monopoly on legitimacy or violence in the contested area, and civilians face real costs from defying either side. We refer to the two combatants as Side 1 and Side 2, where Side 1 is the incumbent (the armed actor exercising greater de facto administrative control at the outset) and Side 2 is the challenger. We summarize our theoretical model's logic here, and present its full structure and proofs in Appendix A1.

The conflict involves three sets of actors: a civilian population and two combatants (Sides 1 and 2). Each combatant's campaign depends to some degree on civilian cooperation (e.g., intelligence, shelter, labor, material support) although the degree of dependence varies. To secure that cooperation, each combatant chooses whether to restrain or escalate punishment.[2] The expected mechanism is coercive. By raising the cost of supporting the opponent, a combatant hopes to redirect civilian cooperation toward itself. How a combatant distributes punishment determines whether this mechanism actually operates. Punishment reaches civilians through two channels. One is selective: the combatant identifies and targets cooperators of the opposing side, making support for that side more costly. The other is indiscriminate: violence inflicts collateral damage on nearby civilians regardless of their allegiances, raising the cost of being present rather than the cost of taking sides.[3] Indiscriminate violence also hurts some enemy collaborators, albeit by chance, at high cost to neutral civilians, and without the deterrent effect of selective violence.

[2] We denote punishment levels L (low) and H (high). Each combatant $k \in \{1, 2\}$ selects $\rho_k \in \{L, H\}$.

[3] Formally, combatant k hunts identified enemy cooperators at rate $\lambda_k \rho_k$, where $\lambda_k \in (0, 1)$ is selectivity and ρ_k is punishment level; collateral damage accrues at rate $(1 - \lambda_k)\rho_k$.

How heavily a combatant depends on local civilian support shapes its incentives to escalate. Combatants with robust outside options (e.g., external recruitment, lootable resource revenue, materiel sourced outside the contested locality) can absorb the cooperation loss that indiscriminate punishment tends to provoke.[4] Combatants with few outside options face stronger incentives to keep the population on side.

Civilians, in turn, are not a homogeneous mass. Each civilian occupies a distinct exposure profile: some face greater risk from selective targeting, because their location, occupation, or social network marks them as potential collaborators. Others face greater risk from indiscriminate fire, perhaps because they live near infrastructure combatants routinely strike or lack the means to evacuate.[5] Combatants know the population's general composition but not which specific civilians belong to which exposure category.

How civilians respond to punishment depends on how precisely that punishment discriminates.[6] When Side 1's violence is precise enough to punish Side 2's collaborators, while sparing bystanders and loyalists, the relative costs of cooperating with Side 2 rise, and civilians protect themselves by cooperating with Side 1: submission. When Side 1's violence is too blunt to spare bystanders or loyalists, cooperation with the punishing side no longer offers protection, and civilians instead cooperate with Side 2: defiance.

Combatants' choices to escalate or restrain hinge on whether their targeting technologies

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[4]We capture outside options with the parameter $c_k \geq 0$.

[5]We index each civilian j's exposure type by $\theta_j \in (0, 1)$, where low θ_j denotes greater vulnerability to selective targeting and high θ_j denotes greater vulnerability to collateral damage. Combatants observe the local type distribution $F(\theta \mid x_i)$ but cannot assign types to individuals before punishing (see Assumption 1).

[6]Civilian j chooses $e_j^* \in [0, 1]$, the share of cooperation directed toward Side 1, to maximize

$$U_j(e_j) = -\big[\theta_j(1-\lambda_1)\rho_1 + (1-\theta_j)\lambda_2\rho_2\big]e_j - \big[\theta_j(1-\lambda_2)\rho_2 + (1-\theta_j)\lambda_1\rho_1\big](1-e_j) - \frac{\gamma}{2}\big(e_j - \tfrac{1}{2}\big)^2, \quad (1)$$

where $\gamma > 0$ governs the curvature of civilian utility (equivalently, the cost of deviating from perfect neutrality $e_j = 1/2$). The first-order condition gives $\partial e_j^*/\partial\rho_1 = (\lambda_1 - \theta_j)/\gamma$, which is positive (submission) when $\lambda_1 > \theta_j$ and negative (defiance) when $\lambda_1 < \theta_j$ (see Proposition 1).

are precise enough to make escalation pay.[7] Each combatant has a selectivity threshold: a minimum share of violence that must befall enemy collaborators and not bystanders, in order to deter cooperation with the enemy. A combatant whose selectivity meets or exceeds this threshold will always prefer to escalate, no matter what the opponent does. A less selective combatant will always prefer to restrain, for the same reason.[8]

When both sides fall short of their selectivity thresholds, mutual restraint follows. When both clear them, mutual escalation results. The more revealing cases are the asymmetric ones, where one side escalates and the other restrains: one-sided violence. These asymmetries arise not because either Side miscalculates, but because they face the same population with different technologies and reach different conclusions about whether escalation pays.

Armed conflicts are not static. Front lines move, populations change, surveillance capacity evolves. As these conditions shift, so does each side's calculus about whether escalation pays. At any point in time and space, the two combatants' behavior falls into one of four patterns: mutual restraint, mutual escalation, or unilateral escalation by Side 1 or 2.[9] Which of these patterns will emerge in the future depends on which one currently

[7]Combatant k chooses $\rho_k \in \{L, H\}$ to maximize

$$U_k(\rho_k, \rho_{-k}) = b \cdot \mathbb{E}[e_k^*(\rho_k, \rho_{-k}, \theta_j) \mid x_i] + c_k(1 - \lambda_k)\rho_k - \kappa_k(\rho_k), \tag{2}$$

where $b > 0$ is the value of a unit of civilian cooperation, e_k^* is the share of cooperation that k receives, $c_k \geq 0$ is k's outside option, and punishment cost $\kappa_k(\cdot)$ satisfies $\kappa_k(L) = 0$ and $\kappa_k(H) > 0$. Taking the difference $U_k(H, \cdot) - U_k(L, \cdot)$ and signing it yields a threshold. k strictly prefers high punishment when

$$\lambda_k > \lambda_k^\dagger \;\equiv\; \bar{\theta}_i + \gamma \frac{\kappa_k(H) - c_k(1 - \bar{\theta}_i)\Delta}{(b - c_k\gamma)\Delta}, \tag{3}$$

where $\bar{\theta}_i = \mathbb{E}[\theta_j \mid x_i]$ is the mean civilian type in locality i, and $\Delta > 0$ is the punishment increment (see Theorem 1). The threshold falls as c_k rises: outside options expand the region where escalation dominates.

[8]Aggregating the civilian response over $F(\theta \mid x_i)$ shows that whether escalation attracts or repels cooperation depends only on λ_k relative to $\bar{\theta}_i$. The outside-options term likewise involves only k's own parameters. Each side's calculus is therefore independent of the opponent's choice, making the game dominance-solvable with a unique Nash equilibrium (Theorem 1).

[9]We model these dynamics as a stochastic game, where combatants re-optimize punishment as the strategic environment shifts, rather than executing a fixed long-run plan. Within any period, each com-

prevails: the chances of mutual restraint tomorrow may be different for localities already experiencing mutual restraint as opposed to one-sided violence or mutual escalation.[10]

Each combatant's behavior reduces to two probabilities: the chance it escalates when the opponent restrained last period, and the chance it restrains when the opponent escalated last period. Together, these determine how durable each form of one-sided violence is. We define *coercive persistence* ω as how much more durable one-sided violence by Side 1 is than one-sided violence by Side 2.[11] When ω is positive, Side 1 escalates persistently while Side 2 restrains. When ω is negative, the asymmetry reverses and Side 2 escalates

batant's action is independent of what the opponent does (Theorem 1). But across periods, the opponent's most recent action serves as an observable signal of how conditions have shifted. Combatants condition on this signal to update their assessment of the current environment, not to react strategically within a period. This time-varying structure gives the model empirical traction: the sequence of observed punishment choices carries recoverable information about which state prevails and why.

