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THE GRAVITY OF VIOLENCE

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and Mathias Thoenig

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THE GRAVITY OF VIOLENCE

Abstract

This paper presents a framework for estimating and simulating a quantitative spatial model of trade and violence. In this new theoretical and empirical setup, designed for the analysis of bilateral flows, we first model the general equilibrium interactions between the economic and fighting margins in a micro-founded setup. We then show how the structural parameters can be recovered from the data in a simple and transparent way. A central element of the procedure consists in estimating a structural gravity equation of violence. Studying continental Africa over the period 1997 to 2023, we test the key predictions of the model and uncover new facts related to spatial frictions and conflicts. Finally, the model is simulated to quantify different policy-relevant experiments in weakly institutionalized contexts where insecurity is pervasive. Positive and spatially-diffusing feedback loops between development and pacification are one of the main findings of our analysis.

JEL Classification: F1, D74, O1, R1

Keywords:

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THE GRAVITY OF VIOLENCE *

—A QUANTITATIVE SPATIAL MODEL OF NON-STATE ARMED GROUPS—

Mathieu Couttenier[†] Julian Marcoux[‡] Thierry Mayer[§] Mathias Thoenig[¶]

June 26, 2026

Abstract

This paper presents a framework for estimating and simulating a quantitative spatial model of trade and violent conflict. In this new theoretical and empirical setup, designed for the analysis of bilateral flows, we first model the general equilibrium interactions between the economic and fighting margins in a micro-founded setup. We then show how the structural parameters can be recovered from the data in a simple and transparent way. A central element of the procedure consists in estimating a structural gravity equation of violence. Studying continental Africa over the period 1997 to 2023, we test the key predictions of the model and uncover new facts related to spatial frictions and conflicts. Finally, the model is simulated to quantify different policy-relevant experiments in weakly institutionalized contexts where insecurity is pervasive. Spatially-diffusing feedback loops between economic shocks and violence are one of the main findings of our analysis.

Keywords: Violence, conflicts, trade, development, gravity.

JEL Codes: F1, D74, O1, R1

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1 Introduction

Violence is observed where it occurs, but is often organized elsewhere. In this paper, we study how non-state armed groups project force across regions and how this geography of violence interacts with the geography of economic activity. We focus on Africa, where limited state capacity makes economic shocks likely to affect not only income, trade, and welfare, but also the incentives to fight. A productivity gain can raise peaceful earnings, reduce recruitment into violence and increase the capacity of local authorities to protect, but it can also increase the value of appropriable resources. Trade integration can raise the returns to peaceful exchange, whereas trade fragmentation can reduce income and make appropriation more attractive. Climate shocks may reallocate agricultural activity, disrupt food chains, and induce migration, all of which can affect violence. Transport infrastructure can connect markets and extend state reach, but it can also lower the cost of projecting violence. These examples point to a common problem: shocks propagate across space through economic linkages, while also changing the spatial allocation of violence.¹ Whether the resulting feedbacks dampen or amplify the initial shock is a central question that we address through a quantitative model in which economic activity and violence are jointly determined.

Our general-equilibrium model describes a multi-regional economy in which individuals freely allocate labor between production and fighting. Trade frictions govern the access of producers to non-local markets, while violence frictions govern the ability of armed groups to appropriate income away from their home base. These two spatial margins generate interconnected gravity equations for trade and bilateral violence, linked through labor-market clearing and occupational choice. The gravity equation of violence is not introduced as a modeling device for its own sake. It provides a tractable way to discipline conflict data that are intrinsically spatial. These data locate violent events and identify the armed groups involved, which we use to construct the origins from which violence is projected. This bilateral structure delivers two main implications for the conflict literature. First, it separates the origin side of violence, where income affects the opportunity cost of fighting, from the destination side, where income affects appropriable resources and local state capacity. Second, bilateral frictions generate uneven spatial competition among armed groups within each destination; we refer to this channel as the Multilateral Resistance of Violence (MRV).

The baseline model follows a long tradition that views conflict and war-making as organized appropriation (Olson, 1993; Tilly, 1985; Dal Bó and Dal Bó, 2011). In the greed-grievance distinction of Collier and Hoeffler (2004), it captures the economic incentives to use violence for resource appropriation, a widely documented motive of conflict (Dube and Vargas, 2013; Berman et al., 2017; Sanchez de la Sierra, 2020; Berman et al., 2021; Eberle et al., 2024; McGuirk and Nunn, 2025). Beyond looting and appropriation, the model can be naturally extended to account for other types of violence, from territorial and political control to identity or religious conflict. We also study extensions with forced recruitment, endogenous state capacity, market power among fighting groups

¹Consistent with this concern, existing evidence shows that development interventions in conflict areas can have unintended effects: Nunn and Qian (2014) show that food assistance can increase conflict, and Crost et al. (2014) document how insurgents undermined a development program in the Philippines. As McGuirk and Burke (2020) emphasize, economic shocks that alter the opportunity cost of violence also affect the spoils of victory and a government's capacity to repel insurgents, so that the net spatial effects are theoretically indeterminate without a general equilibrium framework.

and endogenous entry into the appropriation market. These extensions clarify which parts of the framework are robust: the bilateral allocation logic is preserved, while the compact estimation and inversion structure of the benchmark becomes less tractable. What is essential for the gravity structure is that armed organizations allocate violent effort across destinations under spatial frictions.

The empirical part of the paper is organized in several steps. The first is to construct bilateral flows of violence from standard event-level conflict data. We use the Armed Conflict Location and Event Dataset (ACLED) to identify violent events: ACLED records where violence occurs and the armed groups involved, but not where it originates. We assign each armed group to an origin region using its recruitment base and historical affiliation, and assign each event to the destination where it occurs. The construction does not require ACLED to identify perpetrators and victims as origin-destination pairs: each event involving an armed group generates a flow from the group’s assigned origin to the event location. This transforms “place-based” conflict data into origin-destination flows over the period 1997-2023. Origin and destination coincide when violence is local, and differ when armed groups project violence at a distance. We use historical Murdock homelands as the benchmark spatial partition, which provides a stable historical geography of ethnic territories, and systematically assess the robustness of the construction to border-proximity restrictions, alternative destination units, geocoding precision, actor-matching quality, and Afrobarometer-based measures of contemporary ethnic dispersion.

We then derive and estimate the gravity equation of violence. The estimated equation shows that bilateral violence is strongly shaped by distance and by spatial discontinuities. Violence declines with distance, and flows are lower when origins and destinations are separated by political borders. There is also evidence that fighting groups target their own ethnic homeland less intensely: Conditional on distance and border, intra-regional flows of violence are roughly one order of magnitude below inter-regional flows. These empirical patterns are robust across a wide set of specifications. The distance gradient is the most stable pattern; border effects are more sensitive to how ethnic and political discontinuities are measured, as expected given that they depend directly on the spatial partition used to define origins and destinations. We also classify motives using ACLED event narratives. Among classifiable narratives, nearly three quarters involve some form of appropriation. Estimating the gravity equation separately for appropriation-related and other events shows that distance and border frictions remain present in both samples. This supports the benchmark model while motivating the broader interpretation of violence developed in the theoretical extensions. The empirical gravity equation of violence is at the core of the estimation procedure of the quantitative spatial model. Estimated bilateral violence frictions and origins’ fixed effects are used to recover the structural parameters needed for counterfactual analysis, including fighting capacity and local state capacity. This “inversion” is disciplined by the equilibrium restrictions and by observed economic and violence outcomes. As a real-world consistency check, we show that the recovered measure of local state capacity is positively related to independent measures of institutional quality, and to within-country variation in Afrobarometer respondents’ trust in the police forces.

We use our results to reinterpret standard reduced-form conflict regressions. Most empirical

work observes violence at the local level rather than as bilateral flows. Aggregating the model-consistent bilateral gravity equation over origins yields a monadic specification in which local violence depends not only on local income, but also on a Supply Potential of Violence (SPV). This term captures the supply of violence generated by all potential origin regions, weighted by bilateral violence frictions. It generalizes the standard opportunity-cost channel to a spatial setting and provides a model-based correction for spatial spillovers. Omitting SPV can conflate rapacity and opportunity-cost forces and may therefore mis-specify the effect of local income shocks. We illustrate this point using the data and empirical setting of [Berman et al. \(2021\)](#): adding SPV substantially changes the estimated effect of income shocks and helps separate the mechanisms through which income affects violence.

We then use the recovered model for two counterfactual exercises. The first is a 10% productivity increase in the Kanuri region, the origin assigned to Boko Haram in our data. Its purpose is not to evaluate a specific policy, but to illustrate how the model-implied spatial reallocation of violence contributes to the propagation of a local income shock. The productivity shock raises local income which reduces the supply of fighters from a major violent origin. Violence falls in Kanuri and in nearby regions, and the reduction in destruction raises productivity beyond the initially treated area. Accounting for the feedback from violence to economic activity increases the welfare gain from the productivity shock by about 40%. This exercise answers the initial question: while theoretically ambiguous, the feedback of violence amplifies the initial shock in our empirical context.

The last exercise studies trade fragmentation through Sahelexit, the withdrawal of Burkina Faso, Mali, and Niger from CEDEAO. This shock is closer to a concrete geopolitical event: it reduces trade opportunities for the exiting regions, lowers income, and raises the relative attractiveness of fighting. Violence originating from the Sahel exits rises and propagates through West Africa. These predictions are broadly consistent with post-withdrawal violence trends observed after January 2025, providing an out-of-sample consistency check for the counterfactual exercise. A final trade-fragmentation exercise, which nearly shuts down intra-African trade, shows that trade is not required for a gravity equation of violence to exist, but it matters quantitatively because it shapes income, opportunity costs, state capacity, and the geography of fighting. The exercise predicts that tripling intra-African trade costs leads to a 18% increase in violence across the continent.

Literature: Our modeling and empirical choices position the paper relative to several strands of economic research on conflicts. The empirical part of this literature has experienced notable empirical advances over the past fifteen years, driven by the availability of geolocalized data on violent events at a fine-grained level. Among the most recent papers using such data: [Dube and Vargas \(2013\)](#); [Michalopoulos and Papaioannou \(2016\)](#); [Berman et al. \(2017\)](#); [Harari and Ferrara \(2018\)](#); [McGuirk and Burke \(2020\)](#); [Moscona et al. \(2020\)](#); [McGuirk and Nunn \(2025\)](#). These studies typically look at the *local* socio-economic drivers of conflicts and do not explore the spatial determinants of violence.² Moreover, they do not explicitly aim to bring formal models to the data, making it

²Some of these papers ([Berman et al., 2017](#), for instance) estimate theory-free models that examine the spatial decay of predictors of violent events, such as the impact of a spike in the global market price of locally produced resources (e.g., minerals or crops) on violence at various distances (e.g., 50km, 100km, 500km).

difficult to quantify the welfare implications of counterfactual policy interventions. A related literature studies war as a bilateral phenomenon between states. [Spolaore and Wacziarg \(2016\)](#) show that historically closer populations, measured by genetic distance, are more likely to engage in interstate conflict. The trade-and-war literature also adopts a dyadic perspective, linking economic interdependence, militarized disputes, and trade disruptions ([Martin et al., 2008](#); [Hegre et al., 2010](#); [Morelli and Sonno, 2017](#); [Glick and Taylor, 2010](#); [Thoenig, 2024](#)). We bring this dyadic logic to intrastate organized violence by estimating a structural gravity equation for origin–destination flows across ethnic homelands.

Our theoretical structure also relates to the classic literature modeling conflict as a contest over productive resources, in which agents allocate resources between production and appropriation ([Hirshleifer, 1995](#); [Skaperdas, 1996](#); [Garfinkel and Skaperdas, 2007](#)). A small set of papers has brought related quantitative models to the data to analyze conflicts. The pioneering work by [Francois et al. \(2015\)](#) assesses how much coups and revolutions shape cabinet allocations by ethnicity in sub-Saharan Africa. [König et al. \(2017\)](#) present a structural framework that allows to estimate fighting externalities in networks of military alliances and enmities among armed groups in Africa. [Adhvaryu et al. \(2021\)](#) estimate a two-player model of conflict where military capacities are influenced by natural resource endowments. None of these studies model or estimate the impact of spatial frictions. [Amarasinghe et al. \(2020\)](#) and [Mueller et al. \(2022\)](#) explore with a structural approach the theoretical and empirical aspects of violence diffusion in spatial networks of fighting groups. These two papers provide valuable insights into the violent behavior of geographically located fighting groups. However, they adopt a partial equilibrium analysis that captures the impact of economics on conflict in a reduced form, typically represented by an exogenous “prize of the contest”. As a consequence, they are silent on the feedback loop from the fighting equilibrium on the economy. Closest to our spatial general-equilibrium approach, [Khanna et al. \(2023\)](#) develop a quantitative spatial model of occupational choice between legal employment and crime. The two papers study related mechanisms at very different scales. [Khanna et al. \(2023\)](#) focus on urban crime within a single city, where spatial interactions operate through commuting, residential sorting, and local crime externalities. We also feature occupational choice, but in a coordinated setting where each armed group optimizes the spatial allocation of its fighters across destinations. This organizational margin, together with inter-group appropriation contests, and state capacity, shapes the gravity equation of violence. In particular, a group’s return in a destination depends on the fighting capacity, opportunity costs, and frictions of all other groups operating in the same destination—a contest-based strategic dependence absent from [Khanna et al. \(2023\)](#). This generates the Multilateral Resistance of Violence and, after aggregation to the monadic level, the Supply Potential of Violence. Thus, both papers feature general-equilibrium effects between predatory activity and economic outcomes, but the relevant micro channels differ with the environments they study. More generally, the quantitative literature on conflicts has not yet explored the various general equilibrium channels through which economic development and violence may potentially interact, despite repeated calls from prominent scholars for a better understanding of these mech-

anisms (Dell et al., 2014; Burke et al., 2015).³ Our paper aims at filling this gap by building a quantitative general equilibrium model of violence.

Finally, our paper contributes to the modern literature on spatial economics by extending the existing framework of Quantitative Spatial Models (QSM) to address the context of weakly institutionalized countries. Doing so, we deviate from the standard structure of QSMs (see Redding and Rossi-Hansberg, 2017; Redding, 2022; Allen and Arkolakis, 2025, for surveys) by accounting for a key characteristic of these countries, namely the presence of a violent context characterized by inadequate enforcement of property rights and limited state capacity. Our research aligns with the recommendation put forth by Proost and Thisse (2019) in their survey of the spatial economics literature: “when the economy is mainly informal and market institutions do not function well, we need new models.”

The remainder of the paper is as follows: Section 2 sets up the theoretical microfoundations of our framework, and shows how the two main gravity equations for trade and violence are derived and also how they interact in the general equilibrium of our model. The gravity equation of bilateral violence is the main empirical novelty of our paper, and is estimated in Section 3, which also describes our data. Section 4 uses our estimates to revisit the literature on monadic violence. Section 5 then takes the estimated gravity frictions and explains how the rest of parameters needed to simulate the model are recovered by combining the structure of the model with observables. Section 6 runs counterfactual simulations. The paper is accompanied by an Online Appendix available on the webpage of the corresponding author.⁴

2 Theory

Our theoretical setup models the interactions between two activities in a multi-regional world: producing tradable goods (production) and appropriating them (fighting). Individuals choose to allocate their labor to either production or fighting. The model features mobility frictions that hinder both the ability of workers to ship their production to non-local markets and the ability of fighters to appropriate income generated far from their home base. These frictions generate two gravity equations: one for trade in goods and one for bilateral flows of violent activity. The two equations are interconnected through labor-market clearing and occupational choice in each region, closing the model in general equilibrium.

2.1 Gravity of goods

There are N regions indexed by i , with a population of $\bar{L}_i$ that freely allocates between production (L_i) and fighting (l_i). In this Armington (1969) economy, each region i produces a single variety of the tradable good, and is the sole source of this variety. Consumers in region n have a CES utility which aggregates the quantities q_{in} shipped from producing regions i . It is given by

³The seminal contribution by Dal Bó and Dal Bó (2011) considers such general equilibrium interactions in a purely theoretical setup.

⁴The webpage can be found at: <https://people.unil.ch/mathiasthoenig/>.

$U_n = \left(\sum_{i=1}^N (q_{in})^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}}$ with $\sigma > 1$. With perfect competition and iceberg trade costs τ_{in} , the market price is equal to $p_{in} = \tau_{in} w_i^P / A_i$, with w_i^P and A_i representing the wage of producers and their productivity, respectively. We denote with P_n the CES price index and with π_{in} the share of aggregate expenditure E_n that consumers in region n spend on the variety from i :

$$\pi_{in} \equiv \frac{(\tau_{in} w_i^P / A_i)^{1-\sigma}}{\sum_k (\tau_{kn} w_k^P / A_k)^{1-\sigma}}. \quad (1)$$

The equilibrium bilateral trade flow is given by:

$$Y_{in} = \pi_{in} E_n = \tau_{in}^{1-\sigma} \times \left(\frac{w_i^P}{A_i} \right)^{1-\sigma} \times \frac{E_n}{P_n^{1-\sigma}} \quad \text{with} \quad P_n \equiv \left(\sum_{k=1}^N (\tau_{kn} w_k^P / A_k)^{1-\sigma} \right)^{1/(1-\sigma)}, \quad (2)$$

which is one of the many formulations of the gravity equation for goods belonging to the class of “structural gravity” (Head and Mayer, 2014).⁵ The aggregate trade revenues of producing region i (including internal trade) are the sum of trade revenues from all destination regions n :

$$w_i^P L_i = \sum_{n=1}^N \pi_{in} E_n, \quad (3)$$

where L_i is the endogenous labor supply of producers in region i . Together, these equations provide the framework for understanding the partial equilibrium of trade in our model.

2.2 Violence as appropriation

We model the use of force as a game in which fighters originating from i compete for appropriating resources in destination n , resulting in equilibrium flows of violence. Each origin region hosts at most one fighting group, which recruits l_i fighters at a local competitive wage w_i^F . Each destination region n is characterized by a stock of unsecured resources—referred to as “spoils” in the literature—whose value $V_n \geq 0$ is endogenous and linked below to equilibrium income. The violence block of the model has three ingredients. The first is a *fighting technology* that maps the number of fighters operating in n into observable violent activity. The second is a *contest success function* that determines how V_n is split between fighting groups active in n . The third is an *allocation problem* that determines how fighting groups optimally distribute their fighters across destinations, subject to a spatial friction factor $\xi_{in} > 1$ that makes distant operations costlier. Together, these three ingredients deliver the gravity equation of violence. We assume that local authorities and fighting groups are independent actors: in equilibrium, the group located in i may thus optimally allocate fighters to its own region ($n = i$, generating *intra-regional* violence) as well as to other regions ($n \neq i$, generating *inter-regional* violence).

⁵The most commonly used microfoundations include Anderson and van Wincoop (2003) (which we draw upon here), Krugman (1980), Eaton and Kortum (2002), and Chaney (2008).

On the battlefield of region n , the fighting group originating from i produces observable violence with the following constant returns to scale technology:

$$\text{violence}_{in} = \psi_i l_{in}, \quad (4)$$

where l_{in} is the number of fighters assigned by i to n and the parameter $\psi_i \geq 0$ is referred to as i 's fighting capacity. The special case $\psi_i = 0$ means that region i hosts no fighting group.⁶ In turn, the operational performance of group i on the battlefield is calculated as the ratio of its produced violence to the spatial friction factor ξ_{in} , multiplied by a Frechet unobservable shock, $\tilde{u}_{in}$, with shape parameter $\gamma > 0$ which captures how homogeneous is military luck across different military group-destination combinations. Victory in the battle for appropriating spoils in n goes to the group with the largest operational performance. From our functional form assumptions, the probability that i wins the contest over other groups k active in n is equal to:

$$p_{in} \equiv \text{Prob} \left(\frac{\psi_i l_{in} \tilde{u}_{in}}{\xi_{in}} > \frac{\psi_k l_{kn} \tilde{u}_{kn}}{\xi_{kn}}, \quad \forall k \neq i \right) = \frac{(\psi_i l_{in} / \xi_{in})^\gamma}{\sum_{k=1}^N (\psi_k l_{kn} / \xi_{kn})^\gamma}. \quad (5)$$

This relation corresponds to the ratio-form Contest Success Function (CSF) that is standardly used in the literature (Tullock, 1980). It describes the probability of success and hence the incentives for a fighting group in i to launch operations in n . This derivation of the CSF from primitive distributional assumptions constitutes the first key element to obtain our gravity equation of violence. The second brick for gravity is the optimal spatial allocation of troops (l_{in}).⁷ This allocation aims to maximize i 's expected fighting revenues⁸:

$$R_i \equiv \max_{\{l_{in}\}} \sum_{n=1}^N p_{in} \times V_n \quad \text{s.t.} \quad l_i = \sum_{n=1}^N l_{in}. \quad (6)$$

We interpret p_{in} as the realized share of spoils in n captured by group i .⁹ To obtain a concave maxi-

⁶ We assume ψ_i to be exogenous. A proper treatment of endogenous entry on the appropriation market would need to include a fixed cost of organizing a fighting group. We consider the theoretical consequences of such an extension in Appendix D.7. While the gravity setup survives this augmented model and equilibrium equations driving entry can still be characterized, an important difference is the possible coexistence of multiple equilibria. On top of the difficulty of finding an empirical proxy for fixed cost, including the entry margin therefore raises non-trivial methodological issues regarding the estimation procedure that we leave for future work.

⁷ Formally, this problem belongs to the class of Colonel Blotto games, which model how opponents allocate fighters across multiple battlefields (see, e.g., Shubik and Weber, 1981; Roberson, 2006).

⁸ In the model, fighting groups maximize the value of appropriated resources. This reduced-form representation of predatory behavior assumes that fighting groups are institutionally distinct from the local authorities, themselves represented by the state capacity parameter s_n , and therefore do not internalize the impact of their violent appropriation activities on the welfare of populations. As a result, there is no reason for the allocation of labor between production and fighting to be socially efficient. Appendix D.2 discusses an alternative interpretation in which armed groups exert territorial control and extract revenues through taxation, while Appendix D.3 endogenizes state capacity. In this sense, the baseline formulation is closer to Olson (1993)'s notion of "roving bandits," whereas the territorial-control interpretation corresponds to "stationary bandits".

⁹ Equivalently, destination-level spoils can be viewed as a continuum of elementary contests, so that expected contest shares coincide with aggregate shares. This modeling strategy is similar to various approaches in trade which micro-found aggregate gravity flows out of individual behavior of heterogeneous agents (see section 2.3 of Head and Mayer, 2014).

mization problem of R_i with respect to the optimal allocations of fighters l_{in} , we assume $0 < \gamma < 1$, which is supported by our empirical estimate (our estimates yield $\hat{\gamma} = 0.449$). This assumption also ensures that an interior solution exists for active origins facing destinations with positive unsecured spoils. Finally, looting revenues are redistributed equally among fighters:¹⁰

$$w_i^F = R_i/l_i. \quad (7)$$

From income to spoils. The allocation problem (6) requires to specify the value of spoils V_n at each destination. This is the point at which we distinguish three income terms that are useful throughout the model. First, Y_n denotes *gross* income generated in region n , before appropriation is resolved:

$$Y_n \equiv w_n^P L_n + w_n^F l_n. \quad (8)$$

Second, $s_n \in [0, 1]$ denotes local state capacity, defined as the share of gross income that is protected by local authorities, property-rights enforcement, police, military presence, or related institutions. The unsecured share, $(1 - s_n)Y_n$, is exposed to appropriation. Third, E_n denotes secured expenditure, that is the part of income that can be spent on consumption after appropriation has been resolved.

These objects are equilibrium outcomes of an appropriation game with repeated contests, described in Appendix A. Under the baseline assumptions of this game, fighters compete over the unsecured share of gross income. The appropriable spoils in destination n are therefore

$$V_n = (1 - s_n)Y_n. \quad (9)$$

The same microfoundation implies that secured expenditure is

$$E_n = s_n Y_n. \quad (10)$$

Equations (9) and (10) are two sides of the same accounting logic: gross income is split into a secured component, which finances expenditure, and an unsecured component, which becomes the target of appropriation. The incomes of producers and fighters enter Y_n before appropriation is resolved, but only the secured share $s_n Y_n$ enters expenditure.

The appendix derives these relations from the repeated-contest structure of the appropriation game. In this setup, being a fighter does not itself make income immune to future appropriation. Producers are paid upfront, fighters appropriate unsecured income, repatriate revenues to their origin region, and only a share s_i of those revenues is permanently secured. Iterating this process yields the compact expressions above. The main advantage of this baseline microfoundation is analytical: because $E_n/Y_n = s_n$ does not depend on the equilibrium composition of the workforce, the trade and fighting revenue equations have a parallel structure in general equilibrium. Appendix D.4 discusses an alternative microfoundation in which only producer income is exposed to looting.

¹⁰Thus, $R_i = w_i^F l_i$ denotes gross fighting revenues before the final securing stage. Only the secured share, $s_i R_i$, enters fighters' expenditure; this corresponds to E_i^F in Appendix A.

2.3 Gravity of violence

The theoretical gravity equation of violence follows from the optimal troop allocation problem (6), using probabilities from (5) and spoils from (9), and substituting the resulting allocation l_{in} across regions into (4). Assuming atomistic players, who notably take wages and aggregate violence as given¹¹ in the optimization problem (6), we obtain (see Appendix B for the derivation):

$$\text{violence}_{in} \equiv \psi_i l_{in} = \xi_{in}^{-\frac{\gamma}{1-\gamma}} \times \left(\frac{\psi_i}{w_i^F} \right)^{\frac{1}{1-\gamma}} \times \frac{(1-s_n)Y_n}{\sum_{k=1}^N \xi_{kn}^{-\frac{\gamma}{1-\gamma}} \left(\frac{\psi_k}{w_k^F} \right)^{\frac{\gamma}{1-\gamma}}}. \quad (11)$$

This expression isolates the four forces shaping bilateral violence: Violence from i to n falls with the bilateral violence friction ξ_{in} , falls with origin fighters' cost adjusted for fighting capacity w_i^F / ψ_i , and rises with the destination unsecured income $(1-s_n)Y_n$; the denominator of the last term captures competition from all origins, including i itself, that can contest income in destination n .

This equation for the equilibrium flow of violence from i to n exhibits strong similarities with gravity equations in trade/migration models (the parallel can be seen by comparing with equation 2).¹² However, it is a gravity equation driving the “quantity” of violence, which is what we observe in the dataset at hand. The bilateral violence flows *in value* is $w_i^F l_{in} = \text{violence}_{in} \times \left(\frac{w_i^F}{\psi_i} \right)$. This allows to write an expression (parallel to aggregate trade revenues in equation 3) for the aggregate looting revenues of fighters in region i :

$$w_i^F l_i = \sum_{n=1}^N \text{violence}_{in} \times \left(\frac{w_i^F}{\psi_i} \right). \quad (12)$$

Economic shocks such as changes in wages impact violence in complex ways, channeled by the full spatial structure in equation (11). An increase in income at origin (w_i^F) leads to a decrease in violence emanating from i , while an increase in income at destination (w_n^P , and therefore the amount of appropriable resource Y_n) results in an increase in violence. These two mechanisms, respectively known as the *opportunity cost* and *rapacity* channels, are intuitive and have been extensively tested empirically (e.g., Dube and Vargas, 2013; McGuirk and Burke, 2020). Our spatial framework clarifies that the former operates on outward violence—projected from the source—while the latter operates on inward violence, affecting the destination.

A third mechanism, new to our model, arises through the denominator in equation (11). We refer to it as the *Multilateral Resistance of Violence*, in parallel to the terminology used in trade to account for economic competition in a given destination market (Anderson and van Wincoop, 2003,

¹¹This assumption simplifies strategic interactions; there is, in particular, no market power on the appropriation market. Each fighting group best-responds to other groups' actions but does not internalize its impact on aggregate violence (i.e. denominator of equation 5). Appendix D.1 considers the consequences of allowing for granular groups which are conscious of their impact on overall violence in n .

¹²Note that the model allows for all bilateral flows possibilities: local looting whenever $\xi_{ii} < \infty$, raiding whenever $\xi_{in} < \infty$ with $i \neq n$, and even zero violence when $\xi_{in} = \infty$.

were the first to use this expression):

$$\text{MRV}_n \equiv \sum_k \xi_{kn}^{-\frac{\gamma}{1-\gamma}} \left(\frac{\psi_k}{w_k^F} \right)^{\frac{\gamma}{1-\gamma}}.$$

This is the key spatial-equilibrium object of the violence block. The intuition is the same as in structural gravity models of trade. A destination with a high MRV_n is one in which unsecured income is contested by many effective competitors: origins that can reach it cheaply, have high fighting capacity, or face low opportunity costs of fighting. Holding destination spoils fixed, this lowers the share captured by any given origin i . Conversely, when other origins face higher opportunity costs, lower fighting capacity, or higher violence frictions toward n , competition in destination n weakens and origin i optimally sends more violence there. The empirical relevance of MRV_n depends on the geography of violence frictions. If bilateral frictions are asymmetric, MRV_n varies across destinations because each destination faces a different intensity of competition for appropriation.

The gravity equation of violence is a partial-equilibrium allocation equation: it describes how fighters from a given origin allocate violent activity across destinations, taking wages, spoils, fighting capacity, and bilateral violence frictions as given. We now close the model in general equilibrium. The equilibrium jointly determines wages w_i , the allocation of labor between production L_i and fighting l_i , gross income Y_i , expenditure E_i , trade flows, and bilateral violence flows. This is where the two gravity systems—goods and violence—interact through labor-market clearing and income accounting.