[10]The observed sequence of joint punishment profiles forms a first-order Markov chain, collecting transition probabilities in a 4×4 matrix $\mathbf{M} = [m_{a'a}]$, where $m_{a'a} = P(a' \mid a)$ and $\mathcal{A} = \{LL, LH, HL, HH\}$:

$$\mathbf{M} = \begin{array}{c} \\ LL \\ LH \\ HL \\ HH \end{array} \begin{array}{c} \begin{array}{cccc} LL & LH & HL & HH \end{array} \\ \begin{pmatrix} m_{LL,LL} & m_{LL,LH} & m_{LL,HL} & m_{LL,HH} \\ m_{LH,LL} & m_{LH,LH} & m_{LH,HL} & m_{LH,HH} \\ m_{HL,LL} & m_{HL,LH} & m_{HL,HL} & m_{HL,HH} \\ m_{HH,LL} & m_{HH,LH} & m_{HH,HL} & m_{HH,HH} \end{pmatrix} \end{array} \tag{4}$$

We reduce $\mathbf{M}$'s 12 free parameters (one normalizing constraint per row) to four by restricting each combatant to condition its current action on the opponent's *previous* action. This assumes military decisions reflect adaptation to observed enemy behavior (Smith et al., 2000). For each side k, define $p_k \equiv P(\rho_{kt} = L \mid \rho_{-k,t-1} = L)$ and $q_k \equiv P(\rho_{kt} = L \mid \rho_{-k,t-1} = H)$. Under this restriction, combatants' current actions are conditionally independent and all $m_{a'a}$ become products of p_k and q_k (Proposition 2):

$$\mathbf{M} = \begin{array}{c} \\ LL \\ LH \\ HL \\ HH \end{array} \begin{array}{c} \begin{array}{cccc} LL & LH & HL & HH \end{array} \\ \begin{pmatrix} p_1p_2 & q_1p_2 & p_1q_2 & q_1q_2 \\ p_1(1-p_2) & q_1(1-p_2) & p_1(1-q_2) & q_1(1-q_2) \\ (1-p_1)p_2 & (1-q_1)p_2 & (1-p_1)q_2 & (1-q_1)q_2 \\ (1-p_1)(1-p_2) & (1-q_1)(1-p_2) & (1-p_1)(1-q_2) & (1-q_1)(1-q_2) \end{pmatrix} \end{array} \tag{5}$$

[11]Formally, $\omega_1 \equiv m_{HL,HL} - m_{LH,LH} = (1-p_1)q_2 - q_1(1-p_2)$ (Proposition 2). ω_2 reverses the roles of the two sides. For brevity, we drop the subscript and write $\omega \equiv \omega_1$ unless we state otherwise. Positive ω requires simultaneously that p_1 is near zero (Side 1 escalates even when Side 2 restrains) and q_2 is near one (Side 2 restrains even under pressure).

while Side 1 restrains. When ω is zero, neither form of one-sided violence dominates.

So where and when should we expect one-sided violence, and by which side? Our theory yields several testable predictions about how ω varies across localities and conflicts.[12] Where Side 1's violence is more selective relative to Side 2's, escalation generates a larger cooperation premium for Side 1, and Side 1 becomes more likely to use one-sided violence (i.e., ω rises). Where Side 1 has better outside options, it escalates in hopes of degrading the opponent's base through attrition, even when doing so alienates the population; again, ω rises. Where escalating is costlier for Side 1 (e.g., due to international pressure, logistical constraints, political opposition), Side 1 tilts toward restraint and ω falls. The effect of civilian vulnerability on coercive persistence depends on selectivity: higher vulnerability pushes ω upward if Side 1 is more selective, and downward if it is less selective. Estimating how ω varies with observable proxies for these parameters is our primary empirical test.

2 Estimation

We empirically estimate coercive persistence ω in two steps. First, we model the joint sequence of combatant decisions using dyadic conflict data. Second, we recover predicted transition probabilities from that model, and assemble them into an estimate $\hat{\omega}$.

We observe the two combatants decisions to escalate or restrain as pairs of binary outcomes across localities and time periods.[13] We assume that these decisions are potentially correlated, in that unobserved local and time-specific shocks affecting both Sides (e.g.,

[12] These follow from Corollary 1 and comparative statics on $\lambda_k^\dagger$.

[13] We index combatants $k = 1, 2$, localities i, and periods t. We define $Y_{k,it} = 1$ if combatant k escalates and $Y_{k,it} = 0$ otherwise. Observed outcomes emerge from latent indices via $Y_{k,it} = \mathbf{1}[Y^*_{k,it} \geq 0]$. A zero does not mean no violence occurred. Event datasets record only the most visible acts, which survive archival declassification or publication by media outlets. Violence that available measurement instruments cannot detect goes unrecorded. We treat this observation mechanism as the boundary between restraint and escalation: low punishment is empirically invisible, high punishment is not.

unit rotations, agricultural cycles, population flows) might simultaneously push both combatants toward escalation or restraint.[14] If we ignore this dependence and estimate each combatant's behavior in isolation, we could misstate the uncertainty around $\hat{\omega}$.

In our empirical model, each combatant's propensity to escalate depends on three inputs: the opponent's most recent action, its own most recent action, and an interaction between the two.[15] The opponent's past action raises or lowers the baseline propensity to escalate directly. It also conditions how strongly a combatant's own past behavior carries forward: facing an escalating opponent shifts the weight each side places on its own prior action.[16] We estimate this system by bivariate probit, controlling for pre-conflict local attributes, with corrections for unobserved locality-specific and period-specific confounders.[17]

We recover $\hat{\omega}$ from the fitted model's predicted transition probabilities. For each combatant, we compute two sets of predicted probabilities: the probability of escalation after the opponent restrained last period, and the probability of restraint after the opponent

[14]We allow for this by modeling the two latent indices as jointly normal:

$$\begin{bmatrix} Y^*_{1,it} \\ Y^*_{2,it} \end{bmatrix} \sim N_2\left(\begin{bmatrix} \mu_{1,it} \\ \mu_{2,it} \end{bmatrix}, \begin{bmatrix} 1 & r \\ r & 1 \end{bmatrix} \right),$$

where r is a scalar cross-equation correlation parameter. We test whether the dependence is statistically negligible with likelihood ratio tests, and retain the joint specification where it is not.

[15]The estimating equations take the form, suppressing locality subscript i,

$$\begin{bmatrix} \mu_{1,t} \\ \mu_{2,t} \end{bmatrix} = \begin{bmatrix} y_{2,t-1}\zeta_1 + y_{1,t-1}\big(\alpha_1 + y_{2,t-1}\phi_1\big) + \mathbf{x}_{1,t}\beta_1 \\ y_{1,t-1}\zeta_2 + y_{2,t-1}\big(\alpha_2 + y_{1,t-1}\phi_2\big) + \mathbf{x}_{2,t}\beta_2 \end{bmatrix}, \tag{6}$$

where $y_{k,t-1}$ is combatant k's lagged outcome, $\mathbf{x}_{k,t}$ are vectors of covariates including pre-conflict locality attributes, regional, year, and month fixed effects; α_k, β_k, ζ_k, ϕ_k are regression coefficients.

[16]In equation (6), the effect of $y_{1,t-1}$ on μ_1 equals α_1 when Side 2 restrained last period and $\alpha_1 + \phi_1$ when Side 2 escalated; ϕ_k captures this moderating shift.

[17]We augment the estimating equations with locality-level and period-level time-means of each side's lagged behavior to partial out time-invariant heterogeneity and aggregate period-specific shocks (Mundlak, 1978; Chamberlain, 1984; Wooldridge, 2010). We use Mundlak-corrected specifications for general inference about $\hat{\omega}$, and the base interactive specification for comparative statics tests on time-invariant covariates. We use likelihood ratio tests to select between the fully interactive model and more restricted variants, including non-strategic (opponent lags excluded, $\zeta_k = \phi_k = 0$) and additive (interaction excluded, $\phi_k = 0$).

escalated.[18] Our estimate $\hat{\omega}$ is the difference between the probability that Side 1 sustains the former configuration (unilateral escalation) and the probability that Side 1 sustains the latter (unilateral restraint).[19] We obtain confidence intervals by parametric bootstrap.[20]

To test the comparative statics predictions, we apply the same procedure under counterfactual covariate values, shifting each variable from its observed minimum to its maximum while holding all others at their median or modal values. We report the resulting contrast in $\hat{\omega}$ with a 95% bootstrap confidence interval. A contrast whose sign matches the theoretical prediction confirms the comparative static.

3 Application I: Soviet Union vs. Ukrainian insurgents

A post-World War II armed conflict in western Ukraine offers a well-suited testing ground for our theoretical framework. For over a decade, Soviet security forces waged a sustained campaign against the Ukrainian Insurgent Army (UPA), the armed wing of the Organization of Ukrainian Nationalists (OUN), across territories the Soviet Union had annexed from Poland in 1939. Both sides directed violence against civilians as deliberate strategy, and the archival record is sufficiently complete to support disaggregated quantitative analysis.

[18]This gives two quantities per combatant: $\hat{p}_k \equiv \widehat{P}(Y_k = 0 \mid y_{-k,t-1} = 0)$, the average-marginal probability of restraint when the opponent also restrained, and $\hat{q}_k \equiv \widehat{P}(Y_k = 0 \mid y_{-k,t-1} = 1)$, the corresponding probability when the opponent escalated. Fixing $y_{-k,t-1}$ in equation (6) switches the coefficient on $y_{k,t-1}$ between α_k and $\alpha_k + \phi_k$; $\hat{p}_k$ and $\hat{q}_k$ capture this additional shift. These four quantities are sufficient to construct the self-persistence probabilities of the two asymmetric states. The diagonal entries of the estimated restricted transition matrix are $\hat{m}_{HL,HL} = (1 - \hat{p}_1)\hat{q}_2$, $\hat{m}_{LH,LH} = \hat{q}_1(1 - \hat{p}_2)$.

[19]Formally, $\hat{\omega} \equiv \hat{m}_{HL,HL} - \hat{m}_{LH,LH} = (1 - \hat{p}_1)\hat{q}_2 - \hat{q}_1(1 - \hat{p}_2)$.

[20]Since $\hat{\omega}$ combines predictions from both equations in (6), propagating uncertainty through the system requires joint simulation. We draw from the joint coefficient distribution and recompute $\hat{\omega}$ at each draw.