2.4 General equilibrium

In equilibrium, workers choose between production and fighting to equalize fully secured incomes in regions with $\psi_i > 0$, and thus wages in i :

$$s_i w_i^P = s_i w_i^F = s_i \bar{w}_i. \quad (13)$$

Gross total income can therefore be rewritten as

$$Y_i = w_i^P L_i + w_i^F l_i = w_i \bar{L}_i, \quad (14)$$

with the last equality ensured by the labor market clearing condition under which fighters and producers add up to total workforce $\bar{L}_i$:

$$\bar{L}_i = L_i + l_i. \quad (15)$$

Two parallel market clearing conditions must also hold in equilibrium. The first one is that the sum of demands for the good produced in i has to add up to the trade revenues of i . This is equation (3),

which—combined with equations (2), (13), (14), and (10)—can be rewritten as

$$w_i L_i = \sum_{n=1}^N \frac{\tau_{in}^{-(\sigma-1)} \left(\frac{A_i}{w_i} \right)^{\sigma-1}}{\sum_{k=1}^N \tau_{kn}^{-(\sigma-1)} \left(\frac{A_k}{w_k} \right)^{\sigma-1}} s_n w_n \bar{L}_n. \quad (16)$$

The second market clearing condition is that the bilateral flows of revenues obtained from appropriation sum to the revenues of fighters originating from i . Combining (11), (13), and (14), and inserting the result into (12), we obtain:

$$w_i l_i = \sum_{n=1}^N w_i l_{in} = \sum_{n=1}^N \frac{\xi_{in}^{-\frac{\gamma}{1-\gamma}} \left(\frac{\psi_i}{w_i} \right)^{\frac{\gamma}{1-\gamma}}}{\sum_{k=1}^N \xi_{kn}^{-\frac{\gamma}{1-\gamma}} \left(\frac{\psi_k}{w_k} \right)^{\frac{\gamma}{1-\gamma}}} (1 - s_n) w_n \bar{L}_n. \quad (17)$$

The general equilibrium is characterized by the system of $3 \times N$ equations (15)–(16)–(17) and $3 \times N$ unknowns $\{L_i, l_i, w_i\}$, for $i = 1, \dots, N$.

Existence and uniqueness: We can characterize the general equilibrium more compactly using a fixed-point “master equation” system with the wage vector as the sole endogenous variable. Summing equations (16) and (17) yields

$$w_i \bar{L}_i = \sum_{n=1}^N \beta_{in}(\mathbf{w}) w_n \bar{L}_n, \quad (18)$$

where $\beta_{in}(\mathbf{w})$ is the share of region n ’s income that reaches region i :

$$\beta_{in}(\mathbf{w}) \equiv (1 - s_n) \times \frac{w_i^{-\frac{\gamma}{1-\gamma}} \left(\frac{\psi_i}{\xi_{in}} \right)^{\frac{\gamma}{1-\gamma}}}{\sum_{k=1}^N \left(\frac{\psi_k}{\xi_{kn} w_k} \right)^{\frac{\gamma}{1-\gamma}}} + s_n \times \frac{w_i^{1-\sigma} \left(\frac{A_i}{\tau_{in}} \right)^{\sigma-1}}{\sum_{k=1}^N \left(\frac{A_k}{\tau_{kn} w_k} \right)^{\sigma-1}}. \quad (19)$$

The first term captures unsecured income in n appropriated by fighters from i , while the second captures secured income earned by region i through trade with n . The operator $\beta_{in}(\mathbf{w})$ is homogeneous of degree zero in $\mathbf{w}$, so the master equation is homogeneous of degree one in nominal wages. Hence the model pins down relative wages, while the absolute wage level requires a numeraire normalization. After fixing a numeraire, for instance the wage in one reference region or aggregate nominal income, the wage vector is uniquely determined under the conditions stated in Appendix C. The proof relies on resolution techniques from spatial economics (Allen et al., 2020). Specifically, we use the isomorphism between the trade and fighting revenue equations in order to apply Mas-Colell et al. (1995) and Alvarez and Lucas (2007). We conclude that a general equilibrium exists and is unique up to scale; with the numeraire normalization imposed, it is unique in the wage vector.

2.5 Additional channels and extensions

The baseline model deliberately takes a parsimonious view of violence as spatial appropriation: fighting groups allocate troops across destinations in order to capture unsecured income. This gives a transparent gravity equation and a tractable general equilibrium, but abstracts from other dimensions of violence. Civil conflicts may involve territorial control, political power, identity-based grievances, coercive recruitment, market power among armed groups, endogenous state defense, and entry into violence. Appendix D studies these cases formally as extensions to the base model. We summarize here the main lessons. The central point is that most of the extensions considered preserve the gravity structure of bilateral violence, even when they modify the interpretation of spoils or the equilibrium system used to solve the model.

Market power in the appropriation market. The baseline derivation assumes that fighting groups are atomistic in each destination. Appendix D.1 relaxes this assumption and allows granular fighting groups to internalize their effect on the contest success function. This case bears strong similarities with the literature on trade and oligopoly (notably Eaton et al., 2013; Atkeson and Burstein, 2008; Edmond et al., 2015; Gaubert and Itskhoki, 2021). With non-negligible market power of groups, the elasticity of the probability of success with respect to violence becomes $\epsilon_{in} = \gamma(1 - p_{in})$, where p_{in} is the probability that group i wins the contest in destination n . The resulting bilateral violence equation remains multiplicatively separable, but it is no longer a standard structural gravity equation because the elasticity of violence with respect to frictions varies with the “size” of the group in the destination market for appropriation. When p_{in} is small, the model converges back to the baseline atomistic case. When p_{in} gets larger, market power dampens the effect of spatial frictions. Thus, allowing for market power is conceptually feasible and generates testable implications, but it complicates structural estimation and model inversion because the constant-elasticity gravity form is lost. We provide leads towards an estimation procedure in the appendix, but the full implementation is left for future work.

Nature and motives of violence. Our baseline model is best interpreted as a model of raiding or looting, but the framework can accommodate broader forms of violence, as Appendix D.2 shows. First, the model can be reinterpreted as one of territorial control. If s_n is the share of region n that is effectively secured by local authorities, then $(1 - s_n)Y_n$ is the income generated in unsecured territory. Fighting groups compete to control this territory, and p_{in} can be interpreted as the share of unsecured territory in n controlled by group i . The spoils accruing to group i in destination n are then $p_{in}(1 - s_n)Y_n$. Under repatriation of revenues to the origin region, the fighter-allocation problem is unchanged, and the gravity equation of violence remains exactly the same as in the baseline.

Second, the model can represent political control or fiscal extraction. Suppose that a fighting group controlling territory in n can tax the income generated there at an exogenous rate tax_n . The bilateral spoils become $V_{in} = \text{tax}_n p_{in}(1 - s_n)Y_n$, and the corresponding gravity equation simply replaces $(1 - s_n)Y_n$ with $\text{tax}_n(1 - s_n)Y_n$ in (11). Relative to the baseline case, taxation only rescales

the destination-specific value of spoils. Endogenizing the tax rate is a deeper problem: in a static model a group would set the tax rate to one, whereas realistic fiscal extraction requires an intertemporal trade-off between current extraction and future production incentives, as in stationary-bandit models (?). We therefore leave endogenous taxation to future work.

Third, the framework can incorporate non-economic motives such as ethnic, religious, or identity-based grievances. One way to formalize this is to let a bilateral hostility parameter, denoted $\text{hate}_{in} > 0$, shift the effectiveness of violence in the contest success function. Formally, this means that ξ_{in} is replaced by $\xi_{in}/\text{hate}_{in}$ in equation (5). This specification preserves the gravity equation and the general equilibrium structure. It also clarifies the empirical role of ethnic or religious frictions: if such variables proxy for bilateral hostility, they enter the gravity equation as shifters of the effective cost of violence rather than as a rejection of the gravity logic. This is consistent with the empirical exercise in Appendix OA.B.7, which shows that the distance gradient is present not only for appropriation-related events but also for events classified as driven by other motives.

Endogenous state capacity. The baseline model treats s_n as exogenous. Appendix D.3 considers an extension in which local authorities choose their defense effort. State capacity is increasing in local conscription into defense forces, while conscription is costly because it removes labor from production. The local authority therefore faces a standard security trade-off: more defense protects income from appropriation, but it also reduces the labor available for market activity. Formally, the extension generates a Nash equilibrium in local defense choices coupled with the general equilibrium in wages. The key result is that the gravity equation of violence is unchanged: local defense affects both the security margin (s_n) and aggregate income through the conscription cost, but it does not alter the bilateral allocation logic across origins and destinations. This extension therefore addresses the concern that state capacity should respond to violence and income, while preserving the empirical gravity structure used in the main analysis. To avoid solving this richer Nash equilibrium in the quantitative counterfactuals, the simulated model uses a reduced-form security spillover—empirically disciplined rather than directly derived from the defense extension—in which state capacity increases with local real income, as specified in equation (40).

Alternative microfoundations of the appropriation game. The baseline appropriation game assumes that the unsecured income of both producers and fighters can be looted. Appendix D.4 considers the alternative case in which only producers' income is subject to looting. The gravity structure of violence is preserved, but the useful symmetry between trade revenues and fighting revenues breaks down. As a result, the general equilibrium can no longer be summarized by the single master equation (18); instead it is characterized by a larger system in producers, fighters, and wages. The qualitative mechanisms remain intact, but the analytical tractability of the benchmark is reduced.

Labor market. Appendix D.6 addresses the concern that labor may not move freely between production and fighting. In many conflicts, recruitment into armed groups involves coercion, forced

conscription, social pressure, mortality risk, or stigma. We capture these features through exogenous wedges between producer and fighter earnings. Let $\omega^F < 1$ denote a coercive discount for fighters and $\omega^P < 1$ a compensating differential associated with the cost of fighting. The occupational-choice condition becomes $\omega^P w_i^F = \omega^F w_i^P$. This breaks exact wage equalization but leaves the functional form of the gravity equation of violence unchanged. Once the modified income identity is substituted, however, the destination income term in the gravity and the general equilibrium system change. The comparative statics are also ambiguous: stronger coercion can increase violence directly by making recruitment easier, but it can also reduce the income of fighters, depress market size, and lower the value of spoils through general equilibrium feedbacks.

Trade, autarky, and the role of economic integration. Within our model, trade affects local income, which in turn impacts both the opportunity cost of fighting and the value of spoils. Appendix D.5 studies the limiting case of autarky, where all production and consumption are local. This exercise clarifies that the incentives for violence do not mechanically depend on the presence of interregional trade: even under autarky, groups can still loot locally generated income, and the gravity equation of violence is unchanged. What changes is the quantitative general equilibrium through which income, wages, and state capacity respond to shocks. Hence trade is not imposed merely to obtain a gravity equation; it is a channel through which economic integration changes the spatial incentives for appropriation.

Endogenous entry into violence. Finally, Appendix D.7 allows regions to self-select into the appropriation market. In the baseline model, a region that never supplies violence is represented by $\psi_i = 0$. This is parsimonious but does not explain why some regions host fighting groups while others do not. The entry extension assumes that organizing a fighting group in region i requires paying a fixed labor cost o_i . Entry $\mathcal{E}_i$ occurs when expected net fighting revenues cover this cost: $\mathbb{1}_{\mathcal{E}_i} = 1$ if and only if $R_i - o_i w_i \geq 0$. Conditional on entry, the bilateral gravity structure is preserved. The general equilibrium now jointly determines wages and the set of active fighting origins through a nested fixed point. This extension is important for interpreting the extensive margin of violence: the baseline model disciplines the spatial allocation of violence conditional on observed entry, while a fuller model of the emergence and disappearance of violent origins requires fixed costs and endogenous selection.

Takeaway. These extensions clarify the status of the baseline assumptions. Some assumptions are mainly interpretive: raiding can be reinterpreted as territorial control, political extraction, or grievance-driven violence without overturning the gravity logic. Other assumptions are mainly technical: atomistic groups, free occupational choice, and the benchmark appropriation game deliver a compact general equilibrium characterization, but can be relaxed at the cost of a more complex solution system. The robust element across these environments is the bilateral structure of violence: origin-side opportunity costs and fighting capacity, destination-side spoils and state capacity, and bilateral frictions jointly determine the geography of violence. This is the object we take to the data.

3 Empirical Gravity of Violence

3.1 Data sources and construction

We start by describing our data construction steps. Table 1 summarizes these steps, while Appendix OA.B.1 provides full details.

Conflict data. We use the Armed Conflict Location and Event Dataset (ACLED), which records conflict events across Africa from 1997 to June 2023.¹³ This dataset is extensively used in academic work. ACLED reports the date, location, event type, fatalities, and actors involved in each event. We innovate by constructing bilateral flows of violence with well-defined origins and destinations: event coordinates identify destinations, while actor identities combined with external sources identify origins.¹⁴ Following standard practice, the main outcome is the number of violent events rather than fatalities, which are imprecisely recorded at a disaggregated level.¹⁵ ACLED captures a wide range of violence types and actor categories, so beyond spatial cleaning (Steps 1 to 3), we isolate the type of violence most compatible with our model, by selecting actors and events in Steps 4 to 6.

Table 1: Data-processing steps

Steps	# Events	# Actors	# Fatalities
0-Raw dataset	325541	14137	882975
1- Geographic filter	237489	11138	556016
2- Events filter	234943	11013	555959
3- Information filter	232878	5486	553745
4- Actors selection	87578	1492	379314
5- Murdock filter on actors	80619	220	362672
6- Murdock filter on events	78335	220	353289

Note: **Step 0–Raw dataset:** reshaped from raw data such that the unit of observation is an event $\times$ actor(group). **Step 1–Geographic filter:** considers only events with the highest level of precision and excludes events outside continental Africa. **Step 2–Events filter:** excludes events considered peaceful or of unidentified nature. **Step 3–Information filter:** excludes actors with no external information (e.g., no information on the nature of the actors). **Step 4–Actor selection:** keeps actors identified as “Rebel groups” and “Political Militias”. **Step 5–Murdock filter on actors:** 220 actors that we assign to 87 Murdock ethnic groups. **Step 6–Murdock filter on events:** excludes events that do not intersect with the Murdock map (Sinai region, lakes...).

The raw data (Step 0) contain 325541 violent events and 14137 actors.¹⁶ The *geographic filter*

¹³The “Compatibility” dataset was downloaded from <https://acleddata.com/> on June 28, 2023.

¹⁴The ACLED dataset does not identify perpetrators and victims, and the reported ordering of actors associated with each event does not reflect who initiated the violence (ACLED, 2023). Our construction does not rely on this distinction. Instead, we define bilateral flows: Each fighting group g is associated with an origin given by its ethnic homeland i (interpreted as its recruitment base) and each event involving g generates a flow from this origin i to the location of the event n (defined as the destination). This definition is independent of the role played by the actor in the event. In particular, when two fighting groups from distinct homelands A and B are involved in an event located in C , the event gives rise to two flows, from A to C and from B to C .

¹⁵ACLED (2023, p. 37) advises caution when using fatality counts.

¹⁶ACLED distinguishes eight actor categories: State Forces, Rebel groups, Political Militias, Identity Militias, Rioters,

(Step 1) retains events located in continental Africa and recorded at ACLED’s highest geo-precision level, corresponding to town-level precision (roughly three-quarters of the raw sample).¹⁷ This leaves 237489 events and 11138 actors. The *events filter* (Step 2) removes ACLED records classified as non-violent or unidentified, namely “Agreement” and “Others” in the ACLED nomenclature.¹⁸ The *information filter* (Step 3) then drops actors not assigned to a precise politico-military category. Because most events involve at least one well-identified actor, this Step removes many actors but few events. The resulting sample contains 232878 events and 5486 actors. The *actors selection filter* (Step 4) keeps “Rebel groups” and “Political Militias”, the categories most closely aligned with the model’s mechanism of spatial projection by armed groups.¹⁹ These actors account for 38% of events but 68% of fatalities, and are disproportionately involved in battles and violence against civilians (Table OA.B3).²⁰ Applying this filter leaves 1492 actors and 87578 events in the sample.

Other datasets. We use harmonized nighttime lights from Li and Zhou (2017), population from WorldPop’s 2000 top-down unconstrained estimates (Lloyd et al., 2019), crop suitability from FAO-GAEZ, and crop prices from the World Bank Commodity Price Data.²¹

3.2 Vectorization of georeferenced conflict events

Let us now convert georeferenced ACLED events into directed bilateral flows of violence, denoted violence_{in} . Each armed group g is assigned to a rear base $rb(g) \in i$, interpreted as the origin region from which it recruits fighters. The bilateral flow from origin i to destination n is:

$$\text{violence}_{in} = \sum_g \mathbb{I}_{rb(g) \in i} \times \sum_{t=1997}^{2023} \# \text{events}_{gnt}, \quad (20)$$

where $\# \text{events}_{gnt}$ is the number of events attributed to group g in n over time period t , and $\mathbb{I}_{rb(g) \in i}$ is an indicator which takes a value of 1 if the rear base of the group g is located within region i . This defines a cross-section of flows of violence between geographical units i and n as our dependent variable.

Protesters, Civilians, and External/Other Forces. See Table OA.B2 and footnote oa.5 in the Online Appendix.

¹⁷ Appendix OA.B.8 shows that including lower-precision events leaves the results unchanged.

¹⁸ ACLED records six event types and 25 sub-event types; see footnote oa.6 in the Online Appendix.

¹⁹ Restricting the sample to “Rebel groups” and “Political militias” reflects a trade-off between coverage and measurement. Our empirical strategy requires identifying a meaningful rear base of recruitment, which is not feasible for several ACLED categories. “Rioters”, “Protesters”, and “Civilians” group heterogeneous and often purely local actors under country-level labels, while “State forces” and “External and Other forces” operate at national or transnational scales (ACLED, 2023). For these actors, no clearly defined recruitment area can be consistently matched to an ethnic homeland. In Appendix OA.B.2, we provide evidence on the spatial scope of activity for the three categories that can be meaningfully assigned to ethnic homelands— “Identity militias”, “Political militias”, and “Rebel groups”. We construct, for each actor, the convex hull of its event locations after excluding spatial outliers using the Mahalanobis distance. Figure OA.B1 reports the distribution of these areas. “Identity militias” operate over substantially smaller areas, consistent with their localized nature, while “Political militias” and “Rebel groups” exhibit much broader spatial footprints. Focusing on the latter groups ensures that the analysis captures actors whose activities extend beyond a purely local setting and can be meaningfully linked to a rear base of recruitment.

²⁰ At step 3, ACLED records 553745 fatalities across 232878 events. Rebel groups and political militias account for 379314 fatalities across 87578 events, implying 4.3 fatalities per event, compared with 1.2 for the remaining sample.

²¹ Sources: Nighttime lights; WorldPop; FAO-GAEZ.

The model defines $rb(g)$ as the labor pool from which group g recruits fighters. At the continental scale, such labor markets are unobserved. We therefore proxy recruitment basins using armed groups’ ethnic ties, consistent with evidence that rebel recruitment often follows co-ethnic networks in Africa.²² Ethnic networks facilitate contract enforcement (Caselli and Coleman, 2013), sustain commitment (Weinstein, 2005, 2007), and generate the social incentives that motivate combatants (Moscona et al., 2020). We map armed groups to ethnic groups by prioritizing external sources, using ACLED event geography for ambiguous cases under the decision rules described in Appendix OA.B.4, and use these ethnic ties to assign rear bases $rb(g)$ to historical ethnic homelands as observed on Murdock’s map (Murdock, 1959).²³ This procedure does not presuppose that violence is caused by ethnic cleavages; it assumes only that recruitment networks are structured by ethnic ties. The resulting actor–ethnicity mapping is a data contribution of the paper.²⁴

Figure 1 documents a feature of the data that, to our knowledge, has not been established at this scale in the conflict literature: violence is extremely concentrated across armed groups (panel a). Panel b of the figure shows that the 220 most active groups account for more than 90% of events perpetrated by rebel groups and political militias.²⁵ This concentration makes the actor–ethnicity matching feasible while preserving near-complete coverage of the relevant violence sample. The *Murdock filter on actors* (Step 5) restricts the construction of rear bases, and hence origins of violence, to the 220 matched actors, which are assigned to 87 Murdock homelands. The *Murdock filter on events* (Step 6) then keeps only events whose coordinates intersect the Murdock map, leaving 78335 events. Note that almost 80% of this violence is directly exerted against civilians or takes the form of military battles (Table OA.B.3). Applying equation (20) yields directed flows $violence_{in}$ across the 824 Murdock regions. In the resulting dyadic dataset, 97.46% of flows are zero. Among positive flows, the data cover 87 origins and 623 destinations.²⁶ Figure 1(c) and (d) displays the spatial distribution of origins and destinations of violence across Africa. Note that the relatively small

²²The importance of co-ethnic recruitment is emphasized by Caselli and Coleman (2013), Michalopoulos and Papaioannou (2016), Mueller et al. (2022), and Guarnieri and Tur-Prats (2023). Ethnic mobilization in African conflicts is also documented by Fearon and Laitin (1999), Sambanis (2001), Elbadawi and Sambanis (2000), Gates (2002), Gates (2017), and Cederman et al. (2010). Appendix OA.B.3 provides additional evidence.

²³The recent literature typically infers the ethnic affiliation of violent actors by overlaying the location of their events with ethnic homelands (Michalopoulos and Papaioannou, 2016; Moscona et al., 2020; Adhvaryu et al., 2021; Mueller et al., 2022; Eberle et al., 2024; McGuirk and Nunn, 2025; Gehring and Schaudt, 2024). Our approach differs by prioritizing actor-specific external sources rather than event locations. In this respect, it is closer to Berman et al. (2017), who identify ethnic ties for 109 actors active between 1997 and 2010, and to Sestito (2024), who uses external sources for non-state armed groups in 18 African countries. Using a broader set of sources, we cover more than 90% of violence perpetrated by rebel groups and political militias in Africa. Origin assignment is performed at the actor level, whereas destination assignment is performed at the event level using event coordinates; when ACLED event geography is used to resolve ambiguous actor-origin matches, it enters only through the documented decision rules, and robustness checks exclude lower-confidence matches.

²⁴Appendix OA.B.4 describes the sources and matching procedure. Because the mapping between armed groups and ethnic homelands relies on multiple information sources, its precision may vary across actors. To assess the sensitivity of our results to this heterogeneity, we construct a confidence index capturing the reliability of each match and re-estimate the gravity equation of violence on progressively more restrictive samples. The estimates remain stable. See Appendix OA.B.5 for details.

²⁵The Step 4 sample comprises 1492 violent actors who are involved in 87578 events resulting in 379314 fatalities. Among them, the 220 most violent actors participate in 80619 events leading to 362672 fatalities (92% of the events, 96% of the reported fatalities).

²⁶Appendix OA.B.8 shows that the results are robust to defining destinations with administrative units at alternative levels of aggregation.

number of origins of violence partly reflects our selection of the 220 most violent groups. Since each group is associated with at most one ethnic region, the number of origins is mechanically bounded above by 220. Including the full set of 1492 groups to our analysis would increase the total number of violent events covered by only about 10%, but would likely generate a substantially larger set of origins. In this trade-off, we prioritize data quality, i.e. the hand-checked geo-location of the groups that account for the largest share of events. As a result, many low-intensity flows of violence between regions are likely to be coded as zeros. For this reason, our baseline quantitative framework is designed to discipline the intensive margin of violence, whereas identifying the extensive margin would require additional information to estimate endogenous entry into the appropriation market (on this theme, see Appendix D.7).

3.3 Estimating equation

As a first motivation for our econometric specification, Figure 2 documents the unconditional correlation between $\log \text{distance}_{in}$ and the bilateral share of events at destination $\frac{\text{violence}_{in}}{\text{violence}_n}$ (our dependent variable in the regressions), distinguishing intra- from inter-regional flows. Intra-regional violence accounts for approximately 27% of violent events in the estimation sample. Panel (a) shows a strong negative correlation in the full dyadic sample (explaining around 80% of the variance over 50 bins of shares of events), which persists when we restrict the sample to strictly positive flows (panel b). Visual inspection of both panels indicates that intra-regional violence is well below the regression line, despite much smaller average distances. This means that inter-regional violence is larger once controlling for distance. This pattern is confirmed by the econometric analysis below.

Based on our theoretical prediction, we estimate a gravity equation to reveal the empirical determinants of bilateral violence. Building on equation (11), we obtain:

$$\frac{\text{violence}_{in}}{\text{violence}_n} = \frac{\psi_i l_{in}}{\sum_{k=1}^N \psi_k l_{kn}} = \xi_{in}^{-\frac{\gamma}{1-\gamma}} \times \left(\frac{\psi_i}{w_i} \right)^{\frac{1}{1-\gamma}} \times \left[\sum_{k=1}^N \xi_{kn}^{-\frac{\gamma}{1-\gamma}} \left(\frac{\psi_k}{w_k} \right)^{\frac{1}{1-\gamma}} \right]^{-1}. \quad (21)$$

We estimate this equation by PPML with high-dimensional origin and destination fixed effects, using the *share* of violence in n attributed to origin i as the dependent variable:²⁷

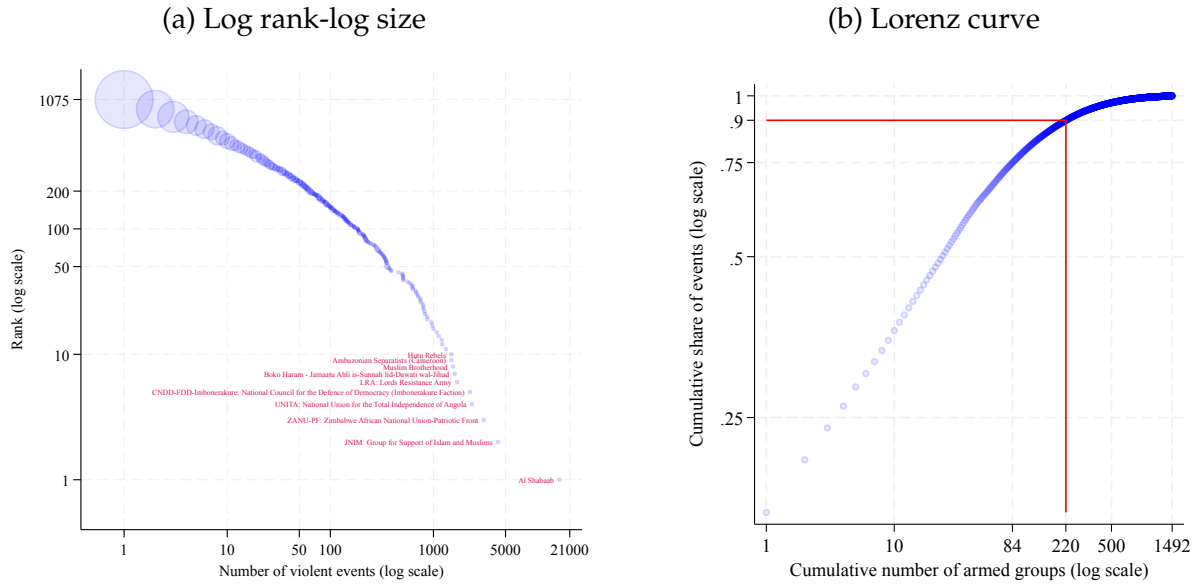
$$\mathbb{E} \left(\frac{\text{violence}_{in}}{\text{violence}_n} \right) = \exp \left[-\frac{\gamma}{1-\gamma} \log \xi_{in} + \text{FE}_i^o + \text{FE}_n^d \right]. \quad (22)$$

The regression provides estimates of the impact of spatial frictions ξ_{in} together with origin and destination fixed effects (FE_i^o and FE_n^d). The origin fixed effects are crucial for the next step when we turn to the task of recovering the structural parameters of the model.²⁸ We specify bilateral frictions

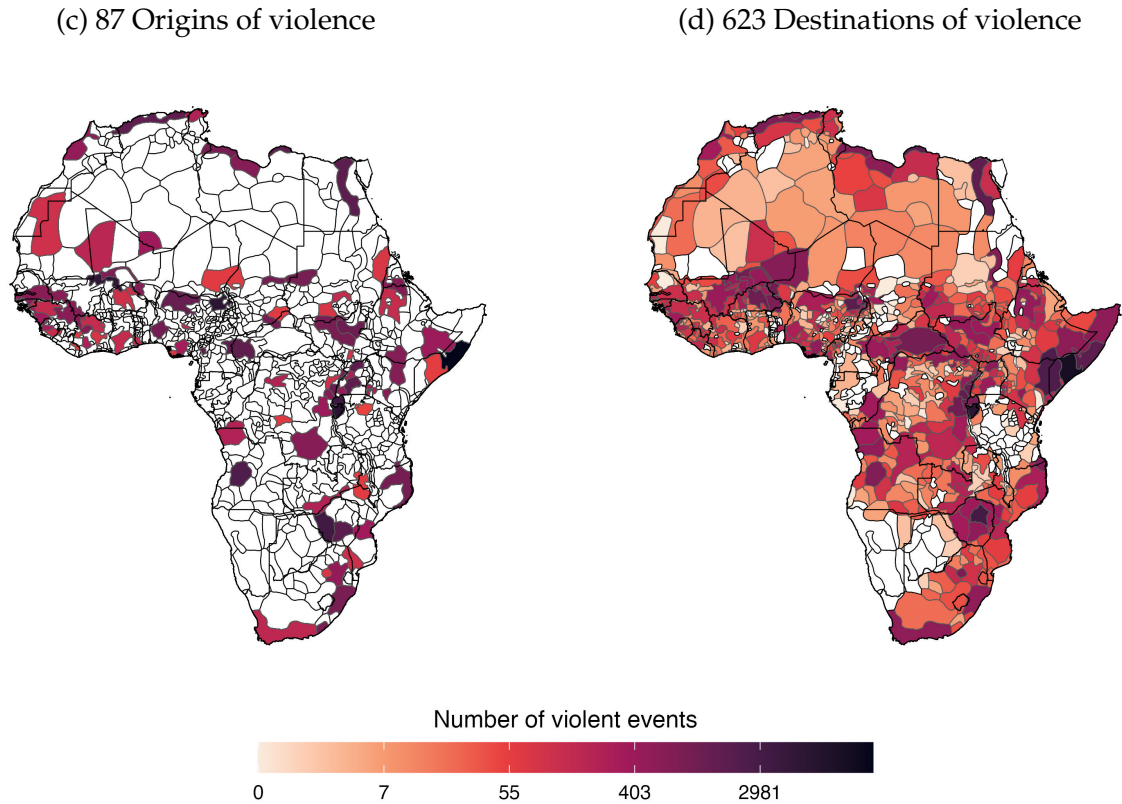
²⁷Using a share is dictated by the model: equation (21) characterizes the conditional allocation of violence across origins within a destination, not the total number of events occurring in that destination. Moreover, Santos Silva and Tenreiro (2006) recommend PPML for gravity equations based on its robustness to non-homoskedastic error terms and its ability to accommodate zero flows. Fally (2015) shows that PPML fixed effects impose the structural interpretation relevant in micro-founded gravity models, while Eaton et al. (2013) show the desirable properties of estimating PPML on shares rather than levels in those same models.

²⁸The structural interpretation of those fixed effects is $\text{FE}_i^o = \frac{1}{1-\gamma} \log \left(\frac{\psi_i}{w_i} \right)$, and $\text{FE}_n^d = -\log \left[\sum_{k=1}^N \xi_{kn}^{-\frac{\gamma}{1-\gamma}} \left(\frac{\psi_k}{w_k} \right)^{\frac{1}{1-\gamma}} \right]$.