3.1 Data

We draw on a published dataset on the Soviet-UPA conflict, which integrates incident reports from declassified secret police, Communist Party of Ukraine, and OUN-UPA documents (Zhukov, 2015; Rozenas et al., 2017). The dataset covers conflict events across Ukraine from 1943 to 1955, with locations, dates, casualties, and tactics for each incident. We aggregate these to the rayon-month level and restrict the sample to Ukraine's eight newly-annexed western oblasts during 1944–1950, where the UPA concentrated its activity and violently contested Soviet administrative control ($N = 20{,}076$ rayon-months).[21]

The binary outcome for Side 1 (Soviets) equals one if any act of Soviet violence (e.g., anti-insurgent sweep, household deportation) occurred in a rayon-month, and zero otherwise. The binary outcome for Side 2 (UPA) equals one if any insurgent-initiated violent incident occurred. We proxy Soviet selectivity as the rayon-level share of Soviet violence directed at insurgents rather than civilians, averaged over the sample period.[22]

We include combatant-specific covariates reflecting the different structural constraints each side faced: measures of administrative reach and state capacity for the Soviets, and measures of mobility and concealment for the UPA.[23] Both sets include fixed effects for region (oblast), year, and month, and a spatial lag of each side's own lagged outcome.

[21] Soviet rayons were second-tier administrative units roughly comparable to U.S. counties. Soviet oblasts were first-tier administrative units similar to U.S. states.

[22] Formally, $\hat{\lambda}_{1i} = \frac{1}{T}\sum_t^T \big(\text{insurgent-targeted incidents}_{it} \,/\, \text{total Soviet incidents}_{it}\big)$, where the numerator counts Soviet operations recorded as targeting combatants, and the denominator counts all Soviet violent incidents in i, t. This matches the theoretical role of $\lambda_k \in (0, 1)$ as the share of k's violence falling on identified enemy cooperators rather than bystanders.

[23] For the Soviets, $\mathbf{x}_{1,t}$ includes railway access, number of village soviets (proxying administrative penetration depth and state capacity), electrification, natural resources, agricultural land share, urbanization, rayon area, and pre-1944 Soviet partisan control. For the UPA, $\mathbf{x}_{2,t}$ includes railway access, forest cover (proxying cover and concealment), electrification, natural resources, agricultural land share, urbanization, number of border crossings to neighboring rayons, and rayon area. Village soviets and pre-1944 partisan control capture the depth of Soviet administrative and intelligence infrastructure, which shaped NKVD/MVD targeting capacity but had no direct analogue for the UPA. Forest cover and local crossings governed insurgent mobility and concealment in ways that do not extend to state security forces.

3.2 Analysis

Soviet coercive persistence is consistently positive and significant across all specifications, indicating that one-sided Soviet violence was more self-sustaining than one-sided violence by the UPA. In the best-fitting model, $\hat{\omega} = 0.2$ (95% CI: [0.16, 0.24]).[24]

Figure 1 shows how estimates of Soviet coercive persistence $\hat{\omega}$ vary across quintiles of selectivity (i.e., share of violence directed at insurgents, not civilians). Soviet coercive persistence increases monotonically with selectivity, from near zero in the lowest quintile ($\hat{\omega} = 0.002$) to strongly positive in the highest ($\hat{\omega} = 0.121$). This pattern aligns with our theoretical expectation that selectivity raises the net benefit of sustained punishment.[25]

Figure 1 also speaks, indirectly, to whether Soviet forces were pursuing a strategy of pure attrition: escalating simply because the costs of doing so were low or because outside options made civilian cooperation irrelevant. According to their own records, roughly 98 percent of Soviet violence in the median western Ukrainian locality fell on civilians rather than combatants, making this one of the most indiscriminate campaigns in the historical record. If attrition alone drove Soviet escalation, coercive persistence should be uniformly positive across localities, irrespective of how indiscriminate the violence was.[26]

The evidence is inconsistent with that prediction. Soviet coercive persistence is indistinguishable from zero in the two lowest-selectivity quintiles, and rises sharply only where targeting precision, however modestly, begins to increase. Even granting that outside options made escalation cheap, the gradient in coercive persistence in Figure 1 indicates that

[24]We use the two-way Mundlak specification for all $\hat{\omega}$ inference. Likelihood ratio tests confirm significant cross-equation correlation, validating joint estimation over independent equations (Appendix A2). $\hat{\omega}$ estimates from independent probit equations are all smaller, with confidence intervals spanning zero. The interactive specification outperforms both the additive and non-strategic models, and the Mundlak correction improves fit further by absorbing rayon-level heterogeneity and period-specific shocks (Table A3).

[25]This follows from Corollary 1.i.

[26]Formally, a pure attrition logic predicts $\hat{\omega}_1 > 0$ even where $\lambda_1 \approx 0$, because the outside option c_1 alone sustains escalation independently of targeting precision.

the Soviets still hesitated to use one-sided violence where their selectivity was near zero.

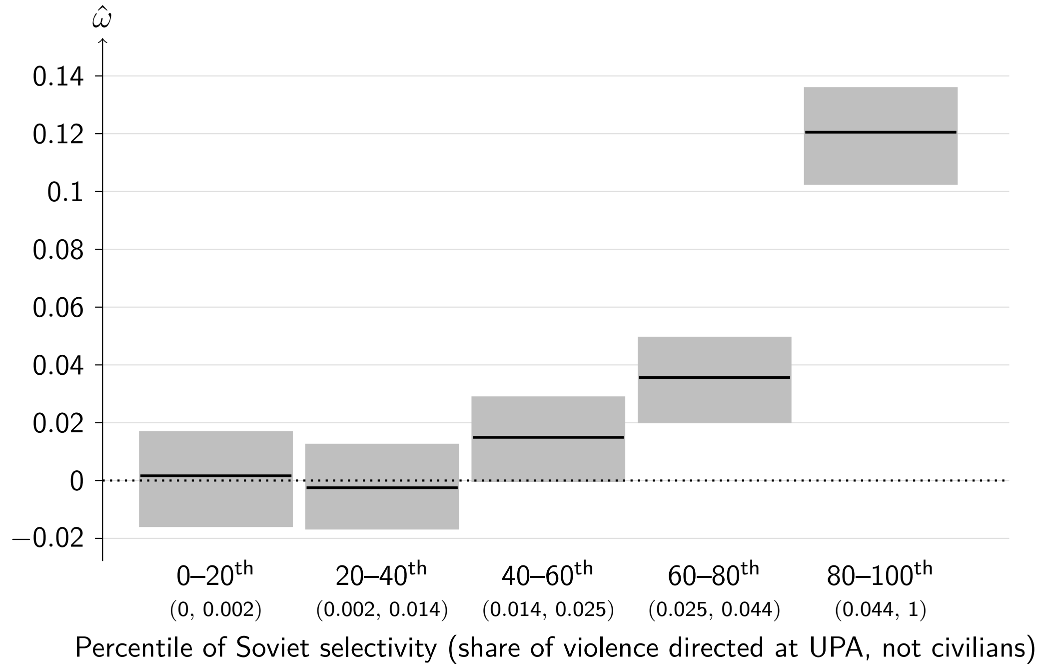

Figure 1: **How Soviet coercive persistence** ($\hat{\omega}$) **varies with selectivity**. Grey bars are 95% bootstrap CIs; black lines are point estimates. Dotted line at $\hat{\omega} = 0$. Parentheses show selectivity range in each quintile.

What structural conditions drove variation in Soviet one-sided violence across localities? To answer this, Table 1 shifts each covariate from its observed minimum to maximum, holding all others at their medians, and reports how much coercive persistence changes.[27] Administrative penetration depth, which we measure by the density of village soviets, produces the largest and most precisely estimated contrast, $\Delta\hat{\omega} = 0.16$ (95% CI: 0.09, 0.27).[28] Village soviets enabled targeting selectivity, in that deeper administrative infrastructure gave security forces more reliable means of identifying and separating insurgents from

[27]Each contrast is $\hat{\omega}_{\text{hi}} - \hat{\omega}_{\text{lo}}$ from specification (6), which we estimated here without the Mundlak correction to preserve identification of the time-invariant covariates.

[28]Village soviets proxy for targeting selectivity (λ_1) and potentially also the state's outside options (c_1).

civilians. A deeper institutional footprint also connected these localities to broader state supply chains, personnel rotations, and organizational resources, reducing dependence on local civilian goodwill to sustain operations. Rayons with denser local administrative networks sustained Soviet escalation more consistently than those without them.

Soviet coercive persistence was also higher in territories with a history of WWII-era Soviet partisan control, $\Delta\hat{\omega} = 0.05$ (95% CI: 0.02, 0.08). The intelligence networks these operations left behind improved targeting precision, making Soviet coercion potentially more efficient.[29] Urban share produces a modest but similarly positive contrast, $\Delta\hat{\omega} = 0.02$ (95% CI: 0.01, 0.04). Cities were both easier to surveil and more strategically valuable, giving security forces incentives to sustain escalation regardless of short-run outcomes.[30] Rail access, rayon area, electrification, and natural resources fall short of conventional significance, suggesting they capture underlying structural channels with considerable noise.

Table 1: **Comparative statics**. Change in $\hat{\omega}$ when each covariate moves from its observed minimum to maximum, holding all others at medians. 95% bootstrap CIs in parentheses.

Covariate	Range	$\Delta\hat{\omega}$ (95% CI)
Village soviets	$7 \to 82$	0.16 (0.09, 0.27)
Partisan control (pre-1944)	$0 \to 1$	0.05 (0.02, 0.08)
Urban share	$0 \to 1$	0.02 (0.01, 0.04)
Railway present	$0 \to 1$	0.01 (-0.01, 0.02)
Area (1000 sq km)	$0 \to 1.8$	0.08 (-0.01, 0.14)
Electrification	$0 \to 1$	0.03 (-0.01, 0.08)
Natural resources	$0 \to 3$	0.01 (-0.03, 0.04)
Agricultural land	$0 \to 1$	-0.00 (-0.03, 0.02)

[29] Partisan control proxies for prior intelligence infrastructure (λ_1).

[30] Urban density raises targeting selectivity (λ_1), but also concentrates economic and administrative assets that increase outside options (c_1), making the two channels difficult to separate.

4 Application II: Cross-National Evidence

The Soviet-UPA analysis demonstrates how the coercive persistence framework can recover theoretically interpretable parameter estimates and comparative statics from a single, well-documented conflict. To understand if the observed asymmetry between government and insurgent persistence is a feature of one idiosyncratic case or of armed conflicts more broadly, we extend the analysis to a cross-national data sample.

4.1 Data

We obtain disaggregated event data on armed conflict from xSub, a publicly available repository of subnational conflict data covering 156 countries from 21 sources (Zhukov et al., 2019). For our purposes, xSub has several attractive properties, including consistent measurement, comparability across cases, and multiple source validation. This standardization of actor-event typologies and aggregation schema ensures that the threshold between restraint and escalation carries the same operational meaning across all cases in the sample.

The scope of our cross-national analyses includes two-sided armed conflicts, in which combatants directed violence against each other and civilians.[31] Our data sample covers 51 countries across Africa, Asia, Europe, the Middle East, and the Americas. We construct it from the Uppsala Conflict Data Program's Georeferenced Event Dataset (UCDP-GED; Sundberg and Melander, 2013) and the Armed Conflict Location and Event Data project (ACLED; Raleigh et al., 2010).[32] xSub harmonizes these event data into consistent actor categories and spatial units, with coverage windows ranging from the late 1980s through

[31]This scope includes both intrastate and interstate wars, where one or more belligerents occupied or contested territory on which civilians live. It excludes periods of non-violent contention (e.g., protests, riots, mobilization without organized armed opposition) and periods in which the primary conflict had ended before or shortly after the coverage window opened, leaving only residual or criminal violence. We identified and removed out-of-scope cases through a combination of automated filters and manual review.

[32]We draw on UCDP-GED and ACLED because they jointly maximize the number of conflict-spell observations that meet our scope conditions of dyadic violence.

2019. Within each country, we further partition the data into discrete conflict spells: contiguous time intervals during which the primary belligerent dyad (i.e., Side A incumbent versus Side B opposition) remained relatively stable.[33] We identify 138 spells across the 51 countries, from one to six per country (see Appendix A2).[34]

For consistency with our Soviet-UPA analyses, our spatial unit of observation is the second-order administrative division (to which we refer generally as "district") and our temporal unit is the calendar month. Throughout, we assign armed formations fighting on the side of incumbent government or occupation authorities to "Side 1," and their armed opponents (including state and non-state actors) to "Side 2."[35] The covariates — across all conflict spells — include road density, log distance to the nearest provincial capital, forest cover, elevation, number of local ethnic groups, petroleum presence, log population (1990 baseline), built-up land area, and fixed effects for province, year and month.[36]

The estimation strategy is identical to the Soviet-UPA application. For each conflict spell, we fit the same joint model of escalation and restraint, recover each side's predicted behavioral tendencies under counterfactual opponent behavior, and assemble them into a

[33]Spell boundaries correspond to major regime changes, state collapse, the entry or exit of a dominant armed actor, or a foreign military intervention that substantially altered the character of the conflict. The spell-based approach to political violence (i.e., treating episodes of organized coercion as units of analysis with identifiable onset and termination) follows Davenport and Appel (2022), who apply it to state repression. However, rather than thresholds in violence intensity, we use changes in dyadic composition as spell boundaries, on the premise that who is fighting matters as much as how much fighting is occurring.

[34]Multi-spell cases are conflicts without a stable dyadic structure, where fundamental changes in the identity or composition of the principal belligerents occurred during the coverage window (e.g., Afghanistan, Iraq, DRC, Somalia). We retain only spell-source combinations for which the variance of $\hat{\lambda}_k$ (rayon-level selectivity) is positive on both sides, a necessary condition for informative comparative statics tests.

[35]For each data source, country and conflict spell, the binary outcome is $Y_{1,it} = 1$ if sources report any Side 1 violence in district i and month t, and $Y_{2,it} = 1$ if sources report any violence by Side 2.

[36]These covariates are equation-invariant across the cross-national sample, trading case-specific tailoring for consistent measurement across a heterogeneous sample. Equation-specific covariate vectors are infeasible in a fully automated cross-national pipeline, as they would require conflict-specific coding decisions for each of the 215 spells. The symmetric specification is therefore a deliberate methodological choice, not a data limitation; we assess its implications in the robustness checks in Appendix A2.

coercive persistence score with bootstrap confidence intervals.[37]

4.2 Patterns of coercive persistence across conflicts

Figure 2 reports $\hat{\omega}$ estimates and 95% bootstrap confidence intervals for 138 conflict spells across 51 countries. A positive $\hat{\omega}$ indicates that Side 1's coercion is self-reinforcing: the asymmetric state where incumbents escalate and the opposition restrains is more persistent than the reverse. A negative estimate indicates that the opposition can sustain unilateral escalation more effectively than incumbents. Null estimates indicate relative symmetry.

The distribution of $\hat{\omega}$ spans a wide range, from strongly negative to strongly positive, with considerable heterogeneity within and across conflict types. Specifically, 27 (20%) of $\hat{\omega}$ estimates are positive and significant at the 95% confidence level, and 25 (18%) are negative and significant.[38] The remaining 86 (62%) are indistinguishable from zero.

The estimates in Figure 2 reveal two distinct types of sign variation in $\hat{\omega}$: shifts across conflict spells within the same country, and disagreements over the same spell across data sources. Within-country sign reversals often track documented shocks to the structural parameters that govern $\hat{\omega}$, particularly shifts in relative selectivity or outside options of Sides 1 and 2 following events like external military intervention or the loss of material support. Afghanistan is a clear example: $\hat{\omega}$ is negative in both pre-2001 spells (1992–1996, 1996–2001), reflecting the persistent coercive advantage of opposition forces over a fragmented central government. The estimates turn sharply positive following the U.S.-led intervention in October 2001, when NATO forces gave the (new) Afghan government ex-

[37]For each source-spell combination, we estimate equation (6) with the two-way Mundlak correction. We recover transition probabilities $\hat{p}_k$, $\hat{q}_k$ by averaging predicted marginal probabilities over the observed covariate distribution under counterfactual opponent behavior, and compute $\hat{\omega} = (1 - \hat{p}_1)\hat{q}_2 - \hat{q}_1(1 - \hat{p}_2)$ with 95% parametric bootstrap CI's drawn from the joint posterior of the bivariate probit coefficient vector.

[38]Negative $\hat{\omega}$ estimates tend to carry wider confidence intervals. In spells with strongly negative $\hat{\omega}$, Side 1 forces rarely escalate unilaterally. Few HL periods enter the denominator of $\hat{p}_1$, and the small count inflates bootstrap variance for this component of $\hat{\omega}$. We test this explanation in Appendix **??**.