Figure 1: The distribution of violent events and their spatial allocation

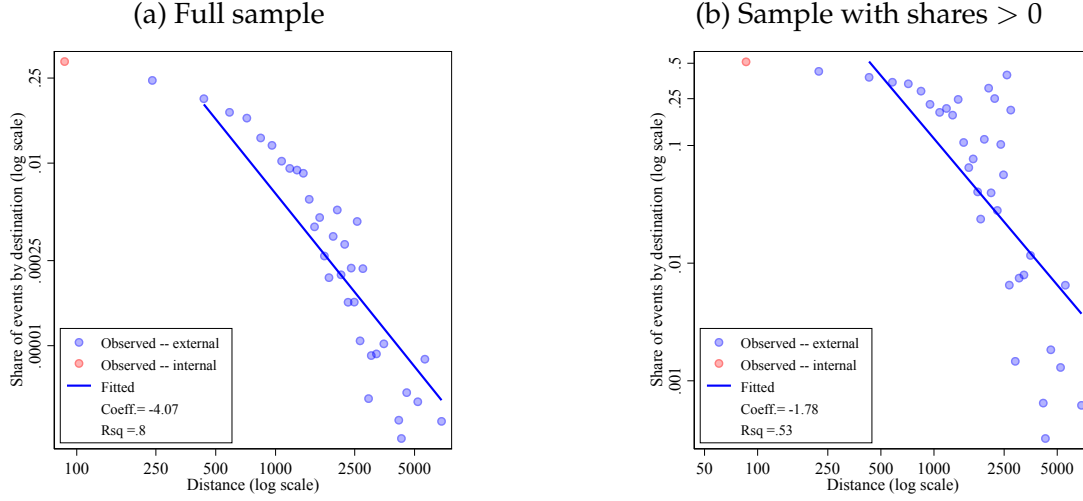


Note: Panels (a) and (b) are based on the sample of Step 4 in Table 1, comprising 1492 actors in 87578 violent events. Panel (a) reports the log rank-log size relationship; the ten major actors are highlighted and circle size reflects the number of actors at a given rank. There are 418 actors with only 1 event (rank 1075); Al-Shabaab is the most active with 16609 events. Panel (b) plots cumulative actor counts (ranked by size) against their cumulative share of events.



Note: Panels (c) and (d) are based on the sample of Step 6 in Table 1, comprising 78335 violent events from 87 origin regions targeting 623 destinations.

Figure 2: Bilateral distance and share of events at destination



Note: These figures are based on the sample of Step 6 in Table 1. It comprises a total of 78335 violent events originating from 87 regions and targeting 623 destinations. Red markers denote intraregional (internal) violence and blue markers denote interregional (external) violence. Panel (a) displays the full sample, while panel (b) restricts the sample to observations with strictly positive destination shares. Both figures are binscatters with 50 identical bins of distance computed on the full sample. Due to the log-scale, bins with zero violence are not displayed. The solid line shows the fitted relationship between log distance and the share of events. Distances are measured in kilometers and both axes are reported on a log scale. Internal distances are computed using the disk approximation of [Head and Mayer \(2000\)](#).

ζ_{in} as a function of three observable components: geographic distance, ethnic border-crossing, and political border-crossing.²⁹ This leads to the following empirical gravity specification for violence:

$$\mathbb{E} \left(\frac{\text{violence}_{in}}{\text{violence}_n} \right) = \exp \left[-\frac{\alpha_1 \gamma}{1 - \gamma} \log \text{distance}_{in} - \frac{\alpha_2 \gamma}{1 - \gamma} \text{Murdock ethnic border}_{in} - \frac{\alpha_3 \gamma}{1 - \gamma} \text{Political border}_{in} + \text{FE}_i^o + \text{FE}_n^d \right], \quad (23)$$

where distance_{in} is the great-circle distance between centroids of i and n when $i \neq n$, and $\text{distance}_{in} = (2/3)\sqrt{\text{area}(i)/\pi}$ when $i = n$ (following [Head and Mayer, 2000](#)). Alternative distance measures are explored in robustness checks, with results reported in section 3.5. Murdock ethnic border $_{in}$ equals one when $i \neq n$, and Political border $_{in}$ equals one when i and n are assigned to different countries. Intra-regional and intra-national flows are the omitted categories.

3.4 Results

Table 2 reports the PPML estimates. The estimation sample contains 87 origins and 623 destinations, corresponding to 54,201 dyads after fixed-effect separation.³⁰ Standard errors clustered by

²⁹In Murdock's map, many ethnic groups are split across countries ([Michalopoulos and Papaioannou, 2016](#)). To construct the border-crossing variable transparently, we assign each ethnic group to the country where it predominantly resides in terms of area. We leave for future work the analysis of heterogeneous border effects for groups that are more or less fragmented across countries.

³⁰The regression drops regions that neither originate nor receive violence (fixed effects would be perfect predictors).

dyad are reported in parentheses. In brackets, we also report bootstrap standard errors based on draws clustered by destination n , following the procedure described in Appendix OA.E. This clustering level is intended to account for spatially correlated measurement uncertainty associated with ACLED data collection. Indeed, the wide set of local, regional, national, and international media reports underlying this process is likely to generate variation in data precision across destinations.

Table 2: Estimates of the frictions to violence

Model	(1)	(2)	(3)	(4)
log distance	-2.65*** (0.046) [0.051]	-2.90*** (0.052) [0.056]	-2.42*** (0.059) [0.058]	-2.49*** (0.080) [0.088]
Murdock ethnic border		2.46*** (0.181) [0.185]	2.52*** (0.176) [0.191]	
Political border			-1.69*** (0.109) [0.099]	
Murdock ethnic border: contiguity				2.06*** (0.185) [0.206]
Murdock ethnic border: no contiguity				2.82*** (0.207) [0.237]
Political border: contiguity				-1.24*** (0.096) [0.091]
Political border: no contiguity				-3.05*** (0.193) [0.172]
Observations	54,201	54,201	54,201	54,201
Pseudo R ²	0.517	0.526	0.546	0.554

Note: Dependent variable is the share of events in region n originating from region i . Cross-section over 1997-2023. Estimated with PPML with i and n fixed effects. Columns (1)-(4) are estimated on the sample of 87 origins attacking a total of 623 destinations. Significant at 10%, ** significant at 5%, *** significant at 1%. Standard errors clustered at the in level are in parentheses. Bootstrap standard errors with destination n clusters, based on 100 valid bootstrap draws, are reported in brackets and are computed as described in Appendix OA.E.

The first column of Table 2 shows a steep distance gradient. The estimated elasticity, -2.65 , implies that doubling distance reduces bilateral violence by 84% ($2^{-2.65} = 0.16$).³¹ This elasticity is larger than the average distance elasticity in trade, around -1.1 in the meta-analysis of Head and Mayer (2014), and close to estimates for land-based trade flows (mostly trucks in advanced economies), around -2 in Combes et al. (2005). The comparison is consistent with the view that projecting violence over land, which heavily relies on road transportation, faces strong spatial frictions.

From columns (2) to (4), we sequentially add the effects of Murdock ethnic and political border-crossing on bilateral violence. Crossing a Murdock ethnic border has a large and precisely es-

³¹Mueller et al. (2022) also documents spatial decay in violence, though using monadic variation in distance to ethnic borders rather than bilateral gravity flows. These methodological differences limit the possibility of a quantitative comparison between their results and our gravity coefficient of distance.

estimated effect on violence. Conditional on distance and on origin and destination fixed effects, inter-regional flows of violence are roughly one order of magnitude larger than intra-regional flows ($\exp(2.46) = 11.70$). Intra-regional violence is therefore present in the data, but occurs at substantially lower intensity. This pattern suggests that, conditional on distance and access to appropriable resources, fighting groups face substantially higher barriers when targeting co-ethnics than when targeting other ethnic groups. Crossing a political border has the opposite sign. Column (3) implies an average five-fold drop in violence across national borders ($\exp(-1.69) = 0.18$), consistent with political borders raising the cost of projecting violence. Column (4) decomposes border effects by contiguity. The impact of crossing a Murdock ethnic border is larger for non-contiguous than for contiguous destination homelands ($\exp(2.82) = 16.78$ versus $\exp(2.06) = 7.85$), meaning that violence increases less when armed groups target contiguous ethnic homelands. This is consistent with contiguous groups sharing denser historical, cultural, or economic ties that dampen inter-homeland violence. By contrast, the political-border penalty is stronger for non-contiguous than for contiguous countries, $\exp(-3.05) = 0.05$ versus $\exp(-1.24) = 0.29$, consistent with overland movement requiring the crossing of additional national borders when countries are non-contiguous. All coefficients are precisely estimated across specifications. It is also reassuring that the bootstrap standard errors are very close to the conventional dyad-clustered standard errors.

3.5 Robustness

This section assesses the robustness of the estimated distance gradient and ethnic-border effect across several dimensions: distance measurement, violence near ethnic borders, ethnic homeland definitions, bilateral-flow construction, panel structure, and violence motives.

Alternative distance measures. Murdock homelands vary substantially in size, with an average area of 35.4 thousand km^2 and considerable dispersion ($\text{SD} = 66.1$ thousand km^2). For regions of this scale, centroid distance may misrepresent relevant interaction distances: it reduces each homeland pair to a single point-to-point distance, implicitly assumes a uniform population distribution inside a region, and also ignores that interactions are more likely to occur in proximate and/or populated areas. In Appendix OA.B.6.1, we therefore re-estimate the gravity equation with an alternative measure of distance, the *effective distance* measure (Head and Mayer, 2010; Hinz, 2019), which accounts for within-region population geography and for the fact that proximate subunits should receive greater weight in bilateral interactions. Because effective-distance itself depends on distance elasticity, the gravity estimation requires a fixed-point procedure. The estimated distance elasticity is slightly attenuated relative to the baseline, while the ethnic-border effect increases, a pattern consistent with the predictions of the model. The gravity pattern is therefore not an artifact of centroid-based distance measurement.

Violence around ethnic borders. A related concern is that the estimated ethnic-border effect may capture local interactions around neighboring homelands rather than a distinct role for distance. As emphasized by Depetris-Chauvín and Özak (2024), violence is often concentrated near historical

ethnic boundaries. Appendix [OA.B.6.2](#) shows that 50% of violent events in our data occur within 16 km of the nearest ethnic boundary. We therefore reconstruct bilateral flows after excluding events located within 16 km of an ethnic boundary, repeat the exercise using a 50 km threshold, and implement a stricter test that drops all homeland pairs sharing an ethnic border. Across these exercises, the gravity estimates remain stable, indicating that the baseline results are not driven by violence concentrated at ethnic borders.

Ethnic dispersion and overlapping homelands. Murdock homelands are historical and non-overlapping, whereas contemporary ethnic presence may be dispersed and locally overlapping. This can misclassify some interactions as inter-regional and distort measured bilateral distances. Appendix [OA.B.6.3](#) aggregates individual information of the Afrobarometer survey to construct ethnicity-weighted distances that allow groups to be present outside their historical homeland. The distance coefficient remains stable. The Murdock ethnic-border coefficient declines, consistent with the baseline variable having partly absorbed contemporary co-presence effects, which the weighted distance measure now captures separately.

Geo-precision, destination aggregation, and matching quality. Three checks address the construction of bilateral flows. First, we include lower-precision ACLED events; the gravity pattern is unchanged (Appendix [OA.B.8](#)). Second, we redefine destinations using Admin-1 and Admin-2 units while keeping Murdock homelands as origins; the distance elasticity remains stable, although border coefficients vary with the spatial partition (Appendix [OA.B.8](#)). Third, we restrict the sample to increasingly reliable actor–ethnicity matches; the estimates remain stable (Appendix [OA.B.5](#)).

Panel structure and temporal diffusion. Collapsing the panel into a cross section may confound spatial frictions with temporal diffusion. If violence propagates over time across regions, the baseline distance gradient could partly reflect a “domino effect” rather than equilibrium spatial interactions. Origin and destination fixed effects absorb persistent local determinants of violence, but they do not directly address spatio-temporal diffusion. Appendix [OA.B.9](#) addresses this concern in two ways. A yearly pooled gravity specification delivers coefficients close to the baseline cross-section. Year-by-year estimates also show stable distance elasticities, which are generally not statistically different from the baseline estimate. This stability suggests that the cross-sectional gradient is not merely an artifact of pooling years.

Forms of violence. Although the baseline mechanism emphasizes appropriation, the theory also allows spatial frictions to shape broader forms of violence. Appendix [OA.B.7](#) uses ACLED event notes and an LLM-assisted classification procedure to distinguish appropriation-related events from other motives (e.g. ethnic or religious grievances); these labels are used as robustness partitions rather than as ground-truth measures of motives. Among classifiable events, nearly three quarters involve appropriation-related motives. Re-estimating the gravity equation by motive shows distance decay and ethnic-border effects in both subsamples. The gravity pattern is therefore not confined to narrowly defined appropriation. This also speaks to the concern that some in-

terethnic conflict in Africa follows a sons-of-soil logic (Fearon and Laitin, 2011), driven by tensions between local populations and recent migrants rather than predatory appropriation; the spatial gradient in the non-appropriation subsample is consistent with such dynamics.

Overall, the robustness exercises point to a clear hierarchy: the distance gradient is highly stable, whereas border effects vary more with the spatial partition used to measure ethnic and political discontinuities.

4 Monadic violence

In much of the empirical conflict literature, violence is observed as a local outcome rather than as a bilateral flow (Dube and Vargas, 2013; Michalopoulos and Papaioannou, 2016; Berman et al., 2017; McGuirk and Burke, 2020, to cite only a few). Identification therefore relies on local variation in socio-economic conditions, raising the question of how the gravity forces emphasized in our framework relate to standard reduced-form estimates. This section derives the model’s testable implications for such monadic settings and shows how standard empirical specifications can be augmented to account for the spatial interactions implied by the gravity structure. Doing so, we clarify what local regressions identify, what spatial forces they omit, and how general-equilibrium interactions reshape the interpretation of reduced-form estimates.

Equation (11) describes bilateral violence: the equilibrium allocation of fighters from origin i to the appropriation of income in destination n , l_{in} , adjusted by their fighting capacity ψ_i . In monadic settings, however, the researcher only observes $\text{violence}_n = \sum_{i=1}^N \text{violence}_{in}$, i.e. total violence in destination n . Combining equation (11) with (13) and (14), and using free mobility between production and fighting, yields:

$$\text{violence}_{in} = \omega_{in} \times \left(\frac{\psi_i}{w_i} \right) \times (1 - s_n) w_n \bar{L}_n, \quad \text{with} \quad \omega_{in} \equiv \frac{\xi_{in}^{-\frac{\gamma}{1-\gamma}} \left(\frac{\psi_i}{w_i} \right)^{\frac{\gamma}{1-\gamma}}}{\sum_{k=1}^N \xi_{kn}^{-\frac{\gamma}{1-\gamma}} \left(\frac{\psi_k}{w_k} \right)^{\frac{\gamma}{1-\gamma}}}. \quad (24)$$

Summing equation (24) over origins and taking logs gives

$$\log(\text{violence}_n) = \log(1 - s_n) + \log \bar{L}_n + \log w_n + \log \left(\sum_i \omega_{in} \frac{\psi_i}{w_i} \right). \quad (25)$$

The first three terms in equation (25) capture local exposure to appropriation: violence falls with the capacity of local authorities to secure income (s_n), and rises with local aggregate income (log of $w_n \bar{L}_n$), which increases the value of predation (the *rapacity* effect). The last term captures a novel object that we label the “Supply Potential of Violence” (SPV): a weighted average of fighting potentials across all origins, including the local origin $i = n$.³² SPV generalizes the standard opportunity-cost channel by embedding it in the geography of violence. Local violence depends

³²The weight ω_{in} , defined in equation 24, is also the equilibrium probability of victory of i in the contest for appropriation in n ; see equation (B.24) in Appendix B.

not only on local opportunity costs, but also on the proximity of origins with low fighting frictions, high fighting capacity, and low wages.³³

Equation (25) implies that standard monadic specifications estimating the effect of local income, w_n , on local violence in n should incorporate the structural SPV term, or an empirical proxy for its observable component. Otherwise, spatial interactions omitted from the regression may bias the estimated effect of local economic conditions. Our gravity estimates (Section 3) show that physical distance is a central component of the frictions to bilateral violence. We therefore construct a proxy that replaces the full equilibrium weights ω_{in} with distance-based exposure and uses origin-level inverse income to capture opportunity costs:

$$\widehat{\text{SPV}}_n \equiv \log \left(\sum_{i=1}^N \frac{\text{dist}_{in}^{\hat{\alpha}}}{\sum_{k=1}^N \text{dist}_{kn}^{\hat{\alpha}}} w_i^{-1} \right). \quad (26)$$

This proxy omits unobserved fighting capacity ψ_i and the non-distance components of bilateral fighting frictions, and should therefore be interpreted as an implementable measure of spatial pressure rather than the full structural SPV. It isolates the component of SPV driven by spatial exposure and origin-level opportunity costs. It is implementable with three standard inputs: a bilateral distance matrix, a proxy for local income, and an estimate of the distance gradient of violence. In the application below, we use our preferred gravity estimate from Table 2 (col. 3), $\hat{\alpha} \simeq -2.5$.

We illustrate the approach using the setup of [Berman et al. \(2021\)](#), who estimate the effect of agricultural productivity shocks on violence in a panel of 0.5×0.5 degree grid cells c observed in year t across Africa. Their empirical design uses cell-specific fertilizer price shocks, FP_{ct} , as negative shifters of agricultural income. As is common in the monadic conflict literature ([Campante et al., 2019](#); [McGuirk and Burke, 2020](#); [McGuirk and Nunn, 2025](#); [Eberle et al., 2025](#), for instance), their baseline specification estimates the extensive margin of violence incidence. This is estimated as a Linear Probability Model (LPM), using two-way OLS fixed effect (TWFE) regressions:

$$\mathbb{1}(\text{violence}_{ct} > 0) = \varrho \log(FP_{ct}) + \text{FE}_c + \text{FE}_t + \varepsilon_{ct} \quad (27)$$

Our model provides an interpretation of what the previous specification captures and what it omits. Assuming that local state capacity and population are time invariant, the panel version of equation (25), transposed to grid cells, is

$$\log(\text{violence}_{ct}) = \log(1 - s_c) + \log \bar{L}_c + \log w_{ct} + \log \left(\sum_o \omega_{oc} \frac{\psi_o}{w_{ot}} \right), \quad (28)$$

where o is the origin cell of violence. The last term is the model-implied SPV. In the empirical

³³ In the fully local case, $\zeta_{nn} > 0$ and $\zeta_{in} = \infty$ for all $i \neq n$, so that $\omega_{nn} = 1$ and equation (25) becomes $\log(\text{violence}_n) = \log(1 - s_n) + \log \bar{L}_n + \log \psi_n$. The local rapacity effect of w_n is then exactly offset by the local opportunity-cost effect. More generally, when non-local frictions are large relative to local frictions, these two forces partly offset each other, attenuating the effect of local income per capita on violence.

application, we approximate it with the observable proxy $\widehat{\text{SPV}}_{ct}$ given by (26):

$$\text{SPV}_{ct} \equiv \log \left(\sum_o \omega_{oc} \frac{\psi_o}{w_{ot}} \right) = \nu \widehat{\text{SPV}}_{ct} + \varepsilon_{ct}. \quad (29)$$

We parametrize local wages as a power function of fertilizer prices, $w_{ct} = \phi_t \times (FP_{ct})^{-\epsilon}$, where both parameters are unknown. This gives

$$\widehat{\text{SPV}}_{ct} \equiv \log \left(\sum_o \frac{\text{dist}_{oc}^{\hat{\alpha}}}{\sum_k \text{dist}_{kc}^{\hat{\alpha}}} w_{ot}^{-1} \right) = \log \left(\sum_o \frac{\text{dist}_{oc}^{\hat{\alpha}}}{\sum_k \text{dist}_{kc}^{\hat{\alpha}}} (FP_{ot})^{\epsilon} \right) - \log(\phi_t), \quad (30)$$

Combining equations (28), (29) and (30) yields a specification estimable by PPML:

$$\text{violence}_{ct} = \exp \left[-\epsilon \log(FP_{ct}) + \nu \log \left(\sum_o \frac{\text{dist}_{oc}^{\hat{\alpha}}}{\sum_k \text{dist}_{kc}^{\hat{\alpha}}} (FP_{ot})^{\epsilon} \right) + \text{FE}_c + \text{FE}_t + \varepsilon_{ct} \right], \quad (31)$$

where $\text{FE}_c \equiv \log((1 - s_c)\bar{L}_c)$ and $\text{FE}_t \equiv (1 - \nu) \log(\phi_t)$. Contrasting the standard reduced-form equation (27) with the model-consistent specification (31) highlights two differences. First, the former estimates violence incidence, whereas the latter is naturally written for event counts. Second, the reduced-form specification omits SPV. Hence, ϱ captures the *net effect* of income, combining the local rapacity channel with the spatially mediated opportunity-cost channel.

Table 3 columns (1) to (4) examine the extensive margin of violence. Column (1) replicates the main specification (and results) of Berman et al. (2021) by estimating equation (27). The coefficient on fertilizer prices is positive: since higher fertilizer prices reduce local agricultural income, this suggests that the opportunity-cost channel more than offsets the rapacity channel in the standard monadic specification. Column (2) restricts the outcome to the violence events used in our sample—those closest to the appropriation motive emphasized by the model (see Table 1)—and yields the same sign pattern. Column (3) augments the specification with our empirical proxy for spatial spillovers, $\widehat{\text{SPV}}_{ct}$, constructed with $\epsilon = 1$ to remain close to the reduced-form literature. The direct effect of fertilizer prices becomes negative, while $\widehat{\text{SPV}}_{ct}$ enters positively and significantly. This is consistent with the model's prediction. Column (4) uses a leave-own-cell-out measure of SPV to address the fact that $\widehat{\text{SPV}}_{ct}$ includes FP_{ct} among the origin terms. The sign pattern is unchanged, although magnitudes should be interpreted cautiously because the incidence specification has no direct quantitative counterpart in the model.

The last four columns of Table 3 turn to the intensive margin, estimated by PPML as in equation (31). Column (5) replicates the count specification reported in Berman et al. (2021, Table F10), while column (6) uses our measure of violence in cell-year ct . Both estimates are positive, as in the incidence specifications. Column (7) implements the model-consistent specification by estimating ϵ iteratively, since FP_{ot}^{ϵ} enters the SPV term non-linearly. We initialize the procedure with $\epsilon = 1$, estimate the coefficient on $\log(FP_{ct})$, update ϵ accordingly, and recompute SPV until convergence. The procedure converges to $\epsilon = 6.9$. The direct effect of fertilizer prices is negative, while the SPV term is positive, consistent with the model's decomposition of local income effects into rapac-

ity and spatially mediated opportunity costs. Column (8) constructs the leave-own-cell-out SPV measure using the converged value of ϵ ; the sign pattern is unchanged, although magnitudes and significance vary.

Table 3: The impact of SPV on the incidence and count of events

LHS source Model	BCS		GoV		BCS		GoV	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
In fertilizer price	0.119*** (0.022)	0.070*** (0.018)	-0.259*** (0.053)	-0.043* (0.025)	1.444* (0.810)	2.512** (1.050)	-6.915*** (1.881)	-1.916 (1.452)
SPV			0.489*** (0.075)				2.008*** (0.373)	
SPV – Outside				0.304*** (0.046)				1.411*** (0.340)
Observations	111,605	111,605	111,605	111,605	42,908	28,594	28,594	28,594
Rsqr	0.333	0.284	0.284	0.284				
Pseudo rsqr					0.573	0.522	0.527	0.527

Note: Columns (1) to (4) are estimated by Linear Probability Model on a dummy set to one if at least one event occurred in the cell. Columns (5) to (8) are estimated by PPML on the number of events occurring in the cell. * significant at 10%, ** significant at 5%, *** significant at 1%.

Overall, the results support the model’s prediction that standard monadic estimates combine two opposing effects of local income: a rapacity effect and a partly spatial opportunity-cost effect. The SPV adjustment provides a simple way to incorporate these general-equilibrium spatial interactions into conventional monadic research designs.

5 Model Inversion

This section presents how we recover the structural parameters of the model required for the counterfactual analysis. The inversion combines the gravity estimates with the equilibrium restrictions of the model to recover fighting capacity, state capacity, labor allocation, productivity, and trade frictions. The sample comprises 824 regions, of which 623 receive violence from 87 origin regions. We proceed in six steps and then assess the internal consistency of the recovered parameters and their relationship with external untargated measures. Table 4 summarizes the results, while additional material is relegated to Appendix OA.C .

Step 1. We start with estimation of (23) to obtain the elasticity of each spatial friction and the set of origin fixed effects $\widehat{FE}_i^o$ (the baseline regression is Column 3 of Table 2). All origins in the gravity sample belong to the “largest connected set”, ensuring that the fixed effects are comparable across origins (there is enough “mobility” to use the terminology from the labor literature initiated by Abowd et al., 1999). Because fixed effects are identified only up to a normalization, we set the fixed effect of one reference origin to zero (hereafter indexed by $i = 1$): $\widehat{FE}_1^o = 0$. We choose the Zaghawa ethnic group, located in Sudan and Chad, because external sources allow us to discipline its total

fighting capacity in Step 2.³⁴

Step 2. We recover the parameters γ and ψ_i by using the theoretical correspondence of $\widehat{\text{FE}}_i^o$ obtained from equations (21) and (22):

$$\widehat{\text{FE}}_i^o - \widehat{\text{FE}}_1^o = -\frac{1}{1-\gamma} \log\left(\frac{w_i}{w_1}\right) + \frac{1}{1-\gamma} \log\left(\frac{\psi_i}{\psi_1}\right), \quad (32)$$

where $\widehat{\text{FE}}_1^o$ is reported for completeness but is in practice taken as the reference. Since wages are not observed at the Murdock-region level for the full continent, we proxy relative wages with nighttime lights per capita, assuming $\frac{w_i}{w_1} = \left(\frac{\text{light}_i}{\text{light}_1}\right)^\lambda$. This gives:

$$\widehat{\text{FE}}_i^o = -\frac{\lambda}{1-\gamma} \log\left(\frac{\text{light}_i}{\text{light}_1}\right) + \text{residual}_i. \quad (33)$$

We estimate equation (33) by two-stage least squares to mitigate any reverse causation effects from violence to development. The instrument is the log average world price of the five crops most suitable for region i :

$$\log(\overline{\text{Price}}_i) = \log\left(\sum_{t=1997}^{2023} \sum_{c=1}^5 \alpha_i^c \times P_t^c\right),$$

where α_i^c is FAO crop suitability and P_t^c is the world real price of crop c , base 100 in 2000. The maintained exclusion restriction is that this shifter affects the origin fixed effect only through the wage component proxied by nighttime lights, and is otherwise orthogonal to the residual fighting-capacity component.

Table OA.C22 reports the OLS, first-stage, reduced-form, and 2SLS estimates. The 2SLS coefficient is -0.490 , which corresponds to $-\lambda/(1-\gamma)$. Using the wage-nighttime-light elasticity $\lambda = 0.27$ from Bruederle and Hodler (2018), we obtain $\hat{\gamma} = 0.449$. This value lies in the admissible range of the model: $\hat{\gamma} < 1$ guarantees concavity of the troop-allocation problem, while $\hat{\gamma} > 0$ implies that bilateral frictions reduce violence flows, given the exponent on ξ_{in} in equation (21). The magnitude of $\hat{\gamma}$ is close to the estimate of 0.5 obtained by Alekseev and Xinjue (2025), who use different information-panel variation in country-level military spending—and estimate a contest-success-function model of interstate arms races by GMM. Comparing equations (32) and (33) shows that the residuals identify relative fighting capacity: $\text{residual}_i = \frac{1}{1-\gamma} \log\left(\frac{\psi_i}{\psi_1}\right)$. To preserve this structural interpretation, the specifications reported in Table OA.C22 exclude a constant term. We use external sources to discipline the fighting capacity of the Zaghawa reference group, ψ_1 ,³⁵ and combine this value with the residuals and $\hat{\gamma}$ to recover $\hat{\psi}_i$ for each of the 87 origins of violence. For regions that produce no violence, we set $\hat{\psi}_i = 0$. The sample mean of $\hat{\psi}_i$ among violent regions is 0.038. Using equation (4), the inverse of this value, approximately 26, provides an

³⁴Figure OA.C9 shows that $\widehat{\text{FE}}_i^o$ are strongly positively correlated with the observed logged number of violent events originating from i , in line with the intuition that $\widehat{\text{FE}}_i^o$ captures the average propensity of each origin to perpetrate violence.

³⁵ACLED reports 944 violent events originating from the Zaghawa, our reference group. Based on external sources, we assign 37500 fighters to this group. Consistent with equation (4), we set the reference fighting capacity equal to the Zaghawa violence-to-fighter ratio, $\hat{\psi}_1 = 944/37500 = 0.02517$. More details are provided in Appendix OA.C.1.

order-of-magnitude measure of the average number of fighters required to generate one ACLED event.

Step 3. We retrieve the unsecured share of income based on the fact that the total fighting revenues across all the fighters active in n originating from the 87 violent origins sum up to the lost income of n :

$$\sum_{i=1}^{87} w_i l_{in} = (1 - s_n) w_n \bar{L}_n. \quad (34)$$

We isolate s_n in equation (34), and use the relationship between wages and nightlights and the theoretical definition of violence (equation 4) to recover an estimate of the state capacity as:

$$\hat{s}_n = 1 - \frac{\sum_{i=1}^{87} (\text{light}_i)^\lambda \frac{\text{violence}_{in}}{\hat{\psi}_i}}{(\text{light}_n)^\lambda \text{pop}_n}, \quad (35)$$

where $\hat{\psi}_i > 0$ for all violent origins, $\bar{L}_n$ is approximated by total population pop_n from the World Pop dataset (Lloyd et al., 2019), ensuring that all elements of the right-hand-side of the equation are estimated, calibrated or observed. By construction, $\hat{s}_n = 1$ for regions that receive no violence; for the 623 destinations that do, $\hat{s}_n$ lies within the $(0, 1)$ interval, with the Bira ethnic group, located in northeastern DRC, displaying the lowest value, securing only 85.9% of their total income.

Step 4. Equations (4) and (15) then recover the number of fighters and producers in each origin:

$$\hat{l}_i = \frac{\sum_{n=1}^N \text{violence}_{in}}{\hat{\psi}_i} \quad \text{and} \quad \hat{L}_i = \text{pop}_i - \hat{l}_i, \quad (36)$$

where we set $\hat{l}_i = 0$ for regions that exert no violence. Table 4 reports statistics on the fighter share, $\hat{l}_i / \text{pop}_i$, across the 87 origins of violence.

Step 5. This step focuses on calibrating the trade module. The GE characterization in Section 2.4 requires estimates of trade frictions (the τ s); following Head and Mayer (2014), we specify their value (in logs) as the sum of three standard trade impediments:

$$(1 - \sigma) \log \hat{\tau}_{in} = \mu_1 \times \log \text{distance}_{in} + \mu_2 \times \text{Political Border}_{in} + \mu_3 \times \text{RTA}_{in}, \quad (37)$$

where distance and political borders are defined as in equation (23). The RTA indicator equals one when two regions are located in different countries that belong to the same regional trade agreement; this is the trade-cost component shocked in one of the counterfactual exercises. Because bilateral trade flows are unavailable at the Murdock-region level, we estimate reduced-form gravity coefficients on national flows for the 39 African countries in our sample over 1970–2018 (Appendix Table OA.C23), interacting each impediment with a dummy for intra-African trade. These coefficients discipline $(1 - \sigma) \log \tau_{in}$ in equation (37): $\mu_1 = -0.85$, $\mu_2 = -5.34$ and $\mu_3 = 1.71$. Following the meta-analysis in Head and Mayer (2014), we separately calibrate the trade elasticity

to $1 - \sigma = -5.03$.

Step 6. Finally, we recover regional productivity from goods-market clearing. Replacing unobservables in equation (16) with the parameters recovered above gives:

$$A_i^{1-\sigma} = \sum_{n=1}^N \frac{\hat{\tau}_{in}^{-(\sigma-1)} (\text{light}_i)^{\lambda \times (1-\sigma)}}{\sum_{k=1}^N \hat{\tau}_{kn}^{-(\sigma-1)} A_k^{\sigma-1} (\text{light}_k)^{\lambda \times (1-\sigma)}} \hat{s}_n \left(\frac{\text{light}_n}{\text{light}_i} \right)^\lambda \frac{\text{pop}_n}{\hat{L}_i}. \quad (38)$$

Productivity is identified up to a normalization. We normalize productivity for the Fon ethnic group in Benin to one—a large group that exerts no violence in the data—and solve equation (38) by fixed-point iteration, as described in Appendix OA.D.2. As a validation check, Figure OA.C10 shows that estimated productivity is positively correlated to observed nighttime lights.

Recovered parameters and untargeted moments. Table 4 summarizes the structural parameters recovered by the inversion: fighting capacity $\hat{\psi}_i$, the implied labor allocation between fighting and production, productivity $\hat{A}_i$, and (log odds ratio of) state capacity $\hat{s}_n$. The estimates are internally consistent. First, among regions that supply violence, the average fighter share is 0.029, and all estimates lie in the unit interval. Second, among destinations receiving violence, estimated state capacity lies in its admissible range, with an average of 0.997 and a minimum of 0.859 (in levels), indicating substantial but not implausible heterogeneity in protection against appropriation (the table reports log-odds statistics). Third, estimated productivity displays substantial cross-regional dispersion, consistent with the spatial heterogeneity in economic activity observed across Africa. Since these parameters are recovered from equilibrium restrictions alone—not targeted to match external institutional or survey measures—their relationship with independent data provides a useful diagnostic for the inversion. Below each statistic, we report the standard deviation of the same figure over our 100 bootstrap samples clustered at the destination level. Overall, the inversion procedure yields precisely estimated parameters. The noisiest one is ψ_i , which is not surprising, since the vector of fighting capacities is directly affected by the estimated origin fixed effects, which themselves vary across bootstrap draws.

Appendix OA.C.3 reports results of two external validation exercises regarding the recovered vector of state capacity $\hat{s}_n$. First, we aggregate $\hat{s}_n$ to the country level using population weights and compare it with the principal component of institutional quality and territorial reach constructed from Worldwide Governance Indicators (World Bank, 2025) and V-Dem (Coppedge et al., 2026). Countries with stronger institutions display higher recovered state capacity, with an R^2 of 0.45. Second, we compare within-country variation in $\hat{s}_n$ with Afrobarometer data on trust in the police forces—a natural counterpart, since s_n measures the share of local income protected against appropriation. Within countries, Murdock homelands with higher recovered state capacity also exhibit higher police trust, indicating that the inversion captures empirically relevant sub-national variation rather than only country-level institutional differences. These correlations are not causal tests, but they show that the spatial variation inferred from the model aligns with independent measures of state presence not targeted in the inversion.

Table 4: Estimated parameters, some statistics

Param.	Numbers	Mean	Median	St. Dev.	Min	Max
<u>Origins</u>						
$\hat{\psi}_i$	87	0.038 [0.012]	0.029 [0.008]	0.032 [0.012]	0.0007 [0.001]	0.179 [0.075]
$\hat{l}_i / \bar{L}_i$	87	0.029 [0.009]	0.007 [0.002]	0.059 [0.027]	0.000 [0.000]	0.321 [0.211]
$\hat{L}_i / \bar{L}_i$	87	0.971 [0.009]	0.993 [0.002]	0.059 [0.027]	0.679 [0.211]	1.000 [0.000]
$\hat{A}_i$	824	3.694 [0.001]	3.614 [0.001]	1.432 [0.001]	0.366 [0.000]	12.645 [0.003]
<u>Destinations</u>						
$\log \left(\frac{\hat{s}_n}{1 - \hat{s}_n} \right)$	623	7.349 [0.295]	7.399 [0.306]	1.801 [0.058]	1.805 [0.620]	12.001 [0.489]

Note: This table presents descriptive statistics for the parameters estimated with our inversion procedure in Section 5. The table reports origin-side parameters for the 87 regions that supply violence and the log odds of destination-side state capacity for the 623 regions that receive violence; only productivity is reported for the full set of regions. Regions with no incoming violence are assigned $\hat{s}_n = 1$ by construction and are excluded from the log-odds statistics because $\log(\hat{s}_n / (1 - \hat{s}_n))$ is not finite at $\hat{s}_n = 1$. Regions with no outgoing violence are assigned $\hat{\psi}_i = \hat{l}_i = 0$ and $\hat{L}_i = \bar{L}_i$. Bootstrap standard errors with destination n clusters, based on 100 valid bootstrap draws, are reported in brackets and are computed as described in Appendix OA.E. The point estimate of $\hat{\gamma}$ is 0.449, with bootstrap standard error equal to 0.066.

6 Counterfactual Simulations

This section uses the recovered structural model to quantify how shocks to productivity and trade integration affect violence, state capacity, and welfare. We first describe the counterfactual methodology, then study two exercises: a local productivity increase in the Kanuri region and the withdrawal of Burkina Faso, Mali, and Niger from CEDEAO.

6.1 Methodology

Factual and counterfactual equilibria. In each exercise, we shock an exogenous parameter of the model—either productivity or bilateral trade frictions—solve for the counterfactual equilibrium, and compare it with the model-implied factual equilibrium. This is the “Difference in Expected Values” (DEV) approach of [Head and Mayer \(2019\)](#): both factual and counterfactual outcomes are model-based expected equilibria evaluated at the observed covariates and estimated parameters (hence the name “covariates-based” approach by [Dingel and Tintelnot \(2026\)](#)).³⁶

Destruction and security spillovers. The benchmark model of Section 2.4 treats vectors of productivity $\mathbf{A}$ and state capacity $\mathbf{s}$ as exogenous. For the counterfactuals, we allow violence to feed

³⁶The alternative Exact Hat Algebra approach ([Dekle et al., 2007](#)) predicts changes in outcomes relative to their observed levels. It requires observed bilateral market shares. We cannot implement it here because bilateral trade shares π_{in} are not observed between African ethnic regions. See also [Dingel and Tintelnot \(2026\)](#).

back into economic fundamentals through two channels. First, a “destruction spillover” lowers local productivity:

$$\log A_n = \log \bar{A}_n - \varepsilon_1 \times \text{violence}_n, \quad (39)$$

Second, a “security spillover” makes state capacity increase with local real income:

$$\log \frac{s_n}{1 - s_n} = \log \frac{\bar{s}_n}{1 - \bar{s}_n} + \varepsilon_2 \times \log \frac{Y_n}{P_n}, \quad (40)$$

where Y_n denotes nominal income (equation 14) and P_n is the CES price index (equation 2). The parameter $-\varepsilon_1 < 0$ captures the semi-elasticity of productivity with respect to violence, while $\varepsilon_2 > 0$ governs the elasticity of state capacity with respect to real income. The log-odds formulation ensures that s_n remains in the unit interval.³⁷

Numerical procedure. Section 5 describes the estimation and inversion procedure used to recover the structural parameters governing the factual equilibrium.³⁸ Omitting hats to simplify notation, the resulting set of structural parameters is:

$$\Theta = \{ \gamma, \sigma, \bar{s}_n, \bar{A}_n, \psi_i, \text{pop}_i, \tau_{in}, \xi_{in} \}.$$

Relative to the equilibrium characterization in Section 2.4, we now solve jointly for wages, productivity, and state capacity. We implement a nested fixed-point algorithm with three layers. The inner loop solves for equilibrium wages conditional on productivity and state capacity. Conditional on these wages, the middle loop updates equilibrium state capacity, while the outer loop updates productivity through the endogenous destruction mechanism. Appendix OA.D.2 provides more details on this part.

Welfare. The welfare impact of the counterfactual scenarios that we simulate can be related to a sufficient statistics formula well-known in trade since Arkolakis et al. (2012). We express the equilibrium level of welfare before the policy change, ω_n , as the secured share of individual income discounted by the CES price index:

$$\omega_n = \frac{s_n w_n}{P_n}. \quad (41)$$

³⁷For regions with $s_n = 1$ in the factual equilibrium, equation (40) implies $\bar{s}_n = 1$, so these regions remain fully protected unless state capacity is explicitly perturbed. The counterfactuals therefore do not generate new violence in destinations that are fully protected in the factual equilibrium.

³⁸This procedure has to be supplemented with the calibration of the destruction and security spillovers. Calibration of ε_1 relies on a 2SLS regression of $\log A_n$ on violence_n , where violence is instrumented using a model-based supply shifter of violence. The estimated semi-elasticity is $-\varepsilon_1 = -0.000439$, implying that one hundred additional ACLED events reduce local TFP by 4.4%. To estimate the dependence of s_n on income, equation (40) is estimated using a model-consistent shifter of trade revenues as an instrument. This yields $\varepsilon_2 = 0.499$. The baseline productivity and state-capacity parameters, $\bar{A}_n$ and $\bar{s}_n$, are then set as residual terms in (39) and (40), so that these equations exactly reproduce the recovered factual values of A_n and s_n at observed violence and income. Appendix OA.D.1 provides additional details.

The share of trade within region n is derived from equation (1) and equal to $\pi_{nn} = (\tau_{nn}w_n / A_n)^{1-\sigma} P_n^{\sigma-1}$ implying that $\frac{w_n}{P_n} = \pi_{nn}^{\frac{1}{1-\sigma}} \frac{A_n}{\tau_{nn}}$. Assuming that τ_{nn} remains unaffected by the counterfactual experiment and using (39), the change in welfare between the factual equilibrium (no superscript) and the counterfactual equilibrium (superscript ') equals:

$$\frac{\omega'_n}{\omega_n} = \left(\frac{\pi'_{nn}}{\pi_{nn}} \right)^{\frac{1}{1-\sigma}} \times \frac{\bar{A}'_n}{\bar{A}_n} \times \exp\{-\varepsilon_1(\text{violence}'_n - \text{violence}_n)\} \times \frac{s'_n}{s_n}. \quad (42)$$

The first term is the standard trade-welfare term in [Arkolakis et al. \(2012\)](#), which embeds an indirect influence of violence on welfare through labor reallocation and changes in trade patterns. The second term is the change in baseline productivity. The third and fourth terms are additional direct effects factoring in the destruction and security spillovers, respectively. They reflect equilibrium changes in violence and income, which lead to alterations in productivity and state capacity.

6.2 Fit of the factual equilibrium

Table [OA.D24](#) in the Appendix reports key moments of the model-implied factual equilibrium. Several features are worth highlighting. The model predicts that 31% of trade occurs within ethnic regions ($i = n$), while less than 7% crosses country borders, and the remaining 62% takes place across ethnic regions within the same country. Violence is more spatially projected: internal flows account for less than 22% of predicted violence, while 29% crosses international borders.

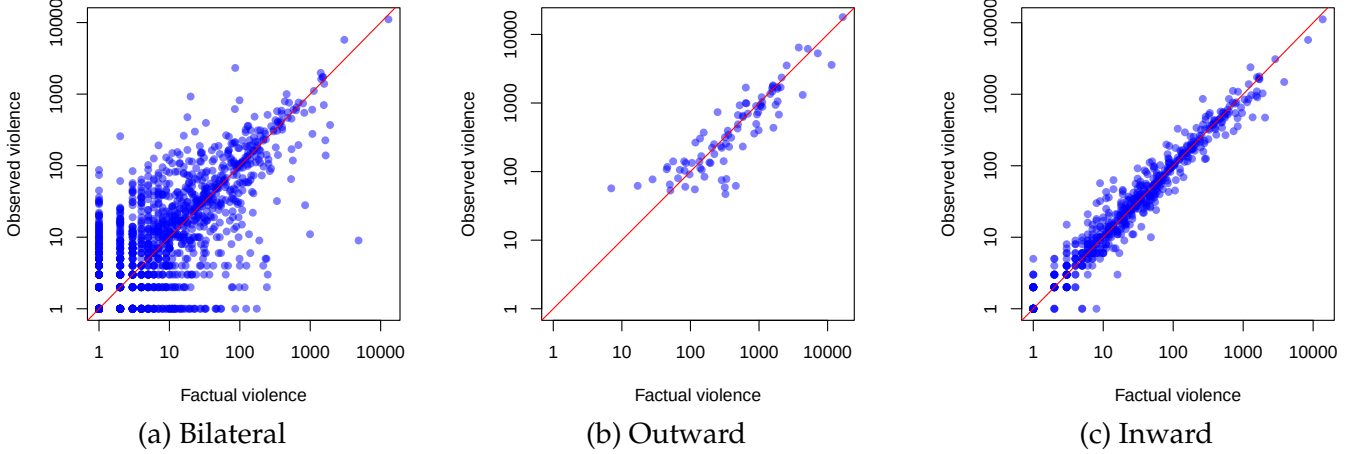
These moments are disciplined by the estimated violence frictions in Section 3.4 and the trade-cost calibration in equation (37). Since bilateral trade flows between ethnic regions are not observed, trade patterns are fully determined by the model structure and the country-level gravity estimates from Step 5. By contrast, bilateral violence flows are observed, providing a direct assessment of model fit. Figure 3 compares predicted and observed violence flows. Panel (a) plots bilateral flows (log scale): deviations are larger for small cells, where idiosyncratic shocks dominate, but the model captures the spatial distribution of violence reasonably well. The fit improves further for aggregate violence by origin (panel b) and by destination (panel c).

6.3 Counterfactual 1: A rise in the Kanuri region's productivity

Our first counterfactual raises baseline productivity $\bar{A}_n$ by 10% in a single region. The exercise illustrates the equilibrium mechanisms of the model and speaks to a central question in the conflict literature: how local income shocks affect violence and propagate spatially. We focus on the Kanuri region, where our procedure allocates Boko Haram, a particularly violent group active in West Africa (see footnote 41). Table 5 reports pre-shock outcomes and counterfactual changes for three groups: the Kanuri region itself ("shock"), regions within 1000 km ("close to shock"), and the regions in the 1000-2000km range ("other").³⁹

³⁹The simulation is run on a restricted set of regions within 2000 km of the shock to reduce computation time. Given the large estimated spatial decay in violence and trade, the impact of the shock becomes negligible at greater distances.

Figure 3: Goodness of fit



Note: The x -axis displays the predicted flows of violence (log scale). The y -axis reports the observed flows of violence (log scale). In panel (a) the bilateral flows of violence between i and n are reported. In panel (b) the total flow of violence perpetrated by i is reported. In panel (c) the total flow of violence suffered by n is reported.

The productivity shock generates sizeable pacification effects. Violence falls by 4.5% in the Kanuri region and by 3.9% in nearby regions, although only Kanuri is directly exposed to the shock. Through the equilibrium condition in equation (25), higher productivity raises local labor income, increasing the opportunity cost of fighting and reducing fighter supply from a major source of regional violence. This lowers the Supply Potential of Violence both in Kanuri (by 9.5%) and in nearby destinations (by 3.7% on average), producing spatial pacification. Within Kanuri, the shock also triggers two opposing forces. Higher wages make local resources more attractive to external predators (w_n rises by 11.5%), while the security spillover in equation (40) strengthens state capacity as real income rises, reducing the appropriable share of resources ($1 - s_n$ falls by 5.3%). Quantitatively, the opportunity-cost, SPV, and security effects dominate the rapacity channel. Through the destruction channel in equation (39), lower violence then amplifies the initial shock: TFP rises by 13.7%, above the 10% increase in baseline productivity, and welfare increases accordingly. The exercise therefore captures a positive counterpart to the “conflict trap”: higher productivity reduces violence, lower violence limits destruction, and lower destruction further raises productivity and income (see Rohner and Thoenig, 2021).

Appendix OA.D.4 decomposes these mechanisms through a sequence of counterfactual exercises that progressively activate the different margins of the model. Allowing security and destruction spillovers to operate jointly raises welfare gains by nearly 40% relative to a specification in which these channels are shut down, showing that welfare effects are driven largely by endogenous changes in violence and destruction rather than by standard trade channels alone. Hence, changes in self-trade shares are no longer sufficient statistics for welfare, in contrast with standard gravity-based trade models. The appendix also uses the bilateral gravity equation of violence to trace the reallocation of violence across origins and destinations. As Kanuri becomes less active militarily, competitive pressure in the appropriation market shifts toward nearby origins, which increase outward violence toward contested destinations, generating spatial gradients even outside

Table 5: Counterfactual changes across regions

Zone	Baseline avg.		Avg. % Change in					
	violence _n	1 - π_{nn}	violence _n	1 - s_n	w_n	SPV _n	TFP (A_n)	Welfare _n
<u>Counterfactual 1: Productivity shock</u>								
shock	1709.4	0.9	-4.5 [-8.7, -2.7]	-5.4 [-10.0, -3.6]	11.5 [8.4, 20.1]	-9.5 [-15.7, -6.9]	13.8 [10.0, 24.4]	11.8 [8.5, 20.9]
close to shock	54.3	0.9	-3.9 [-7.1, -2.6]	-0.1 [-0.2, 0.0]	0.1 [0.0, 0.2]	-3.8 [-6.1, -2.5]	0.1 [0.0, 0.2]	0.1 [0.0, 0.2]
other	79.0	0.8	-0.5 [-0.9, -0.3]	0.0 [0.0, 0.0]	0.0 [0.0, 0.0]	-0.6 [-0.9, -0.3]	0.0 [0.0, 0.0]	0.0 [0.0, 0.0]
<u>Counterfactual 2: Sahelexit</u>								
sahelexit	193.2	0.8	1.2 [0.3, 3.0]	0.9 [0.6, 1.1]	-0.8 [-1.0, -0.7]	1.1 [0.4, 3.2]	-0.1 [-0.3, 0.0]	-1.8 [-2.0, -1.7]
rest of CEDEAO	55.5	0.9	0.3 [0.2, 0.6]	0.1 [0.1, 0.1]	0.0 [0.0, 0.0]	0.2 [0.0, 0.5]	0.0 [0.0, 0.0]	-0.2 [-0.3, -0.2]
other	35.1	0.8	0.3 [0.1, 0.7]	0.0 [0.0, 0.0]	0.1 [0.1, 0.1]	0.2 [0.0, 0.6]	0.0 [0.0, 0.0]	0.0 [0.0, 0.0]

Note: The table reports baseline counterfactual estimates. violence_n is the total violence in region n , $1 - \pi_{nn}$ is the regional openness ratio, $1 - s_n$ captures the lack of state capacity, w_n is nominal wage, SPV_n is the Supply Potential of Violence as defined in equation (25), TFP (A_n) is productivity and Welfare_n refers to the secured per-capita real wage as defined in equation (41). In counterfactual 1, the shock is a 10% increase in baseline TFP (A_n in equation 39) in the Kanuri region. The corresponding zones are defined as follows: “shock” is the Kanuri Region; “close to shock” are regions within 1000km from Kanuri; “other” are regions within 1000km–2000km from Kanuri. In counterfactual 2, the shock corresponds to an increase in trade frictions—a removal of the RTA effect in equation (37)—between all pairs of regions belonging to one of the three exiting countries and the rest of CEDEAO. The bottom and top 5% of the bootstrap draws with destination n clusters, based on 100 valid bootstrap draws, are reported in brackets and are computed as described in Appendix OA.E.

the directly shocked region.

6.4 Counterfactual 2: Sahelexit

Our second counterfactual quantifies the effects of the “Sahelexit”: the withdrawal of Burkina Faso, Mali, and Niger from CEDEAO, announced on January 28, 2024 and effective one year later.⁴⁰ These three Sahel countries are among the poorest economies in the world and are heavily exposed to transborder armed groups, accounting for 36.49% of total violence within the CEDEAO area despite representing only 14.85% of its population.⁴¹ While the economic costs of trade disintegration are well understood, its geopolitical consequences are much less clear. Our framework quantifies how trade fragmentation propagates through equilibrium interactions between income, violence, and state capacity .

The counterfactual removes the RTA link between the three exiting countries and the rest of CEDEAO. Specifically, we increase bilateral trade frictions for all treated region pairs by shutting

⁴⁰CEDEAO, or ECOWAS in English, is the regional economic community of West African states. Its renewed 1993 treaty established a free trade area, and a common external tariff was adopted in 2015 (<https://www.tralac.org/resources/by-region/ecowas.html>).

⁴¹ Two of Africa’s most violent armed groups operate in or around these territories: JNIM, the second most violent actor in the sample (4223 events), and Boko Haram, the eighth (1605 events). Our data construction procedure associates them respectively with the Masina and Kanuri ethnic regions. The Masina homeland spans Mali, Burkina Faso, and Mauritania; the Kanuri homeland straddles Nigeria and Cameroon.

down the estimated RTA effect in equation (37):

$$\tau'_{in} = \tau_{in} \times e^{\mu_3/(\sigma-1)} = \tau_{in} \times e^{1.71/5.03}.$$

This is a large trade shock, implying an approximately 82% decline in trade flows between the Sahel exiters and the remaining CEDEAO countries. Table 5 reports pre-shock outcomes and counterfactual changes for three groups of regions: the exiters, non-exiting CEDEAO regions, and the rest of Africa. Appendix OA.D.5 provides the detailed mechanisms and decompositions.

The model predicts a generalized increase in violence across West Africa, with the strongest effects concentrated in the exiting countries. Violence rises by 1.18% among the Sahel exiters, driven by a deterioration in economic conditions. The trade shock reduces income in these regions by 0.81%, lowering the opportunity cost of fighting and increasing the supply of fighters. Outgoing violence from Sahelexit regions therefore rises toward all destinations, increasing the SPV term throughout West Africa. Within the exiting regions, lower income reduces rapacity incentives by making them less attractive for looting, but it also weakens state capacity ($1 - s_n$ rises by 0.87%). Quantitatively, the SPV and state-capacity channels dominate: violence increases, TFP falls through the destruction spillover, and welfare losses are amplified.

We report (in brackets) the top and bottom values for each of the statistics displayed by Table 5. Looking at those ranges, we see that the conclusions of our counterfactuals are not overly sensitive to sampling variation in the estimation and inversion procedures. This is true for both counterfactuals, with a slightly larger volatility for Sahelexit.

Appendix OA.D.5 further traces the bilateral reallocation of trade and violence. Trade is redirected away from the severed CEDEAO links toward domestic trade and alternative partners. At the same time, violence from the rest of CEDEAO toward Sahelexit regions declines as these regions become poorer and less attractive for looting, while violence originating within the exiting regions rises sharply.⁴²

The Sahelexit counterfactual highlights the role of trade integration as a force mitigating violence in the model. Appendix D.5 extends this logic to a more extreme scenario in which all intra-African trade costs are tripled, bringing trade flows close to zero. In that case, violence increases by around 18% on average across the continent, driven by the same mechanisms: lower income, weaker opportunity costs of fighting, weaker state capacity, and higher equilibrium violence. More generally, the simulations suggest that trade integration generates security gains across the continent, with the largest effects in initially more open regions.

⁴²At the end of Appendix OA.D.5, we examine the evolution of violence patterns in ACLED data over 2024–2026. We relate these dynamics to the timing of the withdrawal process and to the trade-fragmentation shock implied by the model. We implement reduced-form difference-in-differences exercises to assess whether the *observed* level and spatial distribution of violence evolve in a way that is consistent with the model’s predictions. Naturally, the short post-withdrawal window, possible anticipation effects, and confounding shocks all call for caution in interpreting the exercise as an external consistency check rather than as a causal validation of the Sahelexit mechanism. Diff-in-diff estimates are consistent with an increase in violence received by Sahelexit regions relative to the rest of CEDEAO, with moderate statistical significance. Also as predicted, these regions tend to project more violence toward all regions post-treatment, while the rest of CEDEAO projects *less* violence toward Sahelexit regions and more violence internally. All real-data responses are substantially larger than the theory predictions, reinforcing the caution with which these results should be interpreted.

7 Conclusion

In this paper, we build a quantitative spatial model of violence and show that gravity forces are useful both for the conceptual modeling of conflict and for the empirical analysis of bilateral violence. The model incorporates the standard channels through which income affects violence, while also identifying a distinct mechanism generated by spatial competition in appropriation markets: the Multilateral Resistance of Violence. Our structural estimation, covering continental Africa from 1997 to 2023, is consistent with the main predictions of the model and shows that spatial frictions, including distance and the crossing of ethnic or political borders, strongly shape the geography of conflict.

The framework also has direct implications for empirical research on conflict when only aggregate, destination-level measures of violence are observed. In such settings, we show that standard local conflict regressions should control for the Supply Potential of Violence. This model-implied spatial term can be constructed with a limited set of inputs and provides a correction for omitted spatial spillovers from potential origins of violence. In our empirical application, including this term changes the interpretation of the effect of local income on violence by helping separate opportunity-cost forces from rapacity forces. This provides a portable way to bring the bilateral logic of the gravity model into the monadic regressions commonly used in the empirical conflict literature.

The counterfactual analysis further illustrates the quantitative importance of spatial general-equilibrium feedbacks between economic and fighting margins. A local positive productivity shock generates welfare gains that extend beyond the directly affected region. Violence falls locally, and lower conflict pressure also raises productivity and welfare in neighboring regions. We also use the model to simulate the consequences of “Sahelexit,” the January 2024 announcement by Burkina Faso, Mali, and Niger that they would withdraw from CEDEAO. The model predicts economic losses in the withdrawing countries, stronger incentives for outward violence, and destabilizing spillovers across West Africa.

The paper also points to several directions for future research. First, more work is needed to identify the geographic origins of violence for small or short-lived fighting groups in ACLED. In our analysis, we geo-locate the origins of the most active groups, but many smaller groups remain unassigned to a precise home base. This limits the ability to study the extensive margin of violence. Addressing this limitation would require richer information and a shift in data collection from a purely place-based perspective, focused on the location of violent events, to a bilateral perspective that records both the origin and the destination of violence flows. Such data would allow future research to discipline quantitative spatial models of conflict more tightly, especially when studying the emergence of new conflict hotspots or the pacification of previously violent regions.

Second, although many aspects of military operations are inherently dynamic, our framework focuses on a long-run static equilibrium representation of conflict. The model therefore abstracts from short-run dynamics of attacks and counter-attacks, which have been studied in the literature on tactical military interactions and dynamic contests (e.g. [Konrad, 2009](#)). It is also less suited to analyze short-run responses to transitory shocks. Extending the framework to a fully dynamic

setting with forward-looking agents is a natural direction for future work.

Third, follow-up work could refine the modeling of the “industrial organization of armed groups.” Armed groups differ in the organizational structures they use to sustain their activities and exert control over territory and populations, including local and global networks for recruitment and operations. A richer representation of these strategies would help explain heterogeneity in groups’ ability to project violence across space.

Finally, future research could integrate climate shocks and migration decisions into the spatial conflict environment. Changes in the level and variance of temperature are likely to affect local incomes, spatial inequality, and both internal and international migration incentives. Our framework provides a natural starting point for studying these interactions, since the same gravity structure can be extended to include migration flows alongside trade and violence flows.

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Appendix

A Appropriation Game, Spoils, and Expenditures

This appendix provides the accounting details behind equations (9) and (10) in the main text. The purpose is to clarify the distinction between gross income, secured expenditure, and appropriable spoils. These expressions are equilibrium outcomes of an appropriation game with repeated contests, described in the box below.

Definitions. Let $Y_i^P = w_i^P L_i$ denote the gross income of producers in region i , and let R_i denote the total fighting revenues repatriated to region i over the sequence of appropriation contests. Gross regional income is

$$Y_i = Y_i^P + R_i. \quad (\text{A.1})$$

This is income before the final split between secured and unsecured components. By contrast, expenditure E_i is secured income available for consumption.

Box: Sequence of the appropriation game:

1. Front-loaded payment of the gross income $Y_n^P = w_n^P L_n$ of producers in region n ; only a share s_n is immediately and *permanently* secured. The residual share is the stock of unsecured income available for the first contest in region n : $U_n(1) = (1 - s_n)Y_n^P$.
2. “Once-for-all” optimal assignment of fighters l_{in} from region i to region n . Equation (5) sets the share p_{in} of unsecured income that is appropriated by i in n in each stage game.
3. A series of contests based on a repeated stage game begins:

Contest $k \geq 1$:

- (i) Fighters from i compete for spoils across regions n , generating a stage- k looting revenue $R_i(k) = \sum_n p_{in} \times U_n(k)$.
- (ii) $R_i(k)$ is then fully repatriated by fighters in region i .
- (iii) A share s_i of $R_i(k)$ is *definitively* secured. The residual share is the stock of unsecured income available for contest $k + 1$ in region i : $U_i(k + 1) = (1 - s_i)R_i(k)$.

If the residual unsecured income $U_i(k + 1)$ falls below an arbitrary small threshold $\varepsilon > 0$ in all regions i , the series of contests stops, and we move to step 4. Otherwise, we proceed to contest $(k + 1)$ and restart the stage game in (i).^a

4. Production, trade, and consumption take place.

^aThe threshold is relative to the initial unsecured income. An upper bound for the number of contests T is given by the condition $(1 - \min_n s_n)^T < \varepsilon$. In our calibration, the smallest value of s_n inferred from the data is approximately equal to 0.8, implying that after 3 rounds of the stage game, $99.2\% = 1 - (1 - 0.8)^3$, of income is permanently secured.