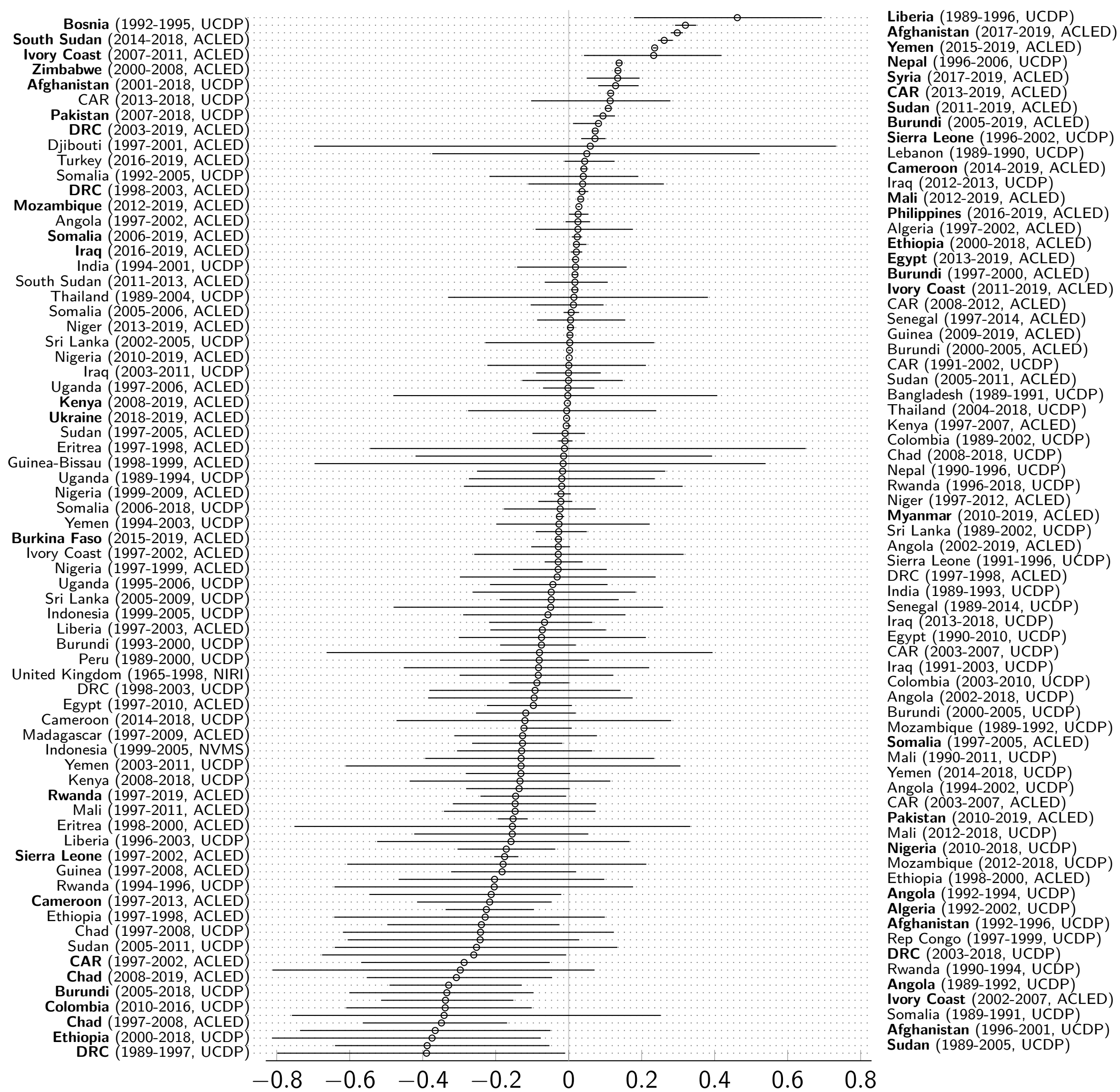

Figure 2: **Cross-national estimates of coercive persistence for Side 1 (incumbent)**. Point estimates and 95% bootstrap confidence intervals for $\hat{\omega}_1$. Bold labels indicate significance at 95% level. Of 138 estimates: 47 (34%) are positive, 91 (66%) are negative, including 27 (20%) positive and significant, 25 (18%) negative and significant.

ternal support that reduced its need to cultivate civilian cooperation to sustain operations.

The Central African Republic (CAR) traces a similar arc. $\hat{\omega}$ is significantly negative during the period of state fragmentation and overlapping rebel factions (1990–2002), drifts toward zero through the transitional period (2003-2007, 2008-2012), and turns significantly positive in the post-2013 spell. The latter shift coincides with the arrival of Russia's Wagner Group forces in 2017–2018, which substantially expanded government-side outside options, supplying external personnel, materiel, and logistical capacity that insulated the government from dependence on local civilian cooperation.

Sudan shows a parallel trajectory: negative and significant in the early civil war period (1989-2005), near-zero during the Comprehensive Peace Agreement era (2005-2011), and significantly positive in the subsequent post-secession Darfur/South Kordofan period. Cameroon follows the same pattern at a smaller scale: negative during the Boko Haram spillover period in the Far North, turning positive after 2014, as government and paramilitary forces consolidated control over the Anglophone crisis.

Taken together, these reversals are consistent with the model's prediction that one-sided violence is a structural feature of the coercive environment rather than a fixed country-level quantity: as the military balance shifts, coercive persistence shifts with it.

A second source of sign variation is less common: disagreement on $\hat{\omega}$ between UCDP-GED and ACLED for the same spell. This pattern affects only five spells — Burundi post-2005, Democratic Republic of Congo (DRC) post-2003, Ethiopia 2000-2018, Pakistan post-2007, Sierra Leone 1996-2002 — and likely reflects systematic differences in the two sources' collection protocols rather than genuine uncertainty about conflict dynamics.[39]

[39] UCDP-GED restricts coverage to events involving organized armed actors, requires documentation of fatalities, and draws primarily on global newswires (Sundberg and Melander, 2013). ACLED casts a broader net, collecting events from local and regional media alongside wire services, and includes non-fatal violence (Raleigh et al., 2010). Because these differences in sourcing and inclusion criteria do not inflate event counts symmetrically across both sides of a dyad, they can shift the relative magnitudes of $\hat{p}_1$ and $\hat{q}_1$, and thus the sign of $\hat{\omega}$, in ways that are conflict-specific and difficult to predict from first principles.

The rarity of such disagreement (five spells out of 138) testifies to the broad convergence of results across the UCDP-GED and ACLED datasets.

4.3 Targeting precision and outside options

Our theory predicts that more selective targeting raises coercive persistence: the more precisely a combatant can identify enemy collaborators, the higher the return to sustained punishment, and the more self-reinforcing one-sided violence becomes.[40] We test this prediction by computing $\hat{\omega}$ at the bottom and top quintiles of the selectivity distribution within each source-spell sample. As in the Soviet-UPA application, we operationalize selectivity as a district-level time average of the share of violence that Side 1 directs at armed opponents rather than civilians, consistent with the theoretical role of selectivity as the share of punishment falling on identified enemy cooperators.[41]

Figure 3 reports the estimated change in coercive persistence as selectivity moves from the bottom to the top of each conflict's distribution, with 95% confidence intervals.[42] Most cases (75%) show a positive contrast, consistent with our theoretical prediction. 53 (38%) of the estimated contrasts are positive and significant, and another 50 (37%) are positive but statistically indistinguishable from zero. No case shows a statistically significant negative contrast. Higher selectivity never reliably reduces government coercive persistence.

These results hold across all 138 source-spell samples, spanning five decades, four continents, and two data sources. They hold regardless of whether government coercive persistence is itself positive or negative.[43] Even where the opposition is generally more persistent,

[40]Formally, Corollary 1(i) establishes $\partial\omega/\partial\lambda_1 > 0$: greater selectivity by Side 1 raises $\hat{\omega}$, while greater selectivity by Side 2 lowers it.

[41]The time-average is a more credible proxy for the underlying technology parameter than short-run tactical choices, and avoids zero-denominator and endogeneity problems.

[42]Formally, the contrast is $\Delta\hat{\omega} = \hat{\omega}^{\text{hi}} - \hat{\omega}^{\text{lo}}$.

[43]Confidence intervals for $\hat{\omega}$ are substantially wider when the point estimate is negative (mean width 0.45) than when it is positive (mean width 0.18), and the same asymmetry carries over to the contrast