The important assumption is that fighting revenues are not automatically immune from subsequent appropriation. Being a fighter affects how income is obtained; it does not by itself protect income once revenues are repatriated to the origin region.

Law of motion for fighting revenues. Let $R_i(k)$ denote the fighting revenue accruing to origin i in contest k . In the first contest, fighters appropriate the unsecured component of producers' income:

$$R_i(1) = \sum_n p_{in}(1 - s_n)Y_n^P. \quad (\text{A.2})$$

In later contests, fighters appropriate the unsecured component of fighting revenues repatriated in the previous round:

$$R_i(k) = \sum_n p_{in}(1 - s_n)R_n(k-1), \quad k > 1. \quad (\text{A.3})$$

Define the appropriation matrix $\mathbf{A}$ by

$$a_{in} = p_{in}(1 - s_n). \quad (\text{A.4})$$

Then

$$\mathbf{R}(1) = \mathbf{A}\mathbf{Y}^P, \quad \mathbf{R}(k) = \mathbf{A}\mathbf{R}(k-1) \quad \text{for } k > 1. \quad (\text{A.5})$$

Iterating,

$$\mathbf{R}(k) = \mathbf{A}^k \mathbf{Y}^P. \quad (\text{A.6})$$

Total fighting revenues and appropriable spoils. Total fighting revenues are

$$\mathbf{R} = \sum_{k=1}^T \mathbf{R}(k) \approx \sum_{k=1}^{\infty} \mathbf{A}^k \mathbf{Y}^P. \quad (\text{A.7})$$

where T indexes the end-game contest. The infinite-sum approximation holds up to the terminal unsecured residual implied by the stopping rule (sub-stage (3-iii) of the appropriation game): the sequence ends once remaining unsecured income is arbitrarily small. Since $\sum_i p_{in} = 1$, each column of $\mathbf{A}$ sums to

$$\sum_i a_{in} = (1 - s_n) \sum_i p_{in} = 1 - s_n.$$

Thus $\|\mathbf{A}\|_1 = \max_n (1 - s_n)$. Under the maintained condition $\min_n s_n > 0$, the spectral radius satisfies $\rho(\mathbf{A}) \leq \|\mathbf{A}\|_1 < 1$. Repeated contests therefore shrink the unsecured residual, $\mathbf{R}(k) = \mathbf{A}^k \mathbf{Y}^P \rightarrow 0$, and the infinite geometric series is well defined.

Using the geometric structure,

$$\mathbf{R} = \mathbf{A}(\mathbf{Y}^P + \mathbf{R}). \quad (\text{A.8})$$

Since $\mathbf{Y} = \mathbf{Y}^P + \mathbf{R}$, we obtain

$$\mathbf{R} = \mathbf{A}\mathbf{Y}. \quad (\text{A.9})$$

Thus, for each origin i ,

$$R_i = \sum_n p_{in}(1 - s_n)Y_n. \quad (\text{A.10})$$

Notice that R_i is gross fighting revenue. It is redistributed to fighters through $w_i^F l_i = R_i$ in the main text. It is not yet their secured expenditure.

Comparing the expression inside the fighting group's maximization problem in equation (6) with equation (A.10) shows that the destination-specific spoils are

$$V_n = (1 - s_n)Y_n. \quad (\text{A.11})$$

Expenditures. Producer expenditure is the secured share of producer income:

$$E_i^P = s_i Y_i^P. \quad (\text{A.12})$$

For fighters, after each contest of the game, only a share of their newly appropriated looting revenues is definitively secured and contributes to their expenditures. Accordingly, fighter expenditure is the secured share of total fighting revenues:

$$E_i^F = \sum_{k=1}^{\infty} s_i R_i(k) = s_i R_i. \quad (\text{A.13})$$

Therefore total expenditure is

$$E_i = E_i^P + E_i^F = s_i Y_i^P + s_i R_i = s_i (Y_i^P + R_i) = s_i Y_i. \quad (\text{A.14})$$

Implication for the general equilibrium. The relation $E_i = s_i Y_i$ is not an accounting identity that would hold under any microfoundation. It follows from the baseline assumption that the same state capacity parameter s_i protects both producer income and repatriated fighting revenues. This is why the secured-expenditure ratio E_i/Y_i does not depend on the equilibrium allocation of labor between production and fighting. This feature is analytically useful because it preserves the symmetry between trade revenues and fighting revenues and allows the general equilibrium to be summarized by the master equation (18). Appendix D.4 considers the alternative case in which only producer income is exposed to looting; the gravity equation of violence is preserved, but the compact general-equilibrium representation is lost.

B Derivation of the gravity of violence

This section details the computations required to derive the theoretical gravity equation of violence (11). This object represents the partial equilibrium flow of violence (quantity) from i to n . We demonstrate below that it is given by:

$$\text{violence}_{in} \equiv \psi_i l_{in} = \xi_{in}^{-\frac{\gamma}{1-\gamma}} \times \left(\frac{\psi_i}{w_i^F} \right)^{\frac{1}{1-\gamma}} \times \frac{(1-s_n) Y_n}{\sum_k \xi_{kn}^{-\frac{\gamma}{1-\gamma}} \left(\frac{\psi_k}{w_k^F} \right)^{\frac{\gamma}{1-\gamma}}}. \quad (\text{B.15})$$

Proof The proof proceeds in three steps:

1. The optimal spatial allocation choice of troops across regions of destination n is given by:

$$R_i \equiv \max_{l_{in}} \sum_n p_{in} (1-s_n) Y_n, \quad \text{s.t.} \quad l_i = \sum_n l_{in}, \quad (\text{B.16})$$

with

$$p_{in} = \frac{(\xi_{in}^{-1} \psi_i l_{in})^\gamma}{\Phi_n}, \quad \text{with} \quad \Phi_n \equiv \sum_k (\xi_{kn}^{-1} \psi_k l_{kn})^\gamma, \quad (\text{B.17})$$

under the assumption $0 < \gamma < 1$ (to get a concave maximization problem) which we estimate to be the case in the empirics. The resulting Lagrangian for this optimization problem writes

as:

$$\mathcal{L} = \sum_n \frac{(\xi_{in}^{-1} \psi_i l_{in})^\gamma}{\Phi_n} (1 - s_n) Y_n + \lambda \left(l_i - \sum_n l_{in} \right).$$

The first-order-conditions write as:

$$\begin{aligned} \frac{\partial \mathcal{L}}{\partial l_{in}} = 0 &\iff l_{in} = (1 - s_n) Y_n p_{in} \frac{\epsilon_{in}}{\lambda}, \quad \text{with} \quad \epsilon_{in} \equiv \frac{\partial \ln p_{in}}{\partial \ln l_{in}} = \gamma(1 - p_{in}) \\ \frac{\partial \mathcal{L}}{\partial \lambda} = 0 &\iff l_i = \sum_n l_{in}. \end{aligned}$$

A key term is ϵ_{in} , the elasticity of winning the contest with respect to the number of fighters allocated to n . As in classical Dixit-Stiglitz monopolistic competition, if we assume that groups are small enough to neglect their impact on the overall conditions of violence in n , $\partial \Phi_n / \partial l_{in} = 0$, which implies that all winning probabilities p_{in} need to be sufficiently small, $\epsilon_{in} = \gamma$. In consequence, the first FOC simplifies to

$$l_{in} = (1 - s_n) Y_n p_{in} \gamma / \lambda. \quad (\text{B.18})$$

Combining the two FOCs and using $l_i = \sum_n l_{in} = \sum_j l_{ij}$:

$$l_i = \sum_j l_{ij} \iff \lambda = \left(\gamma \sum_j (1 - s_j) Y_j p_{ij} \right) / l_i.$$

Plugging back this expression in (B.18), we obtain:

$$\frac{l_{in}}{l_i} = \frac{(1 - s_n) Y_n p_{in}}{\sum_j (1 - s_j) Y_j p_{ij}}. \quad (\text{B.19})$$

2. Using the expression for total looting revenues of i and the fact that it is redistributed to all fighters:

$$R_i = \sum_j (1 - s_j) Y_j p_{ij} = w_i^F l_i, \quad (\text{B.20})$$

we obtain

$$l_{in} = \frac{(1 - s_n) Y_n p_{in}}{w_i^F} = \frac{(1 - s_n) Y_n}{w_i^F} \times \frac{(\xi_{in}^{-1} \psi_i l_{in})^\gamma}{\Phi_n} = \frac{\Omega_n}{w_i^F} \times (\xi_{in}^{-1} \psi_i l_{in})^\gamma,$$

where $\Omega_n \equiv (1 - s_n) Y_n / \Phi_n$. Solving for l_{in} , we get

$$l_{in} = \left(\frac{\Omega_n}{w_i^F} \times (\xi_{in}^{-1} \psi_i)^\gamma \right)^{\frac{1}{1-\gamma}}. \quad (\text{B.21})$$

This allows to solve for equilibrium values of Φ_n and Ω_n as

$$\Phi_n = \sum_k \left[\xi_{kn}^{-1} \psi_k \left(\frac{\Omega_n}{w_k^F} \times (\xi_{kn}^{-1} \psi_k)^\gamma \right)^{\frac{1}{1-\gamma}} \right]^\gamma = \Omega_n^{\frac{\gamma}{1-\gamma}} \sum_k \left(\frac{\xi_{kn}^{-1} \psi_k}{w_k^F} \right)^{\frac{\gamma}{1-\gamma}}$$

$$\Omega_n = \left[\frac{(1-s_n)Y_n}{\sum_k \left(\frac{\xi_{kn}^{-1} \psi_k}{w_k^F} \right)^{\frac{\gamma}{1-\gamma}}} \right]^{1-\gamma}.$$

Substituting back into (B.21) enables to recover the equilibrium l_{in} as

$$l_{in}^* = \left(\frac{1}{w_i^F} \right)^{\frac{1}{1-\gamma}} \times \frac{(\xi_{in}^{-1} \psi_i)^{\frac{\gamma}{1-\gamma}}}{\sum_k \left(\frac{\xi_{kn}^{-1} \psi_k}{w_k^F} \right)^{\frac{\gamma}{1-\gamma}}} \times (1-s_n)Y_n. \quad (\text{B.22})$$

3. Defining $\text{violence}_{in} \equiv \psi_i l_{in}^*$ gives the final equation for gravity of violence:

$$\text{violence}_{in} \equiv \left(\frac{\psi_i}{w_i^F} \right)^{\frac{1}{1-\gamma}} \xi_{in}^{-\frac{\gamma}{1-\gamma}} \frac{(1-s_n)Y_n}{\sum_k \left(\frac{\xi_{kn}^{-1} \psi_k}{w_k^F} \right)^{\frac{\gamma}{1-\gamma}}}, \quad (\text{B.23})$$

which completes the proof.

Finally, we can note that the equilibrium success probability (using B.22 in B.17) is

$$p_{in}^* = \frac{\left(\frac{\psi_i}{w_i^F \xi_{in}} \right)^{\frac{\gamma}{1-\gamma}}}{\sum_k \left(\frac{\psi_k}{w_k^F \xi_{kn}} \right)^{\frac{\gamma}{1-\gamma}}}. \quad (\text{B.24})$$

Therefore, after optimizing the allocation of fighters over space, we have

$$\text{violence}_{in} = \frac{\psi_i}{w_i^F} p_{in}^* (1-s_n)Y_n \Rightarrow w_i^F l_{in}^* = p_{in}^* (1-s_n)Y_n,$$

which implies that the financial flow linked to bilateral violence simply multiplies lootable income with the probability of success.

C Equilibrium existence and uniqueness

The proof of the existence and uniqueness of the equilibrium vector of wages as a fixed-point of equation (18) follows an approach similar to Allen (2019). It proceeds in two stages. Firstly, we show that our model generates “well-behaved” excess demand functions for goods and violence for each region $i \in N$. Secondly, we invoke standard results from Mas-Colell et al. (1995) on excess demand functions to establish the existence and uniqueness of the equilibrium. A comprehensive proof is provided in the Online Appendix, Section OA.A.1. The boundary and uniqueness arguments rely on accessibility conditions: regions with vanishing wages must retain access to at least

one positive-income destination through either the trade or fighting block, and the network must be sufficiently connected for the gross-substitutes property to hold pairwise.

From our master equation (18) we define the following excess demand function $Z_i(\mathbf{w})$ for $i \in N$:

$$Z_i(\mathbf{w}) \equiv \frac{1}{w_i} \left(\sum_n \beta_{in}(\mathbf{w}) w_n \bar{L}_n - w_i \bar{L}_i \right), \quad (\text{C.25})$$

where $\beta_{in}(\mathbf{w})$ is given by Equation (19). Reformulating the previous equation leads to a decomposition of the excess-demand function into two sub-components:

$$\begin{aligned} Z_i(\mathbf{w}) &= \frac{1}{w_i} \left[\sum_n (1 - s_n) \times \frac{w_i^{-\frac{\gamma}{1-\gamma}} \left(\frac{\psi_i}{\xi_{in}} \right)^{\frac{\gamma}{1-\gamma}}}{\sum_k \left(\frac{\psi_k}{\xi_{kn} w_k} \right)^{\frac{\gamma}{1-\gamma}}} w_n \bar{L}_n - (1 - s_i) w_i \bar{L}_i \right] + \frac{1}{w_i} \left[\sum_n s_n \times \frac{w_i^{1-\sigma} \left(\frac{A_i}{\tau_{in}} \right)^{\sigma-1}}{\sum_k \left(\frac{A_k}{\tau_{kn} w_k} \right)^{\sigma-1}} w_n \bar{L}_n - s_i w_i \bar{L}_i \right] \\ &\equiv Z_i^F(\mathbf{w}) + Z_i^P(\mathbf{w}). \end{aligned}$$

The sub-components $Z_i^F(\cdot)$ and $Z_i^P(\cdot)$, and by additivity $Z_i(\cdot)$, are all “well-behaved” in the sense that they satisfy the following set of properties:

- (P1) $\forall \mathbf{w} \gg 0, \forall i \in N, Z_i(\cdot)$ is continuous
- (P2) $\forall i \in N, Z_i(\cdot)$ is homogeneous of degree zero
- (P3) $\forall \mathbf{w} \gg 0$, we have $\sum_{i \in N} w_i Z_i(\mathbf{w}) = 0$
- (P4) $\forall \mathbf{w} \gg 0, \exists k > 0$ such that $\forall i \in N, Z_i(\mathbf{w}) > -k$
- (P5) Consider any $\mathbf{w} \in \mathbb{R}^{|N|}$ such that there exists $(l, l') \in N \times N$ with $w_l = 0$ and $w_{l'} > 0$. Consider any sequence of wages such that $\mathbf{w}^m \rightarrow \mathbf{w}$ as $m \rightarrow \infty$. Then:

$$\max_{i \in N} Z_i(\mathbf{w}^m) \rightarrow \infty.$$

- (P6) $\forall i \in N, \forall j \neq i, \frac{\partial Z_i(\mathbf{w})}{\partial w_j} > 0$ (Gross Substitute property)

Under the accessibility conditions detailed in Online Appendix OA.A.1, since the function $Z_i(\cdot)$ satisfies (P1)–(P5), we can apply Proposition 17.C.1 from Mas-Colell et al. (1995) on page 585, thereby proving the uniqueness of the equilibrium vector of wages up to a common scale normalization; relative wages are uniquely determined, consistent with the homogeneity of degree zero in (P2). Additionally, this function meets the gross substitute property (P6), which is a sufficient condition to apply Proposition 17.F.3 from Mas-Colell et al. (1995) on page 613, thereby proving the uniqueness of the equilibrium vector of wages.

D Additional channels and extensions

This appendix presents a series of extensions to the baseline model. Whenever possible, we discuss how these extensions alter the core predictions, with a particular focus on the gravity equation of violence: whether it remains unchanged or is modified. We also explore implications for the general equilibrium (GE) structure and the associated comparative statics.

D.1 Market power in the appropriation market

For tractability, the baseline model assumes atomistic fighting groups. This assumption substantially simplifies market power in the appropriation market by eliminating strategic interactions : each group best-responds to the actions of others but does not internalize its effect on aggregate violence. Substantively, this corresponds to the assumption that each success probability p_{in} is small. The setup is analogous to the continuum-of-varieties setup in monopolistic-competition models of trade (e.g. [Krugman, 1980](#); [Melitz, 2003](#)), under which firms neglect the impact of their own pricing decisions on the aggregate price index.

Violence with market power We now turn to the case where the size of group i is not negligible in the appropriation market n , which means that they account for the impact of their own violence on overall violence in n . Hereafter, to handle more compact notation, we denote the flow of violence as $v_{in} = \text{violence}_{in} = \psi_i l_{in}$. The first change is that the equations driving the contest success function, the optimal allocation of fighters, and the labor market equilibrium—(B.17), (B.19), and (B.20)—can all be re-expressed as functions of v :

$$p_{in} = \frac{(v_{in}/\xi_{in})^\gamma}{\Phi_n}, \quad \text{with} \quad \Phi_n \equiv \sum_k (v_{kn}/\xi_{kn})^\gamma, \quad (\text{CSF})$$

$$\frac{v_{in}}{v_i} = \frac{(1-s_n)Y_n p_{in} \epsilon_{in}}{\sum_j (1-s_j)Y_j p_{ij} \epsilon_{ij}}, \quad \text{with} \quad \epsilon_{in} \equiv \frac{\partial \ln p_{in}}{\partial \ln v_{in}} = \gamma(1-p_{in}), \quad (\text{OA})$$

$$v_i = \frac{1}{(w_i^F/\psi_i)} \sum_j (1-s_j)Y_j p_{ij}. \quad (\text{LM})$$

We note that the labor market equilibrium (LM) combined with (CSF) implies that total violence from i is a function of the vector of all bilateral violence flows. Furthermore the right hand side of (OA) can be written as a function σ_{in} of the vector of bilateral violence. We therefore express (OA) as a fixed point equation for the vector of all strategically chosen bilateral violence:

$$v_{in} = v_i(\{v_{kj}\}) \sigma_{in}(\{v_{kj}\}).$$

Solving for bilateral violence: The algorithm to solve for that fixed point is as follows: Start with a vector of bilateral violence $\{v_{in}\}$, which plugged into (CSF) provides a vector of $\{p_{in}\}$. The latter can then be used in (LM) and (OA) to yield a new vector of bilateral violence $\{v_{in}\}$. The equilibrium is reached by iterating those steps until $\{v_{in}\}$ stabilizes.⁴³

Non-constant elasticities. We can also work out what this extension to non-atomistic groups mean for the gravity equation of violence. Using (LM) and (CSF) into (OA):

$$v_{in} = A_i \times \left[\xi_{in}^{-\gamma} \epsilon_{in} \right]^{\frac{1}{1-\gamma}} \times B_n, \quad (\text{D.26})$$

⁴³Formally, this problem is the same as a multi-player, multi-battleground lottery Colonel Blotto game with a generalized Tullock contest success function. While we do not prove existence and uniqueness of the Nash equilibrium in this very general case, we conjecture that the proofs for the 2 players, multi-battleground case in [Li and Zheng \(2022\)](#) apply here. The solution algorithm also bears some similarity with the game of oligopolistic competition under CES demand pioneered by [Atkeson and Burstein \(2008\)](#), [Eaton et al. \(2013\)](#), [Edmond et al. \(2015\)](#) and [Gaubert and Itskhoki \(2021\)](#).

with monadic terms

$$A_i \equiv \left[\frac{v_i}{\sum_j (1 - s_j) Y_j p_{ij} \epsilon_{ij}} \right]^{\frac{1}{1-\gamma}}, \quad \text{and} \quad B_n \equiv \left[\frac{(1 - s_n) Y_n}{\Phi_n} \right]^{\frac{1}{1-\gamma}}.$$

Equation (D.26) therefore has a multiplicatively separable structure, which is one of the features of the gravity equation. Taking logs of (D.26), the classical estimation of gravity equation with origin and destination fixed effects can be run, and the elasticity of bilateral violence to bilateral frictions *conditional on those fixed effects* still be obtained:

$$\left. \frac{\partial \ln v_{in}}{\partial \ln \xi_{in}} \right|_{A_i, B_n} = -\frac{\gamma}{1-\gamma} + \frac{1}{1-\gamma} E_{in}, \quad \text{with} \quad E_{in} \equiv \left. \frac{\partial \ln \epsilon_{in}}{\partial \ln \xi_{in}} \right|_{A_i, B_n}. \quad (\text{D.27})$$

Contrary to the atomistic case, this elasticity is not constant and structural gravity, as defined in the literature covered in [Head and Mayer \(2014\)](#), does not hold in (D.26). This difference stems from the presence of the bilateral (super-elasticity) term, E_{in} , which represents the conditional elasticity with respect to frictions of the elasticity ϵ_{in} , holding constant all monadic aggregates A_i and B_n , and in particular Φ_n in (D.26).⁴⁴ After a few manipulations, it can be shown that

$$E_{in} = -\gamma \times \frac{p_{in}}{1 - p_{in}} \times \left(\left. \frac{\partial \ln v_{in}}{\partial \ln \xi_{in}} \right|_{A_i, B_n} - 1 \right).$$

Combined with (D.27), we obtain

$$\left. \frac{\partial \ln v_{in}}{\partial \ln \xi_{in}} \right|_{A_i, B_n} = \frac{-\gamma(1 - 2p_{in})}{1 - p_{in} - \gamma(1 - 2p_{in})}. \quad (\text{D.28})$$

If the group is negligible, p_{in} goes to 0 and we recover the monopolistic-competition elasticity $-\frac{\gamma}{1-\gamma}$. The bilateral friction elasticity expressed in absolute value is reduced by market power as long as the group does not control more than half of the appropriation market ($p_{in} \leq 1/2$). One can build intuition for the sign of this elasticity using the optimal allocation equation (OA) of i fighters to region n : $v_{in} = \gamma C_i D_n \times p_{in}(1 - p_{in})$, where again C_i and D_n are held constant by gravity fixed effects. Bilateral effort of violence peaks when the probability of success is 50%, coming from i) the direct effect p_{in} , capturing the expected marginal appropriation gain and also present when market power is negligible; ii) a countervailing effect $\gamma(1 - p_{in})$, linked to the fact that the marginal return of allocating fighters to a destination decreases with market power. The two effects exactly offset at $p_{in} = 0.5$ due to functional form.

In Table D1, we propose a reduced form estimation of this theoretical prediction, assessing the empirical variations in the elasticity of violence flows to frictions (distance here). The idea is to start from our baseline empirical gravity in Table 2 and interact the effect of distance with variables accounting for the non-constant determinant of the elasticity; i.e. p_{in} in equation (D.28). This is done in three different ways. The easiest, shown in Column (2), is to simply construct bins of proximity (the inverse of distance itself) and interact the effect of distance with those. The second, inspired by [Novy \(2013\)](#), is to interact log distance with the *predicted* level of the dependent variable

⁴⁴This expression for E_{in} should be interpreted as the local elasticity recovered from the gravity specification with origin and destination fixed effects, rather than as the full structural derivative of the non-atomistic equilibrium. The fixed effects absorb the monadic terms A_i and B_n in equation (D.26); conditional on these terms, the expression for E_{in} describes how the bilateral friction term maps into the winning-probability elasticity when the feedback of a change in ξ_{in} onto the contest aggregate Φ_n , competing groups' violence, and the full vector of equilibrium violence flows is held fixed. Allowing these terms to adjust would require differentiating the full equilibrium.

Table D1: Variation of distance elasticity (data)

Model:	(1)	(2)	(3)	(4)
log distance	−2.65*** (0.05)			
log distance × bin #1		−3.13*** (0.11)	−2.49*** (0.09)	−2.41*** (0.08)
log distance × bin #2		−3.17*** (0.13)	−2.59*** (0.07)	−2.74*** (0.10)
log distance × bin #3		−2.61*** (0.09)	−2.64*** (0.06)	−2.67*** (0.07)
log distance × bin #4		−2.47*** (0.05)	−2.64*** (0.05)	−2.58*** (0.06)
log distance × bin #5		−2.16*** (0.05)	−2.49*** (0.06)	−2.39*** (0.06)

Note: Dependent variable is the share of events in region n originating from region i . Cross-section over 1997-2023. Estimated with PPML with i and n fixed effects. Column (1) is the baseline estimate from the first column of Table 2 in the main text. Column (2) estimates the coefficients associated with the interaction of log distance with 5 bins of proximity (1/distance). Columns (3) and (4) repeat the exercise with bins of predicted v_{in} and p_{in} respectively. Significant at 10%, ** significant at 5%, *** significant at 1%. Standard errors clustered at the in level.

(v_{in}/v_n in our case). We first run the benchmark regression (22) imposing a common elasticity (the same -2.65). We then compute the vector of predicted bilateral violence and group the values under five bins. Those are then interacted with log distance, and results are shown in Column (3). The last method, shown in Column (4) uses the predicted v_{in} in equation (CSF) to recover five bins of predicted p_{in} . Market power should dampen the effect of frictions, as shown in equation (D.28), which means that the *effect of bilateral distance should decrease in absolute value as we go down the rows of bins' interactions*. It is the case in the first exercise of Column (2), while Columns (3) and (4) show more stable estimates of the distance coefficient.

In order to estimate the structural parameter γ while accounting for non-atomistic groups, one would need to integrate the algorithm described above in the overall estimation procedure of our model. This seems doable for the first step following Head and Mayer (2026). Indeed, we can rewrite the bilateral violence equation (D.26) as

$$v_{in}\epsilon_{in}^{\frac{-1}{1-\gamma}} = \exp\left(\text{FE}_i - \frac{\gamma}{1-\gamma} \log \zeta_{in} + \text{FE}_n\right). \quad (\text{D.29})$$

If one start with a guess of $\epsilon_{in} = \epsilon_{in}^0$, a first gravity regression can recover γ^0 , which plugged into equation (CSF) and (OA) provides an updated ϵ_{in}^1 . This is used to recompute the LHS of (D.29). The gravity regression can be re-run to obtain γ^1 and so on, until convergence. However, all further stages of the inversion in Section 5 would also have to be redesigned, and probably require a fully integrated estimation via simulation. This would also be true for counterfactuals. We leave this for future research, but the limited variation in the estimated bilateral friction elasticity across bins of proximity suggests that the atomistic benchmark remains a reasonable approximation for the

empirical patterns.⁴⁵

Back to structural gravity Finally, we note that the case with market power collapses back to the structural gravity when groups are sufficiently small, i.e. when p_{in} is negligible such that $\epsilon_{in} = \gamma, \forall \{i, n\}$.

First, the origin monadic and the dyadic terms in (D.26) simplify to $A_i = \left(\frac{\psi_i}{w_i^F}\right)^{\frac{1}{1-\gamma}}$ and $\xi_{in}^{-\frac{\gamma}{1-\gamma}}$. Second, the destination term writes as

$$\Phi_n \equiv \sum_k (v_{kn} / \xi_{kn})^\gamma = \sum_k \left[A_k \xi_{kn}^{\frac{-1}{1-\gamma}} B_n \right]^\gamma = [(1 - s_n) Y_n]^\gamma \left[\sum_k \left(\frac{\psi_k}{w_k^F \xi_{kn}} \right)^{\frac{\gamma}{1-\gamma}} \right]^{1-\gamma},$$

which implies

$$B_n = \frac{(1 - s_n) Y_n}{\sum_k \left(\frac{\psi_k}{w_k^F \xi_{kn}} \right)^{\frac{\gamma}{1-\gamma}}}.$$

Plunging back the previous terms into (D.26) yields the bilateral flow of violence

$$v_{in} = \left(\frac{\psi_i}{w_i^F} \right)^{\frac{1}{1-\gamma}} \xi_{in}^{-\frac{\gamma}{1-\gamma}} \frac{(1 - s_n) Y_n}{\sum_k \left(\frac{\xi_{kn}^{-1} \psi_k}{w_k^F} \right)^{\frac{\gamma}{1-\gamma}}},$$

which is precisely the one of the baseline model.

D.2 Nature of Violence

The model can be extended to accommodate several forms of violence observed in the raw data (see Section 3.1 in the main text). The baseline formulation is best interpreted as a model of piracy and raiding, relying on three core assumptions: (i) fighters originating from region i optimally allocate their violence across destination regions n (as captured by the allocation problem stated in (6)); (ii) the spoils are equally shared among the fighters (as in (7)); and (iii) the spoils are repatriated to region i to finance local consumption.

In many real-world contexts, however, the organization, motivation, and objectives of violence go beyond pure looting. Violent actors may seek to establish permanent territorial control rather than episodic raiding, seize political power or persecute populations for reasons not obviously related to economic incentives. We discuss how several of these alternative forms of violence can be accommodated within the model, and identify cases that would require substantive theoretical extensions.

Territorial control. A geographic reinterpretation of the model's key variables enables us to capture forms of violence aimed at exerting territorial control. Let us consider s_n as the share of region n 's territory that is fully controlled and secured by local authorities. Assuming spatial homogeneity within regions, this parameter thus corresponds to the share of aggregate income Y_n that is protected from looting. The remaining fraction, $(1 - s_n)$, represents an ungoverned no man's land, characterized by the absence of property rights and state presence (but still generating income).

⁴⁵This pattern reflects the fact that, in our data, the average number of active fighting groups at destination is 9, with a median at 5. We observe monopolies on the appropriation market (i.e. one active group only) for 99 out of 664 destinations. These figures correspond to the sample of Step 4 in Table 1.

In this setting, fighting groups exert violence to control these unsecured territories and extract the associated income $(1 - s_n)Y_n$.

Following standard conventions in the conflict literature (Konrad, 2009), the contest success function p_{in} in equation (5), originally interpreted as the probability of successful appropriation of the spoils, can be reinterpreted as the share of unsecured territory in n that is controlled by fighters from region i . The resulting spoils available to group originating from i in destination n are thus

$$V_{in} = p_{in}(1 - s_n)Y_n.$$

Assuming that these spoils are still repatriated to i , the problem of optimal allocation of fighters remains unchanged. Fighting groups continue to solve the same maximization problem (6), relying on (5) and (9) to allocate fighters. Substituting the resulting allocations l_{in} into the condition (4) yields a gravity equation of violence that is identical to the baseline specification (11). As a consequence, the system of general equilibrium conditions remains characterized by the same fixed-point equation (18), and all endogenous variables of interest are preserved. The reinterpretation of violence as territorial control thus results in a model that is formally equivalent to the baseline raiding model: the core structure, gravity equation, and general equilibrium implications are unchanged.