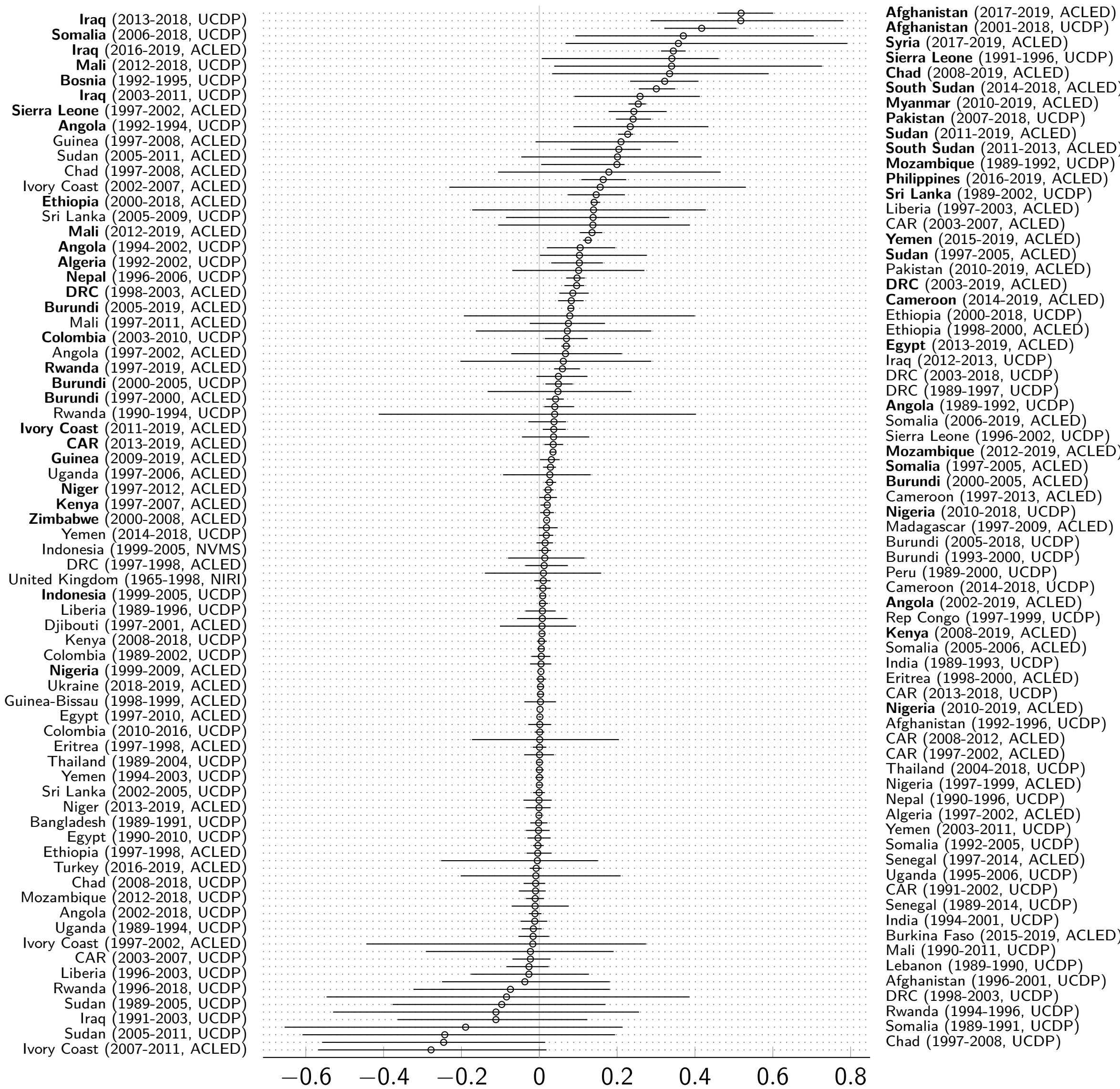

Figure 3: **How Side 1's coercive persistence varies with selectivity of violence**. Point estimates and 95% bootstrap confidence intervals for $\Delta\hat{\omega}_1 = \hat{\omega}_1^{\text{hi}} - \hat{\omega}_1^{\text{lo}}$, where $\hat{\omega}_1^{\text{hi}}, \hat{\omega}_1^{\text{lo}}$ are average values of $\hat{\omega}_1$ for localities in the highest versus lowest quintiles of $\bar{\lambda}_1$. Bold labels indicate significance at 95% level. Of 138 estimates: 103 (75%) are positive, 35 (25%) are negative, including 53 (38%) positive and significant, 0 (0%) negative and significant.

greater government selectivity narrows the gap and sometimes reverses it. In 16 cases where $\hat{\omega} < 0$, the high-selectivity estimate turns positive, and 11 of these reversals are statistically significant (e.g., Iraq, Somalia, Myanmar).

Our theory also predicts that combatants with robust outside options (e.g., external sponsors, lootable resources, forces drawn from outside the locality) can sustain unilateral escalation even without precise targeting, because they do not depend on local civilian cooperation to keep fighting.[44] We test this prediction with two complementary approaches.

First, we ask how often $\hat{\omega}$ is positive and significant even at low selectivity, a pattern that targeting precision alone cannot explain.[45] Of the 138 conflict spells, 16 (12%) show significantly positive coercive persistence even where government operations are mostly indiscriminate, consistent with outside options sustaining escalation independently of targeting capacity. Liberia's first civil war (1989-1996) fits this pattern: Charles Taylor's forces drew on timber and mineral revenues to sustain operations largely without relying on civilian cooperation. Ivory Coast's post-election crisis (2007–2011) coincides with French *Licorne* force involvement that gave the government a coercive backstop. Yemen (2015–2019) reflects the Saudi-led coalition's access to external materiel and logistical support. Bosnia (1992–1995) and CAR (post-2013) similarly point to external reinforcement as the operative mechanism. In each case, access to resources or forces from outside the locality sustained coercive persistence where precision targeting could not.

Second, we ask whether local conditions that proxy for outside options and escalation

estimates (0.24 vs. 0.12). This is not a statistical artifact. Negative $\hat{\omega}$ arises when the opposition sustains unilateral escalation more reliably than the government. In this configuration, government coercion is predominantly indiscriminate and $\hat{p}_1$ is low and variable across space, producing a noisier estimate of the $HL \to HL$ transition and a wider bootstrap distribution for $\hat{\omega}$.

[44] Formally, Corollary 1(iv) establishes $\partial\omega/\partial c_1 < 0$: greater outside options c_1 lower the selectivity threshold $\lambda_1^\dagger$, expanding the region in which Side 1 escalates. pushing $\hat{\omega}$ toward negative values (Remark 1).

[45] Formally, we evaluate $\hat{\omega}$ at the bottom quintile of the λ_1 distribution ($\hat{\omega}^{\text{lo}}$) and identify cases where the 95% bootstrap CI excludes zero from below.

costs shift coercive persistence in the directions our theory predicts.[46] For each spell, as in the Soviet-UPA analysis, we shift each covariate from its observed minimum to maximum while holding all others at their medians, and report the resulting change in coercive persistence. Table 2 summarizes the results.

Three covariates conform most consistently to the model's predictions. Ethnic cohabitation (i.e., the number of unique ethnic settlement zones overlapping each district, Weidmann et al. 2010) yields the most consistent support: 68% of spells show a positive contrast, with significantly positive cases outnumbering significantly negative ones by nearly 4:1. Where multiple ethnic groups' territories overlap, civilians face higher coordination costs for collective resistance, making sustained defiance harder to organize and reinforcing the government's coercive advantage.

Built-up areas produce a similar pattern (59% positive, 27% significantly positive vs. 8% significantly negative), consistent with denser settlement reducing the logistical costs of sustained escalation through better infrastructure, easier force projection, and established administrative presence. Urban economic concentration may also raise outside options directly, providing resource flows that reduce government dependence on civilian support.

Petroleum presence (i.e., a binary indicator of whether any petroleum deposit lies within the district, Lujala et al. 2007) shows the cleanest ratio of significantly positive to negative contrasts (6:1 across 73 spells), consistent with resource rents providing an attrition value that sustains government escalation without requiring precise targeting.

The remaining covariates show no consistent directional pattern. Their relationship to outside options and escalation costs varies too much across conflicts to aggregate cleanly.

[46] Formally, we estimate the contrast $\hat{\omega}^{\text{hi}} - \hat{\omega}^{\text{lo}}$ as each covariate moves from its observed minimum to maximum, holding all others at their medians, and ask whether the sign matches Corollary 1. Outside options correspond to c_k; escalation costs correspond to $\kappa_k(H)$.

Table 2: **Cross-national comparative statics.** Each cell reports the number of source-spell samples in which $\hat{\omega}$ increases or decreases when a covariate moves from its observed minimum to maximum, holding all other covariates at their medians. Sample sizes vary across covariates due to exclusion of cases with no within-spell variation or missing data on the covariate in question. 95% bootstrap confidence intervals determine significance.

			All contrasts		Significant at 95%	
Covariate	Spells	Countries	Positive	Negative	Positive	Negative
Number of ethnic groups	109	41	74 (68%)	35 (32%)	23 (21%)	6 (6%)
Built-up areas	111	43	66 (59%)	45 (41%)	30 (27%)	9 (8%)
Log population (1990)	111	43	64 (58%)	47 (42%)	16 (14%)	8 (7%)
Petroleum presence	73	29	42 (58%)	31 (42%)	12 (16%)	2 (3%)
Road density	111	43	60 (54%)	51 (46%)	10 (9%)	12 (11%)
Forest cover	111	43	56 (50%)	55 (50%)	14 (13%)	14 (13%)
Mean elevation	111	43	55 (50%)	56 (50%)	15 (14%)	17 (15%)
Log distance adm. center	111	43	46 (41%)	65 (59%)	9 (8%)	19 (17%)

5 Conclusion

Why does one side in a contested territory sustain high levels of violence while the other restrains? We have argued that the answer lies not in informational or material deficits, but in surpluses. A combatant commits to sustained unilateral punishment when its violence is selective enough to make civilians submit, or when outside options make civilian cooperation strategically dispensable. One-sided violence, in this view, is not a sign of desperation. Combatants escalate persistently when they are well-positioned to do so.

We built a measure of this commitment, estimated it from sequences of observed acts of violence in dyadic conflict panel data, and used it to locate each combatant in the equilibrium structure of our theoretical model. The approach requires no direct observation of civilian behavior, only the observable record of who escalated, where, and when.

Evidence from Ukraine and our cross-national sample corroborate the framework at both scales. Soviet targeting in western Ukraine was almost uniformly indiscriminate, yet coercive persistence tracked even marginal improvements in precision across localities, a gradient that a pure attrition account cannot explain. Where administrative infrastructure was dense, where wartime partisan networks had already embedded intelligence capacity, and where urban concentration facilitated surveillance, Soviet escalation was significantly more durable. Across the cross-national sample, the same pattern held: government coercive persistence rose with selectivity in a large majority of conflict spells, and shifted in predictable directions when external military interventions or resource endowments changed the structural environment. One-sided violence is not a fixed property of a conflict. It rises as targeting technology improves and access to outside resources expands.

These findings reframe what one-sided violence is and where it comes from. It is not a symptom of weakness or miscalculation. It is a predictable consequence of a conflict's asymmetric structural features, and it persists as long as that asymmetry does.