Political control. Seizing political power is a common motivation for violence, particularly in the case of separatist movements. Through the lens of resource appropriation, effective political control by a fighting group i entails both (de facto) territorial control and (de jure) fiscal/taxation capacity. Extending the model—reinterpreted above in terms of territorial control—to include an *exogenous* tax rate is straightforward. Suppose that a group i can levy a region-specific tax on the portion of region n 's no man's land that it controls, so that the spoils repatriated to i are:

$$V_{in} = \text{tax}_n \times p_{in}(1 - s_n)Y_n.$$

The only difference with the previous extension is that only a fraction tax_n of the income generated in controlled territories is appropriated by group i . The fighter-allocation problem remains unchanged up to this destination-specific rescaling of spoils, so the bilateral gravity logic survives:

$$\text{violence}_{in} \equiv \psi_i l_{in} = \xi_{in}^{-\frac{\gamma}{1-\gamma}} \times \left(\frac{\psi_i}{w_i^F} \right)^{\frac{1}{1-\gamma}} \times \frac{\text{tax}_n(1 - s_n)Y_n}{\sum_{k=1}^N \xi_{kn}^{-\frac{\gamma}{1-\gamma}} \left(\frac{\psi_k}{w_k^F} \right)^{\frac{\gamma}{1-\gamma}}}. \quad (\text{D.30})$$

This expression is identical to the baseline gravity equation (11), except for the appearance of the tax rate tax_n in the numerator of the destination-specific term.

The general-equilibrium accounting block changes because taxation reallocates income between appropriable spoils and secured expenditure. The resulting fixed-point equation has the same structure as (18), but with modified $\beta_{in}(\cdot)$ operators:

$$\beta_{in}^{\text{tax}}(\mathbf{w}) \equiv \text{tax}_n(1 - s_n) \times \frac{w_i^{-\frac{\gamma}{1-\gamma}} \left(\frac{\psi_i}{\xi_{in}} \right)^{\frac{\gamma}{1-\gamma}}}{\sum_{k=1}^N \left(\frac{\psi_k}{\xi_{kn} w_k} \right)^{\frac{\gamma}{1-\gamma}}} + (1 - \text{tax}_n(1 - s_n)) \times \frac{w_i^{1-\sigma} \left(\frac{A_i}{\tau_{in}} \right)^{\sigma-1}}{\sum_{k=1}^N \left(\frac{A_k}{\tau_{kn} w_k} \right)^{\sigma-1}}. \quad (\text{D.31})$$

Endogenizing the tax rate is a challenging task. In a static, one-period framework such as ours, fighting groups controlling territory would always optimally set $\text{tax}_n = 1$ to extract the full surplus. To derive a more realistic and insightful formulation, it is essential to adopt an intertemporal

perspective that explicitly models the trade-off between immediate gains from high taxation and the adverse effects on future income generation due to weakened incentives for production. This trade-off is central in the literature on roving and stationary bandits (Olson, 1993). A proper treatment would require introducing capital accumulation and dynamic incentives, thus necessitating a dynamic extension of the model.

We conjecture that the gravity structure of violence would be robust to such a dynamic extension. However, the implications for the calibration and counterfactual simulations are more ambiguous and would depend on the intertemporal elasticity of production to taxation. Given the increased complexity, we leave this promising avenue for future research.

Grievances. Not all observed violence is *directly* motivated by economic appropriation. In many contexts—especially those involving ethnic, religious, or identity-based conflict—the boundary between appropriation and grievance-driven violence becomes blurred. Within our theoretical framework, bilateral hatred can be modeled as a facilitating factor of appropriation. This formulation captures the empirical observation that political, religious, and cultural grievances are often weaponized or instrumentalized by armed groups to justify or enable acts of appropriation (see footnote 1).

Concretely, we can introduce a bilateral hostility parameter $\text{hate}_{in} > 0$ that attenuates the deterrent role of spatial frictions ξ_{in} in the contest success function. The modified success probability becomes:

$$p_{in} = \frac{(\psi_i l_{in})^\gamma \left(\frac{\text{hate}_{in}}{\xi_{in}} \right)^\gamma}{\sum_{k=1}^N (\psi_k l_{kn})^\gamma \left(\frac{\text{hate}_{kn}}{\xi_{kn}} \right)^\gamma}. \quad (\text{D.32})$$

Therefore, higher hate_{in} lowers effective frictions and increases the probability of fighting success. A convenient implication of this formulation is that the gravity equation of violence, the general equilibrium fixed-point equation (18), and the associated $\beta_{in}(\cdot)$ operators remain structurally identical to the baseline formulation, with ξ_{in} simply replaced by $\xi_{in}/\text{hate}_{in}$ throughout.

Accounting for bilateral hatred is consequential for empirical implementation. Specifically, the estimated gravity equation of violence (22) becomes:

$$\mathbb{E} \left(\frac{\text{violence}_{in}}{\text{violence}_n} \right) = \exp \left[\frac{\gamma}{1-\gamma} \log \text{hate}_{in} - \frac{\gamma}{1-\gamma} \log \xi_{in} + \text{FE}_i^o + \text{FE}_n^d \right], \quad (\text{D.33})$$

where the bilateral term hate_{in} enters as a positive predictor of bilateral violence. The former term can be proxied using ethnolinguistic distance, historical conflicts, or religious dissimilarity, drawing on data sources such as Desmet et al. (2020) and Desmet et al. (2023). Assuming that geography (i.e. distance, administrative borders) affect only ξ_{in} , while ethnolinguistic distance or religious dissimilarity only affect hate_{in} , estimating this augmented gravity specification—possibly in conjunction with counterfactual exercises—could offer a quantitative decomposition of violence into grievance-based and economically motivated components.

D.3 Endogenous Defense Forces

In the baseline model, local state capacity s_n is taken as exogenous. We now extend the model by endogenizing s_n through a conscription game of local military buildup.⁴⁶

⁴⁶In the counterfactual analysis of Section 6.1, s_n is assumed to depend on a baseline state capacity $\bar{s}_n$ and a security spillover increasing with local income Y_n . The present extension is compatible with this framework by treating $\bar{s}_n$ as the endogenous outcome of the conscription game.

Specifically, we assume that local authorities in region n allocate a share of the population to a local defense force of size $0 \leq \text{DEF}_n \leq \bar{L}_n$. The state capacity s_n , now defined as the share of income that is secured from appropriation, increases with the size of the defense force relative to the total population:

$$s_n = \left(\frac{\text{DEF}_n}{\bar{L}_n} \right)^{\mu_m}, \quad (\text{D.34})$$

with $\mu_m > 0$. Defense buildup is costly. We assume it is achieved via compulsory conscription: before all other economic decisions are made, each individual—regardless of occupational choice between production and appropriation—is required to devote a fraction $\text{mil}_n \in [0, 1]$ of their time endowment to military service, without financial compensation.

Implications for General Equilibrium Under conscription, the effective labor supply available for production and appropriation is reduced. The free occupational choice condition (equation 13) is modified as:

$$(1 - \text{mil}_n)w_n^P = (1 - \text{mil}_n)w_n^F = (1 - \text{mil}_n)w_n, \quad (\text{D.35})$$

implying that the equalization of producer and fighter wages still holds, i.e., $w_n^P = w_n^F = w_n$. The labor market clearing condition becomes:

$$(1 - \text{mil}_n)\bar{L}_n = L_n + l_n,$$

since the residual fraction of the workforce is compulsory allocated to the defense force, i.e. $\text{mil}_n \times \bar{L}_n = \text{DEF}_n$. Substituting into equation (D.34) yields:

$$s_n = \text{mil}_n^{\mu_m}. \quad (\text{D.36})$$

From the labor market clearing condition we get the aggregate income :

$$Y_n = w_n L_n + w_n l_n = w_n (1 - \text{mil}_n) \bar{L}_n, \quad (\text{D.37})$$

Importantly, all other structural relationships in the model remain unchanged. In particular, the gravity equation of violence (11) is unaffected by this extension. Similarly, trade and appropriation revenues are characterized by relations isomorphic to (16) and (17), with state capacity and aggregate income being given by (D.36) and (D.37).

Summing trade and appropriation revenues yields a GE fixed-point equation analogous to equation (18) which now incorporates the conscription-adjusted labor supply from equation (D.37):

$$w_i (1 - \text{mil}_i) \bar{L}_i = \sum_{n=1}^N \beta_{in}^{\text{cons.}}(\mathbf{w}) w_n (1 - \text{mil}_n) \bar{L}_n, \quad (\text{D.38})$$

where the wage operators $\beta_{in}^{\text{cons.}}(\cdot)$ use the conscription-adjusted state capacities from equation (D.36)

$$\beta_{in}^{\text{cons.}}(\mathbf{w}) \equiv (1 - \text{mil}_n^{\mu_m}) \times \frac{w_i^{-\frac{\gamma}{1-\gamma}} \left(\frac{\psi_i}{\xi_{in}} \right)^{\frac{\gamma}{1-\gamma}}}{\sum_{k=1}^N \left(\frac{\psi_k}{\xi_{kn} w_k} \right)^{\frac{\gamma}{1-\gamma}}} + \text{mil}_n^{\mu_m} \times \frac{w_i^{1-\sigma} \left(\frac{A_i}{\tau_{in}} \right)^{\sigma-1}}{\sum_{k=1}^N \left(\frac{A_k}{\tau_{kn} w_k} \right)^{\sigma-1}}. \quad (\text{D.39})$$

Given a vector of conscription rates $\mathbf{mil}$, equation (D.38) yields the corresponding equilibrium vector of relative wages $\mathbf{w}(\mathbf{mil})$, determined up to a scale normalization as in the baseline model.

The Conscription Game In a second step, we allow each region to choose its conscription rate mil_n strategically to maximize real income. The welfare of region n is defined as secured income discounted by the local CES price index: $\omega_n = \frac{s_n(1-\text{mil}_n)w_n}{P_n}$. Substituting equation (D.36) into real income yields the local authority's best response function:

$$BR_n(\mathbf{mil}_{-n}) = \arg \max_{\text{mil}_n \in [0,1]} \text{mil}_n^{\mu_m} (1 - \text{mil}_n) \frac{w_n(\mathbf{mil})}{P_n(\mathbf{mil})}, \quad (\text{D.40})$$

where $P_n(\mathbf{mil}) = \left(\sum_{k=1}^N (\tau_{kn} w_k(\mathbf{mil}) / A_k)^{1-\sigma} \right)^{\frac{1}{1-\sigma}}$, and $\mathbf{w}(\mathbf{mil})$ solves equation (D.38). This expression illustrates the trade-off faced by local authorities: higher conscription improves security ($\text{mil}_n^{\mu_m}$) but reduces effective lifetime labor ($1 - \text{mil}_n$), thereby lowering income. Moreover, all regions are linked through the general equilibrium wage vector $\mathbf{w}(\mathbf{mil})$. The Nash equilibrium of the conscription game is defined as the fixed point of best responses:

$$\text{mil}_n^* = BR_n(\mathbf{mil}_{-n}^*), \quad \text{for all } n. \quad (\text{D.41})$$

Solution Method and Implications The $2N$ -equation system (D.38) and (D.41), with $2N$ unknowns $\mathbf{w}$ and $\mathbf{mil}$, jointly characterizes the equilibrium of the conscription game. Its numerical resolution proceeds via a two-step nested algorithm: an inner loop solves the fixed-point (D.38) for wages $\mathbf{w}$ given a vector of conscription rates $\mathbf{mil}$, while an outer loop iterates on $\mathbf{mil}$ to compute the Nash equilibrium in (D.41).

A formal analysis of existence and uniqueness of this equilibrium is beyond the scope of this paper and is left for future work. However, the key insight is that endogenizing state capacity through local defense forces does not alter the gravity equation of violence. This robustness strengthens the empirical relevance and flexibility of our framework while offering a promising avenue to connect local security decisions to the spatial pattern of violence.

D.4 Alternative microfoundations of the appropriation game

In the baseline appropriation game, both producers' and fighters' revenues are subject to looting. This microfoundation is appealing because it allows us to characterize the general equilibrium through a unique fixed-point equation, given by (18). Consider instead an alternative formulation in which only producers are looted, while fighters' income is fully secured, the rest of the game being unchanged. This modification substantially simplifies the resolution of the appropriation game: fighters' income is immediately and fully secured, and the game effectively ends after one round. The destination-specific spoils term is therefore no longer the unsecured share of total gross income. Equation (9) is replaced by

$$V_n = (1 - s_n)w_n^P L_n.$$

Thus, the gravity structure of the violence equation is preserved, but the destination-size term changes: violence is now attracted by unsecured producer income rather than by unsecured total income. This alternative breaks the appealing symmetry of the equilibrium equations. We show below that the resulting system of equations characterizing the general equilibrium can no longer be reduced to a unique fixed-point "master" equation. As a consequence, proving existence and uniqueness of equilibrium becomes more challenging, although numerical resolution of the general equilibrium remains feasible. Apart from this analytical difference, the qualitative economic mechanisms of the model are preserved.

Through the equilibrium of the labor market, if only producers are looted, wages have to be such that workers are indifferent between production and fighting. Therefore the secured share of producers' income is equal to the (fully secured) income of fighters:

$$s_i \times w_i^P = w_i^F = w_i,$$

where w_i therefore now denotes fighters' wage in equilibrium. In turn, aggregate expenditures are given by

$$E_n = s_n w_n^P L_n + w_n l_n = s_n \frac{w_n}{s_n} L_n + w_n l_n = w_n \bar{L}_n$$

And the system of equations (i.e. trade and appropriation revenues) that characterizes the GE is given by

$$\bar{L}_i = L_i + l_i \quad (\text{D.42})$$

$$\frac{w_i}{s_i} L_i = \sum_n \frac{\tau_{in}^{-(\sigma-1)} \left(\frac{s_i A_i}{w_i} \right)^{\sigma-1}}{\sum_k \tau_{kn}^{-(\sigma-1)} \left(\frac{s_k A_k}{w_k} \right)^{\sigma-1}} w_n \bar{L}_n \quad (\text{D.43})$$

$$w_i l_i = \sum_n \frac{\xi_{in}^{-\frac{\gamma}{1-\gamma}} \left(\frac{\psi_i}{w_i} \right)^{\frac{\gamma}{1-\gamma}}}{\sum_k \xi_{kn}^{-\frac{\gamma}{1-\gamma}} \left(\frac{\psi_k}{w_k} \right)^{\frac{\gamma}{1-\gamma}}} \frac{1 - s_n}{s_n} w_n L_n \quad (\text{D.44})$$

The $3N$ -system of equations (D.43)-(D.44)-(D.42), jointly solving for the $3N$ unknowns $\{L_i, l_i, w_i\}_{i=1}^N$, is not reducible to a unique fixed-point "master" equation anymore. This said, numerical simulations are still feasible and the counterfactual analysis could presumably be performed under this alternative model.

D.5 Trade and violence

What is the role of trade in the model, and how does it interact with violence? From a theoretical perspective, in the absence of cross-regional trade, there are still incentives for looting locally generated income. To understand how this special case—where production and consumption are entirely local (backyard farming)—affects equilibrium relations, we must set all bilateral trade frictions to infinity: $\tau_{in}^{1-\sigma} = 0$ for $i \neq n$ and 1 otherwise. Visual inspection of the gravity equation of violence (11) confirms that it remains unchanged under this parametric assumption. However the GE fixed-point equation (18) simplifies into

$$(1 - s_i) w_i \bar{L}_i = \sum_{n=1}^N (1 - s_n) \times \frac{\left(\frac{\psi_i}{\xi_{in} w_i} \right)^{\frac{\gamma}{1-\gamma}}}{\sum_{k=1}^N \left(\frac{\psi_k}{\xi_{kn} w_k} \right)^{\frac{\gamma}{1-\gamma}}} w_n \bar{L}_n, \quad (\text{D.45})$$

as inter-regional trade revenues collapse to zero.

To assess quantitatively how the existence of trade affects violence, we simulate a counterfactual scenario under a no-trade situation. This exercise helps isolate how the trade margin affects the spatial distribution of violence and its associated welfare consequences.⁴⁷ We run a counterfactual simulation where trade costs between regions are multiplied by a factor of three, which brings trade

⁴⁷Note that a related but different exercise is already conducted in Scenario 1 of Table OA.D25, where we freeze the endogenous reallocation of fighting labor in a trade model, which highlights how the violence margin alters the conclusions drawn from a standard trade model simulated in peacetime.

Table D2: Impact of closing trade

Sample	Baseline avg.		Avg. % Change in					
	violence _n	1 - π_{nn}	violence _n	1 - s_n	w_n	SPV _n	TFP (A_n)	Welfare _n
All	71.97	0.85	17.87	24.25	-18.68	15.68	-0.55	-35.47
No Violence	0.00	0.89	NA	NA	-20.72	14.02	0.00	-40.09
Q1	1.36	0.91	21.00	30.53	-20.66	17.17	-0.01	-40.36
Q2	7.61	0.84	17.85	24.48	-17.74	15.61	-0.06	-34.15
Q3	32.91	0.84	17.33	22.20	-16.72	15.57	-0.26	-32.29
Q4	339.68	0.76	15.26	19.74	-17.03	16.44	-2.61	-29.25

Note: Numbers represent average percent changes. The shock is a 200% increase in the baseline inter-regional trade frictions (τ_{in} , $\forall i \neq n$, in equation 1). Each row reports results for a different sample: all regions, regions receiving no violence, and quartiles of regions receiving any positive violence in the baseline. For reported outcomes: violence_n is the total violence in region n , $1 - \pi_{nn}$ is the regional openness ratio, $1 - s_n$ captures the lack of state capacity, w_n is nominal wage, SPV_n is the Supply Potential of Violence as defined in equation (25), TFP (A_n) is the productivity and Welfare_n refers to the secured per-capita real wage as defined in equation (41).

close to 0. Results contained in Table D2 indicate that, over the whole sample⁴⁸, violence would increase by an average of 17.87% in the absence of trade (first row). The mechanisms at work are embodied in equation (25): First, the absence of trade opportunities reduces the nominal income of workers (w_n) in all regions. This reduces the rapacity channel, which means that it becomes less interesting for fighters outside n to come and loot region n . A countervailing force is the security spillover channel which links directly and negatively the level of security to real income. The pie shrinks, but a larger share of it is up for appropriation ($1 - s_n$ rises). Furthermore, in terms of labor allocation, farming becomes less interesting with respect to fighting in all regions. This raises the number of fighters in all origins of violence, which is captured by the increased Supply Potential of Violence of destination n (SPV_n term in 25). The pacifying force operating through the reduced rapacity effect is dominated by the other two in our case. Therefore, the average level of violence in n rises and, as the result of the destruction spillover, TFP in n falls.

The table also shows substantial spatial heterogeneity across regions and in the welfare consequences of shutting down the trade channel. The last four rows divide regions into quartiles of violence in the baseline scenario (reported in the second column). The third column reports the initial openness ratio of regions across those quartiles and reveals that the regions less affected by violence in the baseline are also more open to trade. As is standard in this type of trade models, the real income drop of closing trade in the counterfactual is most pronounced for the places that were initially trading the most. This drop in the real income (last column) here has a direct effect of reducing state capacity and increasing markedly $1 - s_n$. This effect largely dominates in the Q1 row but is substantially dampened as the initial openness falls: hence, the average increase in violence ranges from 21% (Q1) to 15% (Q4). Trade appears to be a violence-mitigating force in our context, especially for the places that have initially low levels of attacks.

D.6 Alternative structure of the labor market

The baseline model assumes that labor is freely mobile between production and appropriation. This occupational choice implies an equalization of earnings between fighters and producers in equilibrium, formally expressed as $w_i^F = w_i^P = w_i$ in equation (13). While this assumption brings

⁴⁸We take here the same sample as in Table OA.D25 in order to make results comparable and also limit computing time.

analytical convenience and tractability, its empirical relevance is debatable—particularly in the context of many violent conflicts in Sub-Saharan Africa, where joining armed groups often reflects coercion rather than free choice. In addition, assuming wage equalization ignores mortality risk premium or the presence of social stigma associated with fighting that both call for compensating fighters' with a higher income.

To account for such asymmetries, the model can be extended to include *compensating differentials* between fighting and producing. Specifically, we introduce two wedges: $\omega^P < 1$ discounts fighter payoffs to reflect mortality risk, and $\omega^F < 1$ discounts the producer outside option under coercive pressure. The occupational-choice condition becomes:

$$\omega^P w_i^F = \omega^F w_i^P,$$

which breaks the strict wage equalization of the baseline model while preserving the tractability of equilibrium characterization. These wedges can be interpreted as reduced-form representations of recruitment frictions faced by armed groups (coercion costs, monitoring constraints, social incentives, mortality risk), which generate a wedge between the marginal value of labor in production and in appropriation. In equilibrium, such frictions generate a wedge between the effective marginal value of labor in production and in appropriation. Let w_i denote the equilibrium wage of fighters. The equilibrium wage for producers can then be written as:

$$w_i^P = \frac{\omega^P}{\omega^F} w_i. \quad (\text{D.46})$$

We assume that the ratio ω^P / ω^F is common across regions. This is what allows the common wedge to cancel out of trade shares. If this ratio were region-specific, trade shares would depend on the effective producer wage $(\omega_i^P / \omega_i^F) w_i$ rather than on w_i alone.

This adjustment modifies the aggregate income and expenditure identity, originally defined in equation (14). The new expression for income generated in region n (and thus expenditure) becomes:

$$E_n = s_n Y_n = s_n \left(\frac{\omega^P}{\omega^F} w_n L_n + w_n l_n \right), \quad (\text{D.47})$$

where L_n and l_n denote the number of producers and fighters in region n , respectively. The gravity structure of equation (11) is preserved, but the destination income term now reflects the wedge between producer and fighter earnings.

However, the general equilibrium (GE) system is modified. The expression for trade shares becomes:

$$\pi_{in} = \frac{(\tau_{in} w_i^P / A_i)^{1-\sigma}}{\sum_k (\tau_{kn} w_k^P / A_k)^{1-\sigma}} = \frac{(\tau_{in} w_i / A_i)^{1-\sigma}}{\sum_k (\tau_{kn} w_k / A_k)^{1-\sigma}},$$

where we used equation (D.46) and the common-ratio assumption to express trade shares in terms of w_i . Goods-market clearing is $w_i^P L_i = \sum_n \pi_{in} E_n$. Substituting $w_i^P = (\omega^P / \omega^F) w_i$ and equation (D.47), then dividing both sides by the common ratio ω^P / ω^F , yields:

$$w_i L_i = \sum_n \frac{\tau_{in}^{-(\sigma-1)} \left(\frac{A_i}{w_i} \right)^{\sigma-1}}{\sum_k \tau_{kn}^{-(\sigma-1)} \left(\frac{A_k}{w_k} \right)^{\sigma-1}} s_n \left(w_n L_n + \frac{\omega^F}{\omega^P} w_n l_n \right). \quad (\text{D.48})$$

Likewise, combining (11) with (D.47), and inserting into (12), we obtain the market clearing condi-

tion on the appropriation market:

$$w_i l_i = \sum_n \frac{\xi_{in}^{-\frac{\gamma}{1-\gamma}} \left(\frac{\psi_i}{w_i} \right)^{\frac{\gamma}{1-\gamma}}}{\sum_k \xi_{kn}^{-\frac{\gamma}{1-\gamma}} \left(\frac{\psi_k}{w_k} \right)^{\frac{\gamma}{1-\gamma}}} (1 - s_n) \left(w_n l_n + \frac{\omega^P}{\omega^F} w_n L_n \right). \quad (\text{D.49})$$

Finally, the labor market clearing condition is:

$$\bar{L}_i = L_i + l_i. \quad (\text{D.50})$$

The general equilibrium is characterized by the system of $3N$ equations (D.48), (D.49), and (D.50), jointly solving for the $3N$ unknowns $\{L_i, l_i, w_i\}_{i=1}^N$. These relations highlight how coercion (or mortality risk) affects the spatial distribution of violence. To see this, consider an equilibrium and an exogenous increase in $\frac{\omega^P}{\omega^F}$, which can be interpreted as stronger coercion into fighting. A visual inspection of (D.48) and (D.49) shows that such a parameter shift affects the equilibrium through two channels.

First, from the perspective of regions i that host fighting groups, stronger coercion is akin to an increase in the relative wage of producers in all lootable destinations n . As a result, the value of spoils and potential fighting revenues increases in nominal terms, raising the demand for fighters l_i . Violence therefore intensifies. This direct channel of forced recruitment is embedded into equation (D.49).

Second, stronger coercion makes fighters poorer in relative terms. Consequently, from the perspective of exporting region i , market size decreases in all destinations n that host fighters. Their trade revenues decline, exerting downward pressure on wages w_i . This income effect operates through the general equilibrium adjustment in equation (D.48) and feeds back into fighting revenues in equation (D.49) by reducing the value of spoils in all lootable destinations n . As a result, the demand for fighters l_i and the level of violence decrease.

Whether the direct effect of forced recruitment dominates the income effect is theoretically ambiguous. We leave a simulation-based exploration of the quantitative impact of coercion on equilibrium violence, income, and welfare across regions for future work.

D.7 Endogenous Entry

In the baseline framework, entry into the appropriation market is exogenous and governed by the fighting capacity parameter ψ_i . If $\psi_i > 0$, region i hosts a fighting group; if $\psi_i = 0$, it does not. While analytically convenient, this assumption imposes a significant limitation: counterfactual simulations can only alter violence at the intensive margin. Flows of violence that are zero in the factual equilibrium remain zero in the counterfactual; only positive flows can be adjusted upwards or downwards.⁴⁹ Consequently, the model cannot account for the endogenous emergence of new hotspots of violence or the complete pacification of previously violent regions.

We relax this assumption by modeling endogenous entry into the appropriation market. We assume that organizing a fighting group from region i requires paying a fixed cost o_i , which can be interpreted as the labor equivalent of setting up a rear base, recruiting fighters, and allocating them across contested destinations.⁵⁰ This fixed cost is paid in terms of labor: a group must hire o_i “of-

⁴⁹ The gravity of violence equation (11) disciplines observed zero flows of violence in three ways: (i) if origin region i generates no violence, the inversion procedure sets $\psi_i = 0$; (ii) if destination region n experiences no violence, the procedure assigns $s_n = 1$; (iii) if origin region i produces violence but not toward all destinations, the model generates strictly positive flows toward all n (since $\xi_{in} < \infty$ in the empirical specification 23).

⁵⁰ The model could be enriched with bilateral fixed costs o_{in} for opening operations in each destination n , which would discipline the extensive margin of bilateral flows from partially violent origin regions (case (iii) in footnote 49).

ficers" to overhead tasks, assumed not to engage in looting. Officers, like all workers, earn the equilibrium wage w_i . We further assume that both the fixed cost o_i and the prospective fighting capacity ψ_i (conditional on entry) are exogenous and region-specific. We define an entry indicator variable $\mathbb{1}_{\mathcal{E}_i}$ equal to one if there is entry in region i , and zero otherwise. Entry occurs if expected looting revenues R_i exceed the fixed cost $o_i w_i$, that is:

$$\mathbb{1}_{\mathcal{E}_i} = 1 \quad \text{if and only if} \quad R_i - o_i w_i > 0. \quad (\text{D.51})$$

If there is no entry ($\mathbb{1}_{\mathcal{E}_i} = 0$), all labor goes into production and $l_i = 0$. If entry occurs ($\mathbb{1}_{\mathcal{E}_i} = 1$), the free occupational choice condition ensures income equalization between producers and fighters:

$$w_i = \frac{R_i - o_i w_i}{l_i}. \quad (\text{D.52})$$

Hence the gross average cost per active fighter is

$$c_i^F \equiv \frac{R_i}{l_i} = w_i \left(1 + \frac{o_i}{l_i} \right). \quad (\text{D.53})$$

This term, rather than the wage w_i alone, is the relevant origin-specific cost term in the gravity equation of violence (11). This follows from the derivation of the equation, which depends on gross looting revenues per active fighter, R_i/l_i (see Appendix B, especially equation B.20), while officers are paid even though they do not directly produce violence.

The labor market clearing condition becomes:

$$\bar{L}_i = L_i + \mathbb{1}_{\mathcal{E}_i}(l_i + o_i), \quad (\text{D.54})$$

and total income is:

$$Y_i = w_i L_i + \mathbb{1}_{\mathcal{E}_i}(w_i l_i + w_i o_i) = w_i \bar{L}_i, \quad (\text{D.55})$$

which matches the baseline expression. Consequently, trade flows and revenues are still determined by relation (16). However, appropriation revenues now depend on both endogenous entry in i , endogenous pool of active groups competing in each destination n , and the gross average cost of active fighters:

$$\mathbb{1}_{\mathcal{E}_i}(w_i l_i + w_i o_i) = \sum_{n=1}^N \frac{\mathbb{1}_{\mathcal{E}_i} \psi_i^{\frac{\gamma}{1-\gamma}} (\xi_{in} w_i (1 + o_i/l_i))^{-\frac{\gamma}{1-\gamma}}}{\sum_{k=1}^N \mathbb{1}_{\mathcal{E}_k} \psi_k^{\frac{\gamma}{1-\gamma}} (\xi_{kn} w_k (1 + o_k/l_k))^{-\frac{\gamma}{1-\gamma}}} (1 - s_n) w_n \bar{L}_n. \quad (\text{D.56})$$

We slightly abuse notation by writing $c_i^F = w_i(1 + o_i/l_i)$ inside the active-set sum; it is understood to be defined only for active entrants, while non-entrants have zero weight in the appropriation block. Combining (16) and (D.56) yields a fixed-point condition similar to, but no longer exactly isomorphic to, the baseline:

$$w_i \bar{L}_i = \sum_{n=1}^N \beta_{in}^{\text{entry}}(\mathbf{w}, \mathbf{c}^F) w_n \bar{L}_n, \quad (\text{D.57})$$

where the β operators now account for endogenous entry and the gross average cost of active fighters:

$$\beta_{in}^{\text{entry}}(\mathbf{w}, \mathbf{c}^F) \equiv (1 - s_n) \times \frac{\mathbb{1}_{\mathcal{E}_i} \psi_i^{\frac{\gamma}{1-\gamma}} (\xi_{in} w_i (1 + o_i/l_i))^{-\frac{\gamma}{1-\gamma}}}{\sum_{k=1}^N \mathbb{1}_{\mathcal{E}_k} \psi_k^{\frac{\gamma}{1-\gamma}} (\xi_{kn} w_k (1 + o_k/l_k))^{-\frac{\gamma}{1-\gamma}}} + s_n \times \frac{\left(\frac{A_i}{\tau_{in} w_i} \right)^{\sigma-1}}{\sum_{k=1}^N \left(\frac{A_k}{\tau_{kn} w_k} \right)^{\sigma-1}}. \quad (\text{D.58})$$

The entry condition (D.51) can be rewritten as:

$$\mathbb{1}_{\mathcal{E}_i} = \mathbb{I} \left(\sum_{n=1}^N \frac{\psi_i^{\frac{\gamma}{1-\gamma}} (\xi_{in} w_i (1 + o_i/l_i))^{-\frac{\gamma}{1-\gamma}}}{\sum_{k=1}^N \mathbb{1}_{\mathcal{E}_k} \psi_k^{\frac{\gamma}{1-\gamma}} (\xi_{kn} w_k (1 + o_k/l_k))^{-\frac{\gamma}{1-\gamma}}} (1 - s_n) w_n \bar{L}_n - o_i w_i > 0 \right), \quad (\text{D.59})$$

where $\mathbb{I}(\cdot)$ is the indicator function and l_i is the prospective number of fighters in case of entry. This condition should be read as an atomistic-entry approximation, holding fixed wages as well as the entry and fighting decisions of other groups. The system composed of (D.56), (D.57), and (D.59) characterizes the general equilibrium with endogenous entry. Conditional on an active set $\mathcal{E}$, the unknowns are wages $\mathbf{w}$ and, for entering regions, active fighters $\{l_i\}$ (non-entering regions have $l_i = 0$). The equilibrium can be solved numerically using a nested algorithm: (i) an inner loop solves for $\mathbf{w}$, and $\mathbf{l}$ conditional on a vector $\mathcal{E}$; (ii) an outer loop updates the entry decisions via (D.59) until convergence. A formal analysis of existence and uniqueness of this equilibrium is left for future work. In particular, it is likely that the entry order needs to be specified in order to avoid multiplicity of equilibria (Atkeson and Burstein, 2008; Eaton et al., 2013).