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A1 Theoretical Appendix

Table A1: **Model notation.**

Symbol	Description
i, t, j, k	Indices for locality, time period, civilian, and combatant ($k \in \mathcal{K}$).
$\mathcal{K}$	Combatant set $\mathcal{K} = \{1, 2\}$, where Side 1 is the incumbent armed actor and Side 2 is the challenging armed actor.
A_k	Action set for combatant k: $A_k = \{L, H\} = \{0, \Delta\}$.
L, H, Δ	Low and high punishment; $L = 0$, $H = \Delta > 0$.
θ_j	Civilian j's type (relative collateral vs. selective vulnerability).
$F(\theta\|x_i), f(\theta\|x_i)$	Type distribution and density in locality i, conditional on local observables x_i. Mean type in locality i is $\bar{\theta}_i = \mathbb{E}[\theta_j\|x_i]$.
ρ_k	Punishment level chosen by combatant k; $\rho_k \in A_k$.
e_j, e_j^*, e_k^*	Civilian j's cooperation with Side 1 ($e_j \in [0, 1]$); e_j^* is optimal value; e_k^* is share directed to k ($e_1^* = e_j^*$, $e_2^* = 1 - e_j^*$).
$\bar{e}_i$	Mean cooperation with Side 1 in locality i: $\bar{e}_i = \mathbb{E}[e_j^*\|x_i]$.
λ_k	Selectivity of k's violence.
$\lambda_k^\dagger$	Critical selectivity level at which H becomes optimal for k.
λ_i^*	Aggregate civilian threshold in locality i: $\lambda_i^* = \bar{\theta}_i$.
b	Value of a unit of civilian cooperation to each combatant.
$\kappa_k(\rho_k)$	Punishment cost for k; $\kappa_k(L) = 0$, $\kappa_k(H) > 0$.
c_k	Combatant k's outside options to local support; $c_k \geq 0$.
γ	Curvature of civilian utility (cost of deviating from $e_j = 1/2$).
Φ_k	Cooperation premium of combatant k: $\Phi_k = \frac{\Delta}{\gamma}(\lambda_k - \bar{\theta}_i)$.
$U_j(e_j), U_k(\rho_k, \rho_{-k})$	Civilian j's utility, combatant k's utility.
S, s_{it}	State space; state of locality i at time t: $s_{it} = (\lambda_{it}, x_{it})$.
g, ε_{it}	Selectivity transition: $\lambda_{i,t+1} = g(\lambda_{it}, \rho_{1,it}, \rho_{2,it}, x_{it}) + \varepsilon_{i,t+1}$.
$v_k(s, \rho_k, \rho_{-k})$	Stage payoff to combatant k in state s under profile (ρ_k, ρ_{-k}).
$\xi_k, V_k(s)$	Strategy and continuation value of combatant k at state s.
p_k, q_k	Reactive strategies: $p_k = P(L_t \mid L_{t-1}^{-k})$, $q_k = P(L_t \mid H_{t-1}^{-k})$.
δ	Common discount factor in the stochastic game.
$\mathcal{A} = A_1 \times A_2$	Set of observable punishment profiles: $\mathcal{A} = \{LL, LH, HL, HH\}$.
$M, m_{a'a}$	4×4 transition matrix over $\mathcal{A}$; $m_{a'a} = P(a' \mid a)$ for $a, a' \in \mathcal{A}$.
ω	Coercive resolve index: $\omega = m_{HL,HL} - m_{LH,LH}$.

Two combatants ($k \in \{1,2\}$) simultaneously choose $\rho_k \in \{L, H\} = \{0, \Delta\}$ in each locality i and period t. Each civilian j draws type $\theta_j \sim F(\theta|x_i)$, with $\bar{\theta}_i \equiv \mathbb{E}[\theta_j|x_i]$; θ_j is private information, but combatants observe $F(\theta|x_i)$.

Assumption 1 (Civilian utility)**.** Civilian j chooses $e_j \in [0,1]$ to maximize

$$U_j(e_j) = -\Big[\theta_j(1-\lambda_1)\rho_1 + (1-\theta_j)\lambda_2\rho_2\Big]e_j - \Big[\theta_j(1-\lambda_2)\rho_2 + (1-\theta_j)\lambda_1\rho_1\Big](1-e_j) - \frac{\gamma}{2}\Big(e_j - \tfrac{1}{2}\Big)^2. \tag{7}$$

Assumption 2 (Combatant utilities)**.** Combatant k chooses $\rho_k \in \{L, H\}$ to maximize

$$U_k(\rho_k, \rho_{-k}) = b \cdot \mathbb{E}[e_k^* \mid x_i] + c_k(1-\lambda_k)\rho_k - \kappa_k(\rho_k), \tag{8}$$

where $b > 0$, $c_k \geq 0$, $\kappa_k(L) = 0$, $\kappa_k(H) > 0$. Note that c_k does not enter civilian utility: defiance and submission depend solely on λ_k and θ_j.

Proposition 1 (Civilian response)**.** *Fix locality i.*

(a) (Interior solution.) If $\gamma > 2|(\lambda_1 - \theta_j)\rho_1 - (\lambda_2 - \theta_j)\rho_2|$, j has a unique best response:

$$e_j^* = \frac{1}{2} + \frac{(\lambda_1 - \theta_j)\rho_1 - (\lambda_2 - \theta_j)\rho_2}{\gamma}. \tag{9}$$

(b) (Defiance and submission.)

$$\frac{\partial e_j^*}{\partial \rho_1} = \frac{\lambda_1 - \theta_j}{\gamma}, \qquad \frac{\partial e_j^*}{\partial \rho_2} = -\frac{\lambda_2 - \theta_j}{\gamma}. \tag{10}$$

Civilian j defies Side 1 iff $\lambda_1 < \theta_j$; submits iff $\lambda_1 > \theta_j$. Symmetrically for Side 2.

(c) (Aggregation.)

$$\bar{e}_i(\rho_1, \rho_2) = \frac{1}{2} + \frac{(\lambda_1 - \bar{\theta}_i)\rho_1 - (\lambda_2 - \bar{\theta}_i)\rho_2}{\gamma}. \tag{11}$$

Define $\lambda_i^* \equiv \bar{\theta}_i$. The mean response $\bar{e}_i$ rises with ρ_1 iff $\lambda_1 > \lambda_i^*$, falls iff $\lambda_1 < \lambda_i^*$.

Proof. Part (a). The FOC $\partial U_j/\partial e_j = 0$ gives $-[(\theta_j - \lambda_1)\rho_1 - (\theta_j - \lambda_2)\rho_2] - \gamma(e_j - \frac{1}{2}) = 0$, which solves to (9). Strict concavity ($\partial^2 U_j/\partial e_j^2 = -\gamma < 0$) confirms uniqueness; the condition on γ ensures $e_j^* \in (0,1)$.

Part (b). Differentiate (9) directly to obtain (10).

Part (c). Take expectations of (9) over $\theta \sim F(\theta|x_i)$ to obtain (11); the sign of $\partial \bar{e}_i/\partial \rho_1 = (\lambda_1 - \bar{\theta}_i)/\gamma$ follows immediately. □

Define the *cooperation premium*:

$$\Phi_k \;\equiv\; \frac{\Delta}{\gamma}(\lambda_k - \bar{\theta}_i). \tag{12}$$

Mean cooperation with k under each profile is $\mathbb{E}[e_k^*|H,L] = \frac{1}{2} + \Phi_k$, $\mathbb{E}[e_k^*|L,H] = \frac{1}{2} - \Phi_{-k}$, $\mathbb{E}[e_k^*|H,H] = \frac{1}{2} + \Phi_k - \Phi_{-k}$, $\mathbb{E}[e_k^*|L,L] = \frac{1}{2}$. Since $\rho_k \in \{0, \Delta\}$, net gain from escalating is

$$U_k(H,\cdot) - U_k(L,\cdot) \;=\; b\,\Phi_k + c_k(1-\lambda_k)\Delta - \kappa_k(H), \tag{13}$$

independent of the opponent's action and strictly increasing in λ_k (since $c_k < b/\gamma$).

Theorem 1 (Equilibrium regimes)**.** *Fix locality i with $\bar{\theta}_i$, (λ_1, λ_2), $\kappa_k(H) > 0$, and $c_k \geq 0$ with $c_k < b/\gamma$ for each k. Define*

$$\lambda_k^\dagger \;\equiv\; \bar{\theta}_i + \frac{\gamma[\kappa_k(H) - c_k(1-\bar{\theta}_i)\Delta]}{(b - c_k\gamma)\Delta}. \tag{14}$$

The game is dominance-solvable with unique Nash equilibrium:

(i) (H,H) *if* $\lambda_1 > \lambda_1^\dagger$ *and* $\lambda_2 > \lambda_2^\dagger$ (mutual escalation)*;*

(ii) (L,L) *if* $\lambda_1 < \lambda_1^\dagger$ *and* $\lambda_2 < \lambda_2^\dagger$ (mutual restraint)*;*

(iii) (H,L) *if* $\lambda_1 > \lambda_1^\dagger$ *and* $\lambda_2 < \lambda_2^\dagger$ (asymmetric escalation by Side 1)*;*

(iv) (L,H) *if* $\lambda_1 < \lambda_1^\dagger$ *and* $\lambda_2 > \lambda_2^\dagger$ (asymmetric escalation by Side 2)*.*

When $\kappa_1(H) = \kappa_2(H)$ and $c_1 = c_2$, the thresholds coincide and only regimes (i)–(ii) arise.