This extension allows the model to generate violence at the extensive margin and thereby improves its ability to capture the endogenous spatial emergence and disappearance of violence.

THE GRAVITY OF VIOLENCE

– ONLINE APPENDIX –

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OA.A Supplementary material for section 2

OA.A.1 Proof of the general equilibrium

The proof of the existence and uniqueness of the equilibrium vector of wages as a fixed-point of equation (18) closely follows Allen (2019).

We start by defining the following function $Z_i(\mathbf{w})$ for $i \in N$ as:

$$Z_i(\mathbf{w}) \equiv \frac{1}{w_i} \left(\sum_n \beta_{in}(\mathbf{w}) w_n \bar{L}_n - w_i \bar{L}_i \right), \quad (\text{OA.A.1})$$

where

$$\beta_{in}(\mathbf{w}) \equiv (1 - s_n) \times \frac{w_i^{-\frac{\gamma}{1-\gamma}} \left(\frac{\psi_i}{\xi_{in}} \right)^{\frac{\gamma}{1-\gamma}}}{\sum_k \left(\frac{\psi_k}{\xi_{kn} w_k} \right)^{\frac{\gamma}{1-\gamma}}} + s_n \times \frac{w_i^{1-\sigma} \left(\frac{A_i}{\tau_{in}} \right)^{\sigma-1}}{\sum_k \left(\frac{A_k}{\tau_{kn} w_k} \right)^{\sigma-1}}.$$

If $Z_i(\mathbf{w}) = 0$ for all $i \in N$, then $\mathbf{w}$ represents a price equilibrium. Similarly, when $Z_i(\mathbf{w}) > 0$, it indicates that country i is selling more goods than it is earning. In this context, we can interpret $Z_i(\cdot)$ as the excess demand function for goods originating from country $i \in N$.

For the remaining of the proof, it will turn out to be useful to write $Z_i(\cdot)$ as:

$$Z_i(\mathbf{w}) = Z_i^F(\mathbf{w}) + Z_i^P(\mathbf{w}), \quad (\text{OA.A.2})$$

where

$$Z_i^F(\mathbf{w}) = \frac{1}{w_i} \left[\sum_n \frac{w_i^{-\frac{\gamma}{1-\gamma}} \left(\frac{\psi_i}{\xi_{in}} \right)^{\frac{\gamma}{1-\gamma}}}{\sum_k \left(\frac{\psi_k}{\xi_{kn} w_k} \right)^{\frac{\gamma}{1-\gamma}}} (1 - s_n) w_n \bar{L}_n - (1 - s_i) w_i \bar{L}_i \right] \quad (\text{OA.A.3})$$

$$Z_i^P(\mathbf{w}) = \frac{1}{w_i} \left[\sum_n \frac{\left(\frac{A_i}{\tau_{in} w_i} \right)^{\sigma-1}}{\sum_k \left(\frac{A_k}{\tau_{kn} w_k} \right)^{\sigma-1}} s_n w_n \bar{L}_n - s_i w_i \bar{L}_i \right]. \quad (\text{OA.A.4})$$

Indeed:

$$\begin{aligned} w_i Z_i(\mathbf{w}) &= \sum_n \beta_{in}(\mathbf{w}) w_n \bar{L}_n - w_i \bar{L}_i \\ &= \sum_n \beta_{in}(\mathbf{w}) w_n \bar{L}_n - w_i \bar{L}_i + s_i w_i \bar{L}_i - s_i w_i \bar{L}_i \\ &= \sum_n \beta_{in}(\mathbf{w}) w_n \bar{L}_n - (1 - s_i) w_i \bar{L}_i - s_i w_i \bar{L}_i \\ &= \sum_n (1 - s_n) \times \frac{w_i^{-\frac{\gamma}{1-\gamma}} \left(\frac{\psi_i}{\xi_{in}} \right)^{\frac{\gamma}{1-\gamma}}}{\sum_k \left(\frac{\psi_k}{\xi_{kn} w_k} \right)^{\frac{\gamma}{1-\gamma}}} w_n \bar{L}_n - (1 - s_i) w_i \bar{L}_i + \sum_n s_n \times \frac{w_i^{1-\sigma} \left(\frac{A_i}{\tau_{in}} \right)^{\sigma-1}}{\sum_k \left(\frac{A_k}{\tau_{kn} w_k} \right)^{\sigma-1}} w_n \bar{L}_n - s_i w_i \bar{L}_i. \end{aligned} \quad (\text{OA.A.5})$$

Hence:

$$\begin{aligned} Z_i(\mathbf{w}) &= \frac{1}{w_i} \left[\sum_n (1 - s_n) \times \frac{w_i^{-\frac{\gamma}{1-\gamma}} \left(\frac{\psi_i}{\xi_{in}} \right)^{\frac{\gamma}{1-\gamma}}}{\sum_k \left(\frac{\psi_k}{\xi_{kn} w_k} \right)^{\frac{\gamma}{1-\gamma}}} w_n \bar{L}_n - (1 - s_i) w_i \bar{L}_i \right] + \frac{1}{w_i} \left[\sum_n s_n \times \frac{w_i^{1-\sigma} \left(\frac{A_i}{\tau_{in}} \right)^{\sigma-1}}{\sum_k \left(\frac{A_k}{\tau_{kn} w_k} \right)^{\sigma-1}} w_n \bar{L}_n - s_i w_i \bar{L}_i \right] \\ &= Z_i^F(\mathbf{w}) + Z_i^P(\mathbf{w}). \end{aligned} \quad (\text{OA.A.6})$$

Two accessibility conditions are maintained in the boundary and uniqueness parts of the proof. First, if the wage of an origin approaches zero, that origin must retain access to at least one destination that has positive secured income in the trade block or positive appropriable income in the fighting block. Second, for every pair $i \neq j$, there must exist at least one destination n such that either both origins have strictly positive trade shares in n , or both have strictly positive fighting shares in an appropriable destination n . These conditions rule out disconnected components in the economic and fighting networks.

Existence

$Z_i(\mathbf{w})$ has the following properties:

(i) For all $\mathbf{w} \gg 0$ (ie, for all $\mathbf{w}$ such that $w_i > 0$ for all $i \in N$) and for all $i \in N$, $Z_i(\cdot)$ is continuous.

For $\mathbf{w} \gg 0$ and each $i \in N$, $Z_i(\mathbf{w})$ is obtained from finite sums, products, and quotients of continuous functions of $\mathbf{w}$ with strictly positive denominators. Hence $Z_i(\mathbf{w})$ is continuous on $\{\mathbf{w} \gg 0\}$.

(ii) For all $i \in N$, $Z_i(\cdot)$ is homogeneous of degree zero.

Indeed, for any $\lambda > 0$:

$$\begin{aligned}
Z_i(\lambda \mathbf{w}) &= \frac{1}{\lambda w_i} \left(\sum_n \frac{\left(\frac{\psi_i}{\xi_{in} \lambda w_i} \right)^{\frac{\gamma}{1-\gamma}}}{\sum_k \left(\frac{\psi_k}{\xi_{kn} \lambda w_k} \right)^{\frac{\gamma}{1-\gamma}}} (1-s_n) \lambda w_n \bar{L}_n - (1-s_i) \lambda w_i \bar{L}_i + \sum_n \frac{\left(\frac{A_i}{\tau_{in} \lambda w_i} \right)^{\sigma-1}}{\sum_k \left(\frac{A_k}{\tau_{kn} \lambda w_k} \right)^{\sigma-1}} s_n \lambda w_n \bar{L}_n \right. \\
&\quad \left. - s_i \lambda w_i \bar{L}_i \right) \\
&= \frac{1}{w_i} \left(\sum_n \frac{\lambda^{\frac{-\gamma}{1-\gamma}} \left(\frac{\psi_i}{\xi_{in} w_i} \right)^{\frac{\gamma}{1-\gamma}}}{\lambda^{\frac{-\gamma}{1-\gamma}} \sum_k \left(\frac{\psi_k}{\xi_{kn} w_k} \right)^{\frac{\gamma}{1-\gamma}}} \frac{1}{\lambda} (1-s_n) \lambda w_n \bar{L}_n - \frac{1}{\lambda} (1-s_i) \lambda w_i \bar{L}_i \right. \\
&\quad \left. + \sum_n \frac{\lambda^{1-\sigma} \left(\frac{A_i}{\tau_{in} w_i} \right)^{\sigma-1}}{\sum_k \lambda^{1-\sigma} \left(\frac{A_k}{\tau_{kn} w_k} \right)^{\sigma-1}} \frac{1}{\lambda} s_n \lambda w_n \bar{L}_n - \frac{1}{\lambda} s_i \lambda w_i \bar{L}_i \right) \\
&= Z_i(\mathbf{w}).
\end{aligned} \tag{OA.A.7}$$

(iii) For all $\mathbf{w} \gg 0$, we have:

$$\sum_{i \in N} w_i Z_i(\mathbf{w}) = 0.$$

Indeed, this property follows directly from the adding-up property of the shares $\beta_{in}(\mathbf{w})$, and does not require imposing market clearing. For each destination n ,

$$\begin{aligned}
\sum_i \beta_{in}(\mathbf{w}) &= (1-s_n) \sum_i \frac{w_i^{-\frac{\gamma}{1-\gamma}} \left(\frac{\psi_i}{\xi_{in}} \right)^{\frac{\gamma}{1-\gamma}}}{\sum_k \left(\frac{\psi_k}{\xi_{kn} w_k} \right)^{\frac{\gamma}{1-\gamma}}} + s_n \sum_i \frac{w_i^{1-\sigma} \left(\frac{A_i}{\tau_{in}} \right)^{\sigma-1}}{\sum_k \left(\frac{A_k}{\tau_{kn} w_k} \right)^{\sigma-1}} \\
&= (1-s_n) + s_n = 1.
\end{aligned} \tag{OA.A.8}$$

Therefore,

$$\begin{aligned}
\sum_i w_i Z_i(\mathbf{w}) &= \sum_i \left(\sum_n \beta_{in}(\mathbf{w}) w_n \bar{L}_n - w_i \bar{L}_i \right) \\
&= \sum_n w_n \bar{L}_n \sum_i \beta_{in}(\mathbf{w}) - \sum_i w_i \bar{L}_i \\
&= \sum_n w_n \bar{L}_n - \sum_i w_i \bar{L}_i = 0.
\end{aligned} \tag{OA.A.9}$$

(iv) For all $\mathbf{w} \gg 0$, it exists a $k > 0$ such that $Z_i(\mathbf{w}) > -k$ for all $i \in N$.

Indeed, the lower bound on $Z_i(\mathbf{w})$ is implied by:

$$Z_i(\mathbf{w}) = \frac{1}{w_i} \left(\sum_n \beta_{in}(\mathbf{w}) w_n \bar{L}_n - w_i \bar{L}_i \right) = \frac{1}{w_i} \underbrace{\left(\sum_n \beta_{in}(\mathbf{w}) w_n \bar{L}_n \right)}_{>0} - \bar{L}_i > -\bar{L}_i.$$

Hence, if we define $k \equiv \max_{i \in N} \bar{L}_i$, it follows that $Z_i(\mathbf{w}) > -k \forall i \in N$.

(v) Consider any $\mathbf{w} \in \mathbb{R}_+^{|N|}$ such that there exist $l, l' \in N$ with $w_l = 0$ and $w_{l'} > 0$. Consider any

sequence $\mathbf{w}^m \rightarrow \mathbf{w}$ as $m \rightarrow \infty$. Then

$$\max_{i \in N} Z_i(\mathbf{w}^m) \rightarrow \infty.$$

We show this for Z_i^P and Z_i^F separately; by additivity the result follows for Z_i .

We construct a sequence of strictly positive wage vectors converging to $\mathbf{w}$: choose $\mathbf{w}^m$ such that (i) $w_i^m > 0$ for all $i \in N$ and $m \geq 1$ and (ii) $\mathbf{w}^m \rightarrow \mathbf{w}$ as $m \rightarrow \infty$. From (i) and (ii) it follows that $w_l^m > 0$ for every m and $w_l^m \rightarrow 0$, so in particular $w_l^m \rightarrow 0^+$, while $w_{l'}^m \rightarrow w_{l'} > 0$.

For notational purposes, define

$$K(i, n; \mathbf{w}) := \frac{w_i^{1-\sigma} \left(\frac{A_i}{\tau_{in}} \right)^{\sigma-1}}{\sum_{k \in N} \left(\frac{A_k}{\tau_{kn} w_k} \right)^{\sigma-1}}, \quad Z_i^P(\mathbf{w}) = \frac{1}{w_i} \sum_{n \in N} K(i, n; \mathbf{w}) s_n w_n \bar{L}_n - s_i \bar{L}_i.$$

First,

$$\begin{aligned} \max_i Z_i^P(\mathbf{w}^m) &= \max_i \left\{ \frac{1}{w_i^m} \sum_n K(i, n; \mathbf{w}^m) s_n w_n^m \bar{L}_n - s_i \bar{L}_i \right\} \\ &\geq \max_i \frac{1}{w_i^m} \sum_n K(i, n; \mathbf{w}^m) s_n w_n^m \bar{L}_n - \max_i s_i \bar{L}_i, \end{aligned} \quad (\text{OA.A.10})$$

by $\max_i (a_i - b_i) \geq \max_i a_i - \max_i b_i$. Since each summand is nonnegative,

$$\begin{aligned} \max_i \frac{1}{w_i^m} \sum_n K(i, n; \mathbf{w}^m) s_n w_n^m \bar{L}_n &\geq \max_i \frac{1}{w_i^m} \max_n K(i, n; \mathbf{w}^m) s_n w_n^m \bar{L}_n \\ &= \max_{i,n} \frac{w_n^m}{w_i^m} K(i, n; \mathbf{w}^m) s_n \bar{L}_n. \end{aligned} \quad (\text{OA.A.11})$$

Evaluating at $(i, n) = (l, l')$ gives^{oa.1}

$$\max_i Z_i^P(\mathbf{w}^m) \geq \frac{w_{l'}^m}{w_l^m} K(l, l'; \mathbf{w}^m) s_{l'} \bar{L}_{l'} - \max_i s_i \bar{L}_i. \quad (\text{OA.A.12})$$

Next, write

$$K(l, l'; \mathbf{w}^m) = \frac{(w_l^m)^{1-\sigma} C_l}{\sum_k (w_k^m)^{1-\sigma} C_k}, \quad C_k := \left(\frac{A_k}{\tau_{kl'}} \right)^{\sigma-1} > 0. \quad (\text{OA.A.13})$$

Since $1 - \sigma < 0$, $x \mapsto x^{1-\sigma}$ is decreasing, so $(w_k^m)^{1-\sigma} \leq (\min_j w_j^m)^{1-\sigma}$ for all k , hence

$$\sum_k (w_k^m)^{1-\sigma} C_k \leq (\min_j w_j^m)^{1-\sigma} \sum_k C_k. \quad (\text{OA.A.14})$$

Therefore:

$$K(l, l'; \mathbf{w}^m) = \frac{(w_l^m)^{1-\sigma} C_l}{\sum_k (w_k^m)^{1-\sigma} C_k} \geq \frac{(w_l^m)^{1-\sigma} C_l}{(\min_j w_j^m)^{1-\sigma} \sum_k C_k}. \quad (\text{OA.A.15})$$

^{oa.1}To ensure the lower bound is nonzero, assume $s_{l'} > 0$. If some s_i can be zero, choose any n^* with $w_{n^*} > 0$ and $s_{n^*} > 0$ and evaluate at $(i, n) = (l, n^*)$.

Because $w_l^m \rightarrow 0$ while $w_j^m \rightarrow w_j > 0$ for $j \neq l$, there exists M such that $\min_j w_j^m = w_l^m$ for all $m \geq M$. ^{oa.2} Hence:

$$K(l, l'; \mathbf{w}^m) \geq \frac{C_l}{\sum_k C_k} =: c_* > 0 \quad (m \geq M). \quad (\text{OA.A.16})$$

Plugging OA.A.16 into OA.A.12 yields:

$$\max_i Z_i^P(\mathbf{w}^m) \geq \frac{w_{l'}^m}{w_l^m} c_* s_{l'} \bar{L}_{l'} - \max_i s_i \bar{L}_i. \quad (\text{OA.A.17})$$

Finally, by construction of the sequence $\mathbf{w}^m \rightarrow \mathbf{w}$, we have

$$w_{l'}^m \rightarrow w_{l'} > 0 \quad \text{and} \quad w_l^m \rightarrow 0^+. \quad (\text{OA.A.18})$$

Hence,

$$\frac{w_{l'}^m}{w_l^m} \rightarrow +\infty. \quad (\text{OA.A.19})$$

Since $c_* > 0$ and $s_{l'} \bar{L}_{l'} > 0$, ^{oa.3} the lower bound

$$\frac{w_{l'}^m}{w_l^m} c_* s_{l'} \bar{L}_{l'} - \max_i s_i \bar{L}_i \quad (\text{OA.A.20})$$

diverges to $+\infty$ as $m \rightarrow \infty$. Therefore,

$$\max_{i \in N} Z_i^P(\mathbf{w}^m) \rightarrow +\infty. \quad (\text{OA.A.21})$$

The fighting block requires the same boundary argument, but with the exponent and accessibility conditions of the fighting share. Define

$$\eta \equiv \frac{\gamma}{1 - \gamma} > 0$$

and, for each destination n ,

$$K_F(i, n; \mathbf{w}) := \frac{w_i^{-\eta} \left(\frac{\psi_i}{\xi_{in}} \right)^\eta}{\sum_{k \in N} w_k^{-\eta} \left(\frac{\psi_k}{\xi_{kn}} \right)^\eta}.$$

Then

$$Z_i^F(\mathbf{w}) = \frac{1}{w_i} \sum_{n \in N} K_F(i, n; \mathbf{w}) (1 - s_n) w_n \bar{L}_n - (1 - s_i) \bar{L}_i.$$

To obtain a positive lower bound, assume that the zero-wage origin l has access to at least one positive-income approprable destination. That is, there exists $n^* \in N$ such that

$$w_{n^*} > 0, \quad (1 - s_{n^*}) \bar{L}_{n^*} > 0, \quad \psi_l > 0, \quad 0 < \xi_{ln^*} < \infty.$$

^{oa.2}Since $w_j^m \rightarrow w_j > 0$ for $j \neq l$, there exists $\epsilon > 0$ such that for a large enough m , $w_j^m > \epsilon$ for all $j \neq l$. At the same time, $w_l^m \rightarrow 0$, so for large enough m , $w_l^m < \epsilon$. That means that eventually $w_l^m < w_j^m$ for all $j \neq l$, hence: $\min_j w_j^m = w_l^m$ for all large enough m .

^{oa.3}If some s_i may be zero, choose n^* with $w_{n^*} > 0$ and $s_{n^*} > 0$ and evaluate at $(i, n) = (l, n^*)$.

Evaluating the nonnegative sum at $(i, n) = (l, n^*)$ gives

$$\max_i Z_i^F(\mathbf{w}^m) \geq \frac{w_{n^*}^m}{w_l^m} K_F(l, n^*; \mathbf{w}^m) (1 - s_{n^*}) \bar{L}_{n^*} - \max_i (1 - s_i) \bar{L}_i.$$

For this destination, write

$$K_F(l, n^*; \mathbf{w}^m) = \frac{(w_l^m)^{-\eta} D_l}{\sum_k (w_k^m)^{-\eta} D_k}, \quad D_k := \left(\frac{\psi_k}{\xi_{kn^*}} \right)^\eta.$$

Since $\eta > 0$, $x \mapsto x^{-\eta}$ is decreasing. For large enough m , $\min_j w_j^m = w_l^m$, and therefore

$$\sum_k (w_k^m)^{-\eta} D_k \leq (w_l^m)^{-\eta} \sum_k D_k.$$

Hence

$$K_F(l, n^*; \mathbf{w}^m) \geq \frac{D_l}{\sum_k D_k} =: \tilde{c}_* > 0.$$

It follows that

$$\max_i Z_i^F(\mathbf{w}^m) \geq \tilde{c}_* (1 - s_{n^*}) \bar{L}_{n^*} \frac{w_{n^*}^m}{w_l^m} - \max_i (1 - s_i) \bar{L}_i.$$

Because $w_{n^*}^m \rightarrow w_{n^*} > 0$ and $w_l^m \rightarrow 0^+$, the right-hand side diverges to $+\infty$. Therefore,

$$\max_i Z_i^F(\mathbf{w}^m) \rightarrow +\infty.$$

We have now verified condition (v) for Z^P and, under the stated fighting-accessibility condition, for Z^F . Since $Z_i(\mathbf{w}) = Z_i^P(\mathbf{w}) + Z_i^F(\mathbf{w})$, condition (v) holds for Z whenever at least one of the two blocks provides the required boundary divergence.

Therefore, Z satisfies conditions (i)–(v). We conclude the proof of existence by invoking the following theorem:

Theorem 1. *If a function $\{Z_i(\cdot)\}_{i \in N}$ satisfies conditions (i) to (v), then there exists a $\mathbf{w}^* \gg 0$ such that $Z_i(\mathbf{w}^*) = 0 \ \forall i \in N$. (This theorem comes directly from [Mas-Colell et al. \(1995\)](#) Proposition 17.C.1 on p.585.)*

Uniqueness

A differentiable excess demand function $\{Z_i(\cdot)\}_{i \in N}$ is said to satisfy the gross substitute property if $\forall i \in N$:

$$\frac{\partial Z_i(\mathbf{w})}{\partial w_j} > 0 \quad \forall j \neq i,$$

We show that $\{Z_i(\mathbf{w})\}_{i \in N}$ satisfies the gross-substitutes property. Let

$$\rho \equiv \sigma - 1 > 0, \quad \eta \equiv \frac{\gamma}{1 - \gamma} > 0,$$

and define the destination-specific shares

$$K_P(i, n; \mathbf{w}) := \frac{w_i^{-\rho} \left(\frac{A_i}{\tau_{in}} \right)^\rho}{\sum_{k \in N} w_k^{-\rho} \left(\frac{A_k}{\tau_{kn}} \right)^\rho}, \quad K_F(i, n; \mathbf{w}) := \frac{w_i^{-\eta} \left(\frac{\psi_i}{\xi_{in}} \right)^\eta}{\sum_{k \in N} w_k^{-\eta} \left(\frac{\psi_k}{\xi_{kn}} \right)^\eta}.$$

For $j \neq i$, the numerator of $K_P(i, n; \mathbf{w})$ does not depend on w_j . Differentiating the denominator gives

$$\frac{\partial K_P(i, n; \mathbf{w})}{\partial w_j} = \frac{\rho}{w_j} K_P(i, n; \mathbf{w}) K_P(j, n; \mathbf{w}) \geq 0.$$

Hence

$$\frac{\partial Z_i^P(\mathbf{w})}{\partial w_j} = \frac{1}{w_i} \left[K_P(i, j; \mathbf{w}) s_j \bar{L}_j + \sum_{n \in N} s_n w_n \bar{L}_n \frac{\rho}{w_j} K_P(i, n; \mathbf{w}) K_P(j, n; \mathbf{w}) \right] \geq 0. \quad (\text{OA.A.22})$$

The inequality is strict under the maintained trade-accessibility condition: there exists at least one destination n with $s_n \bar{L}_n > 0$ such that both i and j have strictly positive trade shares in n .

The same calculation applies to the fighting block. For $j \neq i$,

$$\frac{\partial K_F(i, n; \mathbf{w})}{\partial w_j} = \frac{\eta}{w_j} K_F(i, n; \mathbf{w}) K_F(j, n; \mathbf{w}) \geq 0.$$

Therefore,

$$\frac{\partial Z_i^F(\mathbf{w})}{\partial w_j} = \frac{1}{w_i} \left[K_F(i, j; \mathbf{w}) (1 - s_j) \bar{L}_j + \sum_{n \in N} (1 - s_n) w_n \bar{L}_n \frac{\eta}{w_j} K_F(i, n; \mathbf{w}) K_F(j, n; \mathbf{w}) \right] \geq 0. \quad (\text{OA.A.23})$$

The inequality is strict under the corresponding fighting-accessibility condition: there exists at least one destination n with $(1 - s_n) \bar{L}_n > 0$ such that both i and j have strictly positive fighting shares in n .

Thus, for every $i \neq j$,

$$\frac{\partial Z_i(\mathbf{w})}{\partial w_j} = \frac{\partial Z_i^P(\mathbf{w})}{\partial w_j} + \frac{\partial Z_i^F(\mathbf{w})}{\partial w_j} > 0$$

whenever at least one of the two accessibility conditions holds for the pair (i, j) .

Under the maintained global accessibility condition that, for every pair $i \neq j$, at least one of the two accessibility conditions above holds, the excess-demand system satisfies the gross-substitutes property. We can therefore invoke the following theorem:

Theorem 2. *If a function $\{Z_i(\cdot)\}_{i \in N}$ satisfies the gross substitute property and is homogeneous of degree zero, then the equilibrium $\mathbf{w}^* \gg 0$ such that $Z_i(\mathbf{w}^*) = 0 \forall i \in N$ is unique (to scale). (This theorem comes directly from [Mas-Colell et al. \(1995\)](#) Proposition 17.F.3 on p.613.)*

Since we have already established homogeneity in (ii), uniqueness of $\mathbf{w}^*$ follows under this global accessibility condition.

OA.B Supplementary material for section 3

OA.B.1 The Armed Conflict Location & Event Data Project (ACLED)

Our aim is to process geolocalized violent events into bilateral flows of violence with well-defined origins and destinations. We detail our data construction procedure, which consists of six steps, outlined in Table [OA.B1](#).

General Overview We use conflict event data from the Armed Conflict Location and Event Dataset (ACLED) which contains information on the geo-location of conflict events in all African countries

over the period from 1997 to June 23th, 2023.^{oa.4} In the raw data, the unit of observation is a violent event for which we have information about the nature of the actors involved^{oa.5}, the nature of the events^{oa.6}, the location (longitude and latitude), fatalities and the precise date. The dataset covers 325541 distinct events spread over 57 countries. For each event, the database reports the involved actors under the categories *actor1*, *actor2*, *associated actor1*, and *associated actor2*.^{oa.7} We refer to these four categories collectively as the actors. In the raw data, there are 14137 distinct actors.

Table OA.B1: Data-processing steps

Steps	# Events	# Actors	# Fatalities
0-Raw dataset	325541	14137	882975
1- Geographic filter	237489	11138	556016
2- Events filter	234943	11013	555959
3- Information filter	232878	5486	553745
4- Actors selection	87578	1492	379314
5- Murdock filter on actors	80619	220	362672
6- Murdock filter on events	78335	220	353289

Note: **Step 0–Raw dataset:** reshaped from raw data such that the unit of observation is an event×actor(group). **Step 1–Geographic filter:** considers only events with the highest level of precision and excludes events outside continental Africa. **Step 2–Events filter:** excludes events considered peaceful or of unidentified nature. **Step 3–Information filter:** excludes actors with no external information (e.g., no information on the nature of the actors). **Step 4–Actor selection:** keeps actors identified as “Rebel groups” and “Political Militias”. **Step 5–Murdock filter on actors:** 220 actors that we assign to 87 Murdock ethnic groups. **Step 6–Murdock filter on events:** excludes events that do not intersect with the Murdock map (Sinai region, lakes...).

^{oa.4}The dataset “Compatibility” was downloaded on June 28, 2023 (2pm).

^{oa.5} ACLED defines 8 natures of actors. “Rebel groups” are violent political entities aiming to challenge national government. “Political Militias” encompass actors that for specific objectives and/or a defined period of time make use of violence to achieve some political objectives. “State forces” (military and police units) are actors executing governmental functions. “Identity Militias” are actors organized around a collective identity or motive (e.g. community, ethnicity, region, religion, livelihood). “Rioters” are actors who engage in violence either during demonstrations or in spontaneous acts of violence. “Protesters” are peaceful demonstrators. “Civilians” are victims of violence. “External/Other Forces” encompass different actors, such as international organizations, state forces active outside of their main country, private security and mercenaries

^{oa.6} They record six event types (and 25 sub-event types). “Battles” are defined as a violent interaction between two actors. “Explosions/Remote violence” correspond to incidents in which one side uses weapon types that are widely destructive. “Protests” corresponds to non-violent meetings with more than three participants. “Riots” are violence committed by groups of three or more demonstrators or mobs engaging in destructive behavior. “Strategic developments” encompass events involving groups that are not classified as “Political violence” or “Demonstrations”, but may have the potential to influence political dynamics within and between states. “Violence against civilians” corresponds to violent events where an organized armed group inflicts violence upon unarmed non-combatants

^{oa.7}For a given event, information on the nature of the actors (see footnote ^{oa.5}) is reported only for those assigned to the categories *actor1* and *actor2*. For those assigned to the other two categories, we recover this information by cross-matching their names with those reported in the *actor1* and *actor2* categories for *other* events, exploiting the fact that an actor can be assigned to *actor1* in one event but to *assoc_actor1* in another. However, we are not able to recover this information for all actors. Here is the list of the 10 actors with the highest number of events for which we do not have information on their nature: Labor Group (Morocco); Labor Group (Nigeria); Labor Group (South Africa); Labor Group (Tunisia); Oromo Ethnic Group (Ethiopia); Pastoralists (Nigeria); Resistance Committees (Sudan); Students (South Africa); Women (Democratic Republic of Congo)

Step 0-Raw dataset: We first reshape the raw data so that the unit of observation becomes an actor×event cell. We end up with 624571 observations. Tables OA.B2 and OA.B3 respectively report, at different steps of the data-processing procedure, the percentage of events by actor type and by type of violence.^{oa.8}

Table OA.B2: Actors of violence

Nature of actors	Step 0		Step 3	
	% Events	% Actors	% Events	% Actors
Rebel groups	26.5	2.7	22.9	5.8
Political Militias	30.8	10.3	17.4	21.6
State Forces	39.8	6.5	39.3	15.5
Identity Militias	9.8	29.8	6.4	50.9
Rioters	11.1	.4	13.1	1
Protesters	23.6	.5	30	1.1
Civilians	33.5	.7	30.4	1.6
External/Other Forces	30.7	2.6	29.1	6.1
Missing nature	29.2	47.9	0	0

Note: The figures in this table are provided at different steps of the data-processing described in Table 1: for the raw data (Step 0) and after the information filter (Step 3). For more information on the definition of the nature of the actors, see footnote oa.5. *Missing nature* corresponds to actors for which there is no information on the nature in the ACLED dataset.

Table OA.B3: Nature of violence

Type of violence	Step 0	Step 4	Step 6
	% Events		
Battles	25.3	44.8	49.8
Explosions/Remote violence	6.7	8.2	9.12
Protests	19.7	7.5	7.77
Riots	12.5	6.2	6.47
Strategic developments	7	7.6	8.62
Violence against civilians	28.7	25.6	29.57

Note: The figures in this table are provided at different steps of the data-processing described in Table 1: for the raw data (Step 0), after the *actors' selection* (Step 4) and after the *Murdock filter on events* (Step 6). For more information on the definition of the nature of violence, see footnote oa.6.

^{oa.8}Note that the columns do not sum to 100% because some events involve actors which are associated to at least two different natures. Here is the list of actors with multiple natures: Darul-Islam (Nigeria); Dinka Ethnic Militia (South Sudan); FDPC: Democratic Front for the People of the Central African Republic; FNL: National Forces of Liberation; HSGF: Homeland Study Group Foundation; MAPI: Ituri Popular Self-Defense Movement; Mayi Mayi Militia (UPLC: Union of Patriots for the Liberation of Congo); NDA: National Democratic Alliance (Sudan); Ngumino Ethnic Militia (Democratic Republic of Congo); OLF: Oromo Liberation Front (Shane Splinter Faction); RRR: Return, Reclamation and Rehabilitation; Red Ant Security Relocation and Eviction Services; Salafist Muslim Militia (Tunisia); Sinai Tribal Union; TPLF: Tigray People's Liberation Front; UFDR: Union of Democratic Forces for Unity; UNITA: National Union for the Total Independence of Angola.

Step 1- Geographic filter: The ACLED dataset documents three levels of precision for the spatial location of events.^{oa.9} A total of 74.58% of the events are recorded with the highest level of precision (town level) while the rest are associated with lower levels of precision (22.95% at the small region level and 2.47% at the large region level). Table OA.B4 displays the percentage of events by actors and geo-precision. Our *geographic filter* (Step 1) retains only observations with the highest level of precision (geo-precision 1). It also excludes events that are not part of continental Africa, i.e., events happening at sea and on islands (such as Madagascar). This restriction leaves us with 237489 distinct events covering 11138 actors.

Table OA.B4: Percentage of events by actors and geoprecision

Nature of actors	Geo-precision 1	Geo-precision 2	Geo-precision 3
Rebel groups	63.4	33.2	3.4
Political Militias	72.7	24.6	2.7
State Forces	73.4	23.5	3.1
Identity Militias	52.3	45.1	2.5
Rioters	87	12.2	.8
Protesters	93.3	5.6	1.1
Civilians	67.2	30.3	2.6
External/Other Forces	69.5	27	3.4
Missing nature	74.7	23	2.4

Note: The figures in this table are provided at the step of the data-processing described in Table 1: 0-Raw dataset (Step 0). The actors are defined as in the note of Table OA.B2. See footnote oa.9 for the definition of the levels of geo-precision.

Step 2- Events filter: ACLED reports information on the nature of violence attached to each event. A small fraction of events are categorized as non-violent or non-identified (sub-event: “Agreement” and sub-event: “Others”, respectively). The *events filter* (Step 2) excludes those events. After this filter, the sample comprises 234943 events involving 11013 actors. This filter is applied at the sub-event level: ACLED event types such as “Protests” or “Strategic developments” may still appear in Table OA.B3 when their sub-event is neither peaceful nor unidentified. These observations enter the baseline sample only if they subsequently involve a rebel group or political militia and pass the Murdock filters.

Step 3- Information filter: Table OA.B2 shows that, for 29.2% of events, ACLED does not report precise information on their political or military status.^{oa.10} The information filter excludes them from the analysis in the following manner. First we exclude actors assigned by ACLED to the category “Unidentified”. This represents 33502 distinct events covering 161 actors. Second, we

^{oa.9}Geo-precision code 1 (the highest precision level): “If the source reporting indicates a particular town, and coordinates are available for that town, the highest precision level, Geo-precision code 1, is recorded”. (p35, ACLED, 2023) Geo-precision code 2: “If the source material indicates that activity took place in a small part of a region, and mentions a general area, the event is coded to a town with geo-referenced coordinates to represent that area, and the Geo-precision code 2 is recorded. If activity occurs near a town or a city, this same Geo-precision code 2 is employed.” (p35, ACLED, 2023) Geo-precision code 3: “If a larger region is mentioned, the closest natural location noted in reporting (like “border area”, “forest”, or “sea”, among others) – or a provincial capital is used if no other information at all is available – is chosen to represent the region, and Geo-precision code 3 is recorded.”

^{oa.10}Here are the 10 actors with the highest number of events for which we do not have information on the nature: Labor Group (Morocco); Labor Group (Nigeria); Labor Group (South Africa); Labor Group (Tunisia); Oromo Ethnic Group (Ethiopia); Pastoralists (Nigeria); Resistance Committees (Sudan); Students (South Africa); Women (Democratic Republic of Congo)

exclude actors for which there is no information recorded on their nature (see footnote [oa.7](#)). This represents 71951 distinct events covering 5388 actors. Last, for actors for which the name is “Militia (Pro-Government)” or “Militia (Students)”, we amend their name by mentioning the country in which the event is taking place. We construct 9 different actors for “Militia (Students)” and 15 different actors for “Militia (Pro-Government)”; they are involved in 593 distinct events. Note that the number of events is not affected by this relabeling of names. Overall, after this filter, we end up with 232878 distinct events covering 5486 actors.

Step 4- Actor selection: In line with our theoretical model of raiding, we focus our analysis on violence perpetrated by actors classified as “Rebel groups” and “Political Militias”. These groups are indeed the most likely to project violence outside their rear base and to engage in violence for appropriation. Together, rebels and political militias represent 1492 actors (more than one quarter of the total number of actors). In the data, they are involved in the most lethal forms of violence, namely battles and violence against civilians (see Table [OA.B3](#)), participating in 38% of events but responsible for 68% of the total fatalities recorded in the Step 3 sample.^{oa.11} The *actors selection* filter (Step 4) restricts the analysis to these two categories. The resulting sample is made of 1492 actors participating in 87578 events resulting in 379314 fatalities.

OA.B.2 Selection of actors

In this appendix, we provide additional detail on the criteria governing the selection of actor types in Step 4 of the data processing procedure. As documented in Table 1, this filtering step substantially reduces the sample from 232878 events involving 5486 actors to 87578 events involving 1492 actors. This restriction reflects a trade-off between coverage and measurement.

First, our analysis requires assigning each actor to a geographic origin (ethnic homeland) and constructing bilateral distances. This is feasible only for actors that are clearly identified and observed operating across multiple locations under a stable organizational label. Several ACLED actor categories do not satisfy this requirement. “Rioters”, “Protesters”, and “Civilians” aggregate heterogeneous and typically local actors under country-level labels (e.g., “Riots (Algeria)”). “State forces” operate at the national level, while “External and Other forces” include actors operating at a continental or international scale ([ACLED, 2023](#)). For these categories, no specific regional origin can be consistently assigned, and they are therefore excluded. This leaves three actor types for which origins and bilateral distances can be meaningfully constructed: “Identity Militias”, “Political Militias”, and “Rebel groups”. Second, a central mechanism of the framework is the strategic allocation of violence across space. Accordingly, the actors most relevant for the empirical analysis must exhibit military operations extending beyond a single locality. We document below the spatial outreach of these three remaining actor categories.

Measuring spatial footprint. We measure the spatial extent of each actor’s armed activity using the convex hull of its event locations, defined as the smallest convex polygon containing the set of events associated with the actor. To do so, we first filter spatial outliers within each set. Let

$$\mathbf{y}_{\text{event},g} = (\text{longitude}_{\text{event},g}, \text{latitude}_{\text{event},g}),$$

^{oa.11} At Step 3, ACLED records a total of 553745 fatalities associated with 232878 events. Among those, rebel groups and political militias are responsible for 379314 fatalities in 87578 distinct events. Hence, the average number of fatalities per event for rebel groups and militias is 4.3. In contrast, for the rest of the sample, it is 1.2 $\left(\frac{553745 - 379314}{232878 - 87578} \right)$. This indicates that events involving rebel groups and political militias tend to be more deadly.

denote the coordinates of each event involving a given actor g . We define μ_g as the centroid of these locations and Σ_g as their covariance matrix. The Mahalanobis distance (Mahalanobis, 1936) for each event is

$$d_{\text{event},g} = \sqrt{(\mathbf{y}_{\text{event},g} - \mu_g)^\top \Sigma_g^{-1} (\mathbf{y}_{\text{event},g} - \mu_g)}.$$

This metric measures the distance of each event from the center of actor g 's spatial distribution, accounting for both dispersion and orientation. For each g , we exclude the 5% most distant observations, thereby removing isolated events that would otherwise disproportionately inflate the convex hull while preserving the core area of armed activity. We then compute the area of the resulting filtered convex hull and compare its distribution across actor types.

Table OA.B5: Area (thousands of sq. km) of actors' convex hulls, by actor type

Actors	Min	Max	Median	Mean	SD
State Forces	0	3924	105	236	412
Rebel Groups	0	14567	74	316	1171
Political Militias	0	3499	22	141	320
Identity Militias	0	1109	6	48	120
Rioters	2	25415	251	998	3617
Protesters	2	26615	359	1520	4042
Civilians	1	33477	605	3095	6077
External and Other Forces	0	12811	198	560	1202

Note: Areas (thousands of sq. km) are computed based on the filtered convex hull of each actor. Statistics are reported by actor type.

Table OA.B5 reports summary statistics for the convex hull areas of actors for all eight ACLED categories. "Rioters", "Protesters", and "Civilians" display the largest convex hulls. This pattern primarily reflects their aggregation under broad country-level labels rather than the geographic footprint of coherent armed organizations. "State forces" and "External and Other forces" likewise operate at national or supra-national scales, which precludes the assignment of a meaningful regional origin (ACLED, 2023). As discussed above, these categories are therefore not well suited to the empirical requirements of our framework.

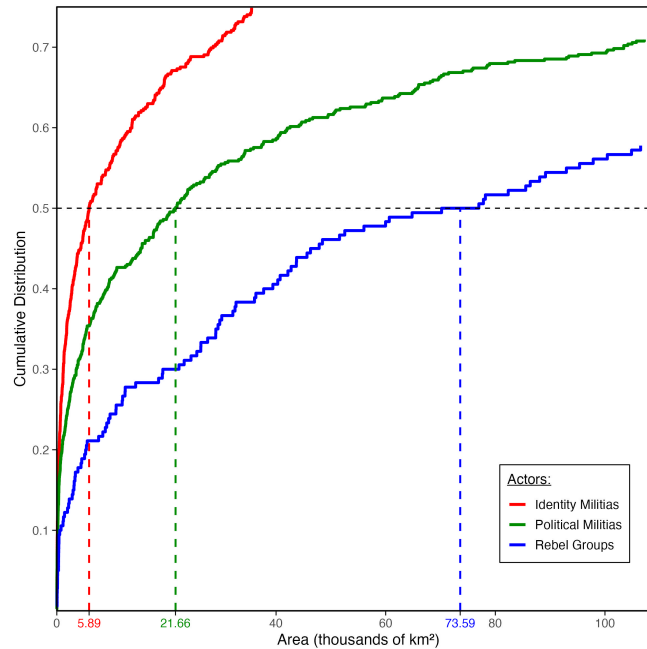
Focusing on the three remaining categories of actors, we find a sharp contrast in spatial footprint. "Identity Militias" operate over substantially smaller areas than the other two groups: the median convex hull area is around 6 thousand km², compared to 22 thousand for "Political Militias" and 74 thousand for "Rebel groups". This pattern is further illustrated by Figure OA.B1, which reports the cumulative distribution of convex hull areas. The entire distribution for identity militias is shifted markedly to the left, indicating violence concentrated within a limited geographic range and consistent with their predominantly local character.^{oa.12} By contrast, political militias and rebel groups operate over broader areas, consistent with actors projecting violence across multiple locations.

While "Identity Militias" could in principle be assigned an origin, their activity remains largely confined to a single homeland. Consequently, bilateral distances contain little meaningful variation, and the strategic spatial allocation mechanism at the core of the model becomes empirically less relevant. Accordingly, they are excluded from the analysis. The two retained actor categories—"Political Militias" and "Rebel groups"—are those for which the model's central spatial mechanism is both conceptually appropriate and empirically informative, while still accounting for the vast

^{oa.12} According to the definition provided by ACLED (2023), "Events involving identity militias are often referred to as communal violence, as these violent groups typically act locally in pursuit of local goals, resources, power, security, and retribution."

majority of violent events and fatalities. The estimates should be interpreted as applying to this spatially projected form of organized violence, not to all non-state violence.

Figure OA.B1: Cumulative distribution of convex hull areas



Note: Red, green and blue colors represent respectively “Identity Militias”, “Political Militias” and “Rebel Groups”. Areas are computed based on the convex hull of each actor, after dropping the 5% of observations with the largest Mahalanobis distances. For readability, we plotted the CDF up to 0.75 and areas up to 100 thousand km². All values are reported in thousands of km².

OA.B.3 Anecdotal evidence: recruitment from ethnic groups

We present a range of anecdotal evidence supporting the assumption that an armed group’s credible recruitment base originates from its connections to ethnic groups. Interestingly, this holds true not only for small rebel groups or militias but also for large armed group organizations. In 2016, the BBC reported that “[Boko Haram] draws its fighters mainly from the Kanuri ethnic group”, while in Uganda the predominantly Muslim Baganda and Basoga ethnic groups make significant contributions to the ranks of the Ugandan ADF fighters^{oa.13} and in the Democratic Republic of Congo, the M23 rebel group is “made up primarily of ethnic Tutsis”.^{oa.14} Often, recruitment aligns with the ethnicity of the leaders. For instance, the leadership of the Revolutionary United Front is primarily drawn from the Temne ethnic group, thus influencing the composition of the troops.^{oa.15} The same observation is made for the Resistência Nacional Moçambicana (RENAMO): many leaders are from the Ndau ethnic group (Nuvunga and Adalima, 2001; Jentzsch, 2021). Finally, the leadership of UNITA predominantly consisted of members from Angola’s majority Ovimbundu

oa.13 <https://allafrica.com/stories/200001040079.html>

oa.14 <https://www.cfr.org/global-conflict-tracker/conflict/violence-democratic-republic-congo>

oa.15 <https://www.refworld.org/reference/countryrep/marp/2003/en/46214>

ethnic group, reflecting ethnic favoritism within the organization.^{oa.16} Remarkably, even groups operating across multiple countries still recruit along ethnic lines. For instance, reports indicate that the membership of Al-Qaeda primarily hails from Algerian and local Saharan communities, including the Tuaregs and Berabiche tribal clans of Mali, as well as Moroccans residing in urban areas.^{oa.17} Similarly, in Mali, tribal affiliations significantly shape the composition of Ansar Dine, with a notable presence from the Ifoghas tribe, highlighting a consistent pattern of ethnic alignment (Maïga, 2016). Furthermore, ethnic recruitment can also result in division and the splintering of armed groups, underscoring the significance of the ethnic dimension. For example, the Liberians United for Reconciliation and Democracy (LURD) initially included members from both the Mandingo and Krahn ethnic groups but eventually divided into two factions due to ethnic tensions. The Movement for Democracy in Liberia (MODEL) emerged predominantly composed of Krahn members, while the Mandingo contingent remained affiliated with LURD.^{oa.18} Ultimately, many Renamo leaders originated from the Ndau ethnic group; however, leadership later diversified, and ethnic tensions diminished (Jentsch, 2021). Some anecdotal evidence highlights that ethnic grievances can be a central driver of recruitment. For instance, Kamwina Nsapu Militia members are mostly from Luba ethnic group and selectively killed non-Luba.^{oa.19} One can find many other anecdotal evidence: the core of Rally for Congolese Democracy (RCD) is composed of Banaymulenge people^{oa.20}; the National Movement for the Liberation of Azawad is mostly made up of ethnic Tuareg^{oa.21}; the Fano Youth Militia ethno-nationalist Amhara militia^{oa.22}; and the Front for Patriotic Resistance of Ituri draws soldiers from Ngiti ethnolinguistic group, a subgroup of Lendu.^{oa.23}

OA.B.4 Matching ACLED actors with Murdock ethnic groups

In this section, we detail the procedures underlying Steps 5 and 6 in Table 1. The first step consists of linking ACLED violent actors to Murdock ethnic groups, a task facilitated by the granularity of the violence data (Figure 1). As explained in the main text, this feature enables us to concentrate our analysis on the 220 most violent actors, who are responsible for 90% of the total violence. The second step involves linking the location of each violent event to an ethnic group.

Our methodology delineates origins and destinations based on ethnic homelands covered in the Ethnographic Atlas (Murdock, 1959). This atlas provides insights into the spatial distribution of African ethnicities and compiles various quantitative indicators reflecting the political institutions, cultural practices, and economic characteristics of 1291 societies.^{oa.24} This dataset has been extensively used in the literature in economics.^{oa.25} Although it has faced some criticism (Wright, 1999; Abad and Maurer, 2021), recent work by Bahrami-Rad et al. (2021a) evaluates the Atlas's validity and concludes that it is a "meaningful source of information".^{oa.26}

^{oa.16}<https://en.wikipedia.org/wiki/UNITA>

^{oa.17}See Cristiani and Fabiani (2011) and https://www.upi.com/Top_News/Special/2011/01/05/Morocco-nabs-members-of-AQIM-cell/UPI-65581294251807/

^{oa.18}https://en.wikipedia.org/wiki/Liberians_United_for_Reconciliation_and_Democracy

^{oa.19}https://en.wikipedia.org/wiki/Kamwina_Nsapu_rebellion

^{oa.20}https://en.wikipedia.org/wiki/Rally_for_Congolese_Democracy

^{oa.21}<https://www.jeuneafrique.com/32589/politique/nord-du-mali-de-l-irr-dentisme-touareg-la-guerre-tribale/>

^{oa.22}[https://en.wikipedia.org/wiki/Fano_\(militia\)](https://en.wikipedia.org/wiki/Fano_(militia))

^{oa.23}https://en.wikipedia.org/wiki/Patriotic_Resistance_Front_of_Ituri

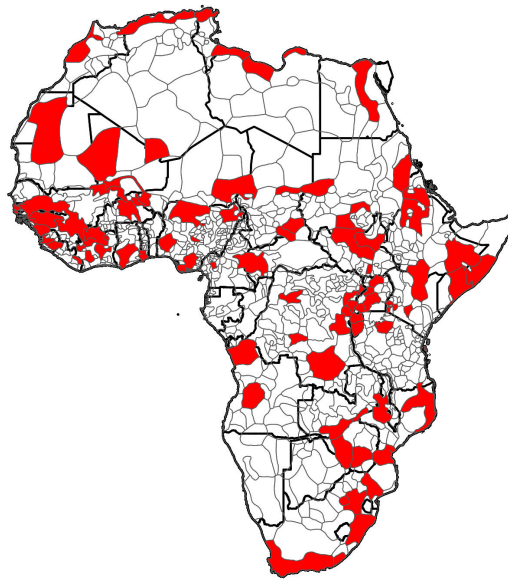
^{oa.24}The dataset was later digitized by Gray (1999) and the location of those ethnic groups has been downloaded from <https://nathannunn.arts.ubc.ca/data/>

^{oa.25}See for instance: Gennaioli and Rainer (2007); Nunn (2008); Nunn and Wantchekon (2011); Michalopoulos and Papaioannou (2013); Berman et al. (2023); Eberle et al. (2024); McGuirk and Nunn (2025).

^{oa.26}Specifically, they document positive associations between the historical measures collected by ethnographers and self-reported data from 790,000 individuals across 43 countries.

Step 5- Murdock filter on actors: To identify the origin of violence, we assign a unique Murdock ethnic group to the 220 violent actors. This task was conducted by the authors and independently cross-validated by a research assistant. The matching procedure involves three main steps: (5a) linking the actors to one or multiple ethnic groups (not necessarily Murdock ethnic groups); (5b) converting these ethnic groups into Murdock ethnic groups; and (5c) selecting a unique Murdock ethnic group among the groups found in the previous steps. At the end of this procedure, the 220 actors are associated with 87 different Murdock ethnic groups. Figure OA.B2 depicts their spatial distribution.

Figure OA.B2: Murdock ethnic groups matched to actors



Note: Spatial distribution of the 87 Murdock ethnic groups associated with the 220 most violent actors in ACLED (exerting 90% of the violence perpetrated by rebel groups and political militias). The maps displayed in thick black lines the African countries.

5a- Direct and indirect inference: It is possible to unambiguously link 99 ACLED violent actors to an ethnic group ("*direct inference*"). For the 121 remaining actors, we combine various informational sources, as outlined below, to identify the ethnic group(s) associated with the actor ("*indirect inference*"):

- *Splits and mergers (35 actors).* We can identify the ethnic affiliation of several violent actors by simply leveraging the affiliations of other actors. First, 6 actors result from the merger of two other groups (e.g. *Islamic State (West Africa) - Lake Chad Faction* and/or *Boko Haram - Jamaatu Ahli is-Sunnah lid-Dawati wal-Jihad*). If both actors are linked to the same ethnic group, we assign that group. Otherwise, we assign the ethnic group of the most violent actor. Second, 25 actors are linked to others because they are factions, splinter groups, or were or became part of another group. In this case, we attribute the same ethnic group as the main group to which they are related (see, for instance, *OLF: Oromo Liberation Front (Shane Splinter Faction)*). Third, 4 actors form coalitions (e.g. *CPC: Coalition of Patriots for Change*). In this scenario, we select the ethnic group that forms the majority. If no clear majority

- *Ethnicity of the leader (25 actors)*. In absence of clear-cut information, we primarily use information on the ethnicity of its leader to link an ACLED violent actor to an ethnic group. For instance, for *MDC: Movement for Democratic Change (Tsvangirai Faction)*, the leader, Morgan Tsvangirai, is Karanga. Therefore, we link the MDC to the Karanga ethnic group.
- *Main ethnic group of the country (36 actors)*. If no information on the leader is available, we check if the ACLED actor is clearly associated with a country; in such cases, we refer to the predominant ethnic group within that country. For instance, for the actor *Islamist Militia (Somalia)*, we use the predominant ethnic group in Somalia, which is Somali.
- *Location of events (14 actors)*. If none of the previous pieces of information are available or relevant, we use external sources that report on the territory of military operations to link a violent actor to an ethnic group. This can be at the regional level, such as the actor *Mayi Mayi Militia (FPP/AP: Popular Patriotic Forces People's Army-Kabido)*, which is primarily active in the Lubero territory, or at the city level, such as *Ansar al-Sharia (Libya)*, which is mainly active in Benghazi and Derna. In the absence of external sources, we project ACLED events onto the Murdock map to determine the distribution of violent events across ethnic groups and retain the most frequently affected one as the ethnic affiliation. For example, most events involving *IM: Islamic Movement* are concentrated in the Murdock region identified as Gwandara. Whenever possible, we prioritize external sources to minimize reliance on the spatial distribution of ACLED events.
- For 10 actors we combine various pieces of information (such as the leader's ethnicity and the ethnic composition of the country) because each piece on its own is uncertain, and multiple sources are needed to verify it.
- For one actor, we directly rely on the information available in the ACD2EPR database because no other sources are available.

After this step, 185 actors are associated with only one identified ethnic group, 22 actors with two ethnic groups, 8 actors with three ethnic groups, 3 actors with four ethnic groups and 2 actors with more than four ethnic groups.

5b- Ethnic conversion: Following the *direct and indirect inference* procedures, we convert the identified ethnic groups into Murdock ethnic groups. For 26% of the actors, the identified ethnic groups do not match any ethnic group in the Murdock dataset. To address this issue, we use ethnic conversion tables provided by the Linking Ethnic Data from Africa (LEDA) project (Müller-Crepon et al., 2022), which uses a measure of ethnic proximity between groups based on the Ethnologue language tree. This method connects 8100 ethnic categories from eleven databases, including surveys, geographic data, and expert-coded lists. Specifically, we use four of these databases: the Ethnic Power Relations Dataset from the Geographical Research on War, the Unified Platform (Girardin et al., 2015), the Afrobarometer Surveys (<https://www.afrobarometer.org/>), the All Minorities at Risk dataset (<https://cidcm.umd.edu/research/all-minorities-risk-project>) and the Ethnic groups from (Fearon, 2003).^{oa.27} However, there are instances where the conversion using LEDA is either not possible or insufficient. In these cases, we rely on credible external sources, which we thoroughly document, to establish a correspondence with Murdock ethnic groups. For actors classified as mergers and factions, we assign the ethnic group(s) of the main group from which they originated (22 actors). The different sources and the number of actors involved are summarized in Table OA.B6:

^{oa.27}The first three databases are the largest among the eleven available. Additionally, we use the database from Fearon (2003) because it includes a relatively large number of ethnic groups (822 ethnic groups in 160 countries).

Table OA.B6: Procedure for converting ethnic group names

Sources for the conversion	(short) Description	Number of actors
No conversion	The ethnic group identified is already a Murdock ethnic group.	135
	Links with other actors	28
LEDA	The conversion results in a unique Murdock ethnic group.	21
	The conversion results in multiple Murdock ethnic groups.	13
External sources	The conversion results in a unique Murdock ethnic group.	9
	The conversion results in multiple Murdock groups.	4
LEDA and external sources	LEDA is either not precise enough or provides too many conversions	6
	Some ethnic groups are in LEDA, while others are not.	3
No conversion was possible		1

5c- Decision rule: To construct the origins of the bilateral flows of violence between Murdock ethnic regions, we need to assign each violent actor to a unique Murdock ethnic group. The accounting is exhaustive over the 220 actors: 28 actors are assigned through links with other actors, 165 actors are assigned to a unique Murdock group without further information, and 27 actors require an additional decision rule. For the latter, the procedures identify multiple Murdock groups linked to a given actor, and we rely on additional external information to select the most appropriate ethnic group. The various sources that we use are listed below:

- Population (17 actors): Among the ethnic group candidates, we select the ethnic group with the largest population.
- Events (6 actors): We select the ethnic group with the highest number of violent events. For example, *Mayi Mayi Militia* is associated with the Konjo and Hunde ethnic groups. As the fighting activity of the *Mayi Mayi Militia* is concentrated in the Lubero and Beni regions, where the Konjo is the predominant ethnic group, we attribute the Konjo ethnic group to *Mayi Mayi Militia*.
- Alternative sources (4 actors): For these actors, we use both actor-specific information and decision rules. For the actor *Ansaroul Islam*, we use external information on ethnicity to select among the candidates. For the actor *Tigray People's Liberation Front*, we use information from the ACD2EPR database. Finally, for the actor *Janjaweed*, we use information on the group's leader.

5d- Validation exercises of the matching procedure: To assess the quality of our matching procedure, we conduct two validation exercises. The first involves a research assistant who independently processed the data for a random subsample of 161 out of the 220 actors. In 87% of the cases (i.e., for 140 actors), the research assistant identifies at least one Murdock ethnic group that exactly

matches the one found by the authors. The second validation exercise is based on the ACD2EPR 2021 dataset (Wucherpfennig et al., 2012), which links UCDP Armed Conflict Data (v. 20.1) to EPR-Core 2021 groups.^{oa.28,oa.29} This dataset identifies all politically relevant ethnic groups worldwide from 1946 to 2021 and includes data on over 800 groups, coding their access to state power. Among the 220 actors for which we collected ethnic group information, 38 actors are also covered in the ACD2EPR dataset and matched by ACD2EPR to a Murdock group.^{oa.30} Encouragingly, our procedure assigns the same Murdock ethnic group to 35 out of those 38 actors.

Step 6- Murdock filter on events: This filter restricts the dataset to violent events located in Murdock ethnic regions, resulting in the exclusion of 2284 events. Several factors contribute to the exclusion of certain violent events from the dataset. First, the Sinai Peninsula is entirely absent from the Murdock map, leading to the loss of all violent events from that region. Second, lakes are depicted on the Murdock map but are not associated with specific ethnic groups, causing events occurring on lakes to be excluded. Third, the Murdock map has more detailed boundaries compared to the ADMIN 0 map, resulting in events along the coastline potentially falling outside the Murdock map boundaries and being excluded.

General Statistics. In Figure OA.B3, we look at the distribution of violence originating from the 87 Murdock ethnic groups (Step 6 of our data construction procedure). Panel (a) displays the log rank-log size relationship, highlighting the ten most violent ethnic groups, while panel (b) plots the cumulative counts of ethnic groups (ranked by size) against their cumulative share of events. The distribution is highly skewed, with the 38 most violent ethnic groups responsible for 90% of total violence.

OA.B.5 Confidence index for actor-to-ethnicity matching

The mapping between armed groups and ethnic homelands relies on heterogeneous sources of information, which may differ in precision across actors. To account for this variation, we construct a confidence index that captures the reliability of each match along three dimensions, each evaluated using a discrete grading system. The grading categories below are constructed for the final set of actor–Murdock matches used in the gravity sample. They do not mechanically coincide with the raw source categories reported in Appendix OA.B.4: in particular, actors matched through factions, splits, or mergers inherit the grade of the referenced primary actor. We then re-estimate the gravity equation of violence on samples that progressively broaden the set of accepted matches. The