Proof. Substituting $\Phi_k = \Delta(\lambda_k - \bar{\theta}_i)/\gamma$ into (13):

$$U_k(H,\cdot) - U_k(L,\cdot) = \Delta\lambda_k\left(\frac{b}{\gamma} - c_k\right) + \Delta\left(c_k - \frac{b\bar{\theta}_i}{\gamma}\right) - \kappa_k(H).$$

Since $c_k < b/\gamma$, the coefficient on λ_k is positive. Setting equal to zero and solving yields (14). H strictly dominates iff $\lambda_k > \lambda_k^\dagger$; L strictly dominates iff $\lambda_k < \lambda_k^\dagger$. Since (13) is independent of the opponent's action, each combatant has a strictly dominant action, making the game dominance-solvable. Crossing the two independent conditions yields regimes (i)–(iv); symmetry of thresholds under $\kappa_1(H) = \kappa_2(H)$, $c_1 = c_2$ rules out asymmetric profiles. $\square$

The threshold $\lambda_k^\dagger$ is strictly decreasing in c_k: outside options expand the region in which escalation dominates. When $c_k > \kappa_k(H)/[\Delta(1-\bar{\theta}_i)]$, the threshold falls below $\bar{\theta}_i$, and k escalates despite a negative cooperation premium (Remark 1).

Remark 1 (Attrition sub-regime)**.** When $\lambda_k^\dagger < \bar{\theta}_i$, any k with $\lambda_k \in (\lambda_k^\dagger, \bar{\theta}_i)$ escalates despite $\Phi_k < 0$: the outside-option term $c_k(1-\lambda_k)\Delta$ covers both the cooperation loss and $\kappa_k(H)$. From the perspective of ω, attrition-driven and cooperation-driven escalation are observationally equivalent; separating them empirically requires variation in proxies for c_k.

Suppose each combatant k conditions its current action on the opponent's previous action.[47] Define

$$p_k \equiv P(\rho_{kt} = L \mid \rho_{-k,t-1} = L), \qquad q_k \equiv P(\rho_{kt} = L \mid \rho_{-k,t-1} = H). \tag{15}$$

Proposition 2 (Coercive resolve index)**.**

(a) (Transition matrix.) Under the independence restriction,

$$m_{HL,HL} = (1-p_1)q_2, \qquad m_{LH,LH} = q_1(1-p_2). \tag{16}$$

(b) (Coercive resolve index.)

$$\omega \;\equiv\; m_{HL,HL} - m_{LH,LH} \;=\; (1-p_1)q_2 - q_1(1-p_2). \tag{17}$$

(c) (Structural decomposition.) Under the MPE of the stochastic game,

$$\omega = \omega(\lambda_1, \lambda_2, c_1, c_2, \kappa_1(H), \kappa_2(H), \bar{\theta}_i, b, \gamma, g). \tag{18}$$

$\omega > 0$ iff Side 1 escalates ($\lambda_1 > \lambda_1^\dagger$) and Side 2 restrains ($\lambda_2 < \lambda_2^\dagger$); $\omega < 0$ iff Side 1 restrains and Side 2 escalates; $\omega = 0$ iff both occupy the same regime.

Proof. Part (a). Under independence, $m_{a'a} = P(a_1'|a_2) \cdot P(a_2'|a_1)$. For $HL \to HL$: Side 1 sees L and plays H with probability $1-p_1$; Side 2 sees H and plays L with probability q_2; so $m_{HL,HL} = (1-p_1)q_2$. $m_{LH,LH} = q_1(1-p_2)$ follows by symmetry.

Part (b). Subtract (16) directly.

Part (c). The MPE pins down $\xi_k : S \to A_k$, making (p_k, q_k) functions of structural primitives, establishing (18). For sign identification: when Side 1 escalates ($p_1 = q_1 = 0$) and Side 2 restrains ($p_2 = q_2 = 1$), $\omega = 1\cdot 1 - 0\cdot 0 = 1 > 0$. Reversing gives $\omega = 0\cdot 0 - 1\cdot 1 = -1 < 0$. When both occupy the same regime, $p_k = q_k$ and $\omega = (1-p_1)p_2 - p_1(1-p_2) = p_2 - p_1 = 0$ under symmetry. In the stochastic game, intermediate values arise as weighted averages over periods in each configuration. □

[47] At any fixed state $s_{it} = (\lambda_{it}, x_{it})$, Theorem 1 implies $p_k = q_k$. The inequality $p_k \neq q_k$ can hold in the time series because λ_{it} evolves stochastically: the opponent's lagged action proxies for the unobserved current state, and the reactive strategies encode equilibrium belief-updating, not strategic history-dependence.

Remark 2 (MPE existence)**.** The stochastic game admits a stationary MPE satisfying

$$V_k(s) = \max_{\rho_k}\Big\{v_k(s, \rho_k, \xi_{-k}(s)) + \delta \int V_k(s')\, P(ds' \mid s, \rho_k, \xi_{-k}(s))\Big\}.$$

Existence for finite state and action spaces follows from Fink (1964); for continuous state spaces from Mertens and Parthasarathy (1987) under norm-continuous transition probabilities, satisfied by g.

Remark 3 (Folk theorem)**.** In an infinitely repeated game against a fixed population, the folk theorem (e.g., Fudenberg and Maskin, 1986) makes virtually any payoff vector sustainable as a subgame-perfect equilibrium, eliminating testable predictions. The stochastic game resolves this: time-varying s_{it} makes dominant actions pin down behavior uniquely at each state, and the observed transition dynamics of punishment profiles carry structural information about the prevailing regime.

Remark 4 (Limiting case $\gamma \to 0$)**.** As $\gamma \to 0$, (9) degenerates to a corner: $e_j^* \to 1$ if $(\lambda_1 - \theta_j)\rho_1 > (\lambda_2 - \theta_j)\rho_2$, and $e_j^* \to 0$ otherwise. The threshold (14) converges to $\bar{\theta}_i$ as $\gamma \to 0$, collapsing the critical selectivity to the mean civilian type. The qualitative predictions of Proposition 1 and Theorem 1 hold across the full range of γ.

Corollary 1 (Comparative statics on ω)**.**

(i) $\partial\omega/\partial\lambda_1 \geq 0,\ \ \partial\omega/\partial\lambda_2 \leq 0.$

(ii) $\partial\omega/\partial\bar{\theta}_i \gtrless 0$ *as* $\lambda_1 \gtrless \lambda_2.$

(iii) $\partial\omega/\partial\kappa_1(H) \leq 0,\ \ \partial\omega/\partial\kappa_2(H) \geq 0.$

(iv) $\partial\omega/\partial c_1 \geq 0,\ \ \partial\omega/\partial c_2 \leq 0.$

Proof. Parts (i)–(iii) follow from Proposition 2(c) and Theorem 1. For part (iv): $\partial\lambda_k^\dagger/\partial c_k < 0$ since both the numerator $\kappa_k(H) - c_k(1-\bar{\theta}_i)\Delta$ and denominator $b - c_k\gamma$ decrease in c_k, with net derivative negative under $c_k < b/\gamma$. A lower $\lambda_1^\dagger$ expands the region $\lambda_1 > \lambda_1^\dagger$, raises $m_{HL,HL}$ and ω. The symmetric argument for c_2 lowers $\lambda_2^\dagger$, raises $m_{LH,LH}$, reduces ω. □

A2 Additional Empirical Results

Table A2: **Comparison of bivariate probit to independent probits**. $\hat{\omega}_1$: coercive persistence for Side 1 (Soviets). $\hat{\omega}_2$: coercive persistence for Side 2 (UPA). $\hat{\omega}_{2p}$: two independent probit benchmark. 95% CIs from parametric bootstrap.

	Coercive Persistence				Fit	
Model	$\hat{\omega}_1$ (95% CI)	$\hat{\omega}_2$ (95% CI)	$\hat{\omega}_{2p,1}$ (95% CI)	$\hat{\omega}_{2p,2}$ (95% CI)	N	AIC
Independent	0.10 (0.08, 0.12)	-0.29 (-0.33, -0.24)	0.02 (-0.04, 0.08)	-0.01 (-0.06, 0.05)	20076	27329
Additive	0.17 (0.14, 0.22)	-0.26 (-0.32, -0.22)	0.02 (-0.04, 0.07)	-0.00 (-0.06, 0.05)	20076	27125
Interactive	0.18 (0.14, 0.23)	-0.27 (-0.32, -0.22)	0.02 (-0.04, 0.07)	-0.00 (-0.06, 0.05)	20076	27109
+ Mundlak	0.17 (0.14, 0.20)	-0.22 (-0.28, -0.18)	0.02 (-0.04, 0.07)	-0.00 (-0.06, 0.05)	20076	25961
+ Mundlak (2-way)	0.20 (0.16, 0.24)	-0.25 (-0.29, -0.20)	0.02 (-0.04, 0.07)	-0.00 (-0.06, 0.05)	20076	25847

Table A3: **Bivariate probit model comparison**. LRT columns report χ^2 statistic vs. named nested model. Significance: $^{**}p < 0.01$, $^{*}p < 0.05$, $^{\dagger}p < 0.1$.

	Fit		Likelihood Ratio Test				
Model	N	AIC	v. 2-probit	v. indep.	v. add.	v. inter.	v. Mundlak
Independent	20076	27329	361.1**	—	—	—	—
Additive	20076	27125	374.1**	207.7**	—	—	—
Interactive	20076	27109	371.9**	227.9**	20.2**	—	—
+ Mundlak	20076	25961	320.0**	1379.8**	1172.1**	1151.9**	—
+ Mundlak (2-way)	20076	25847	343.2**	1497.7**	1290.0**	1269.8**	117.9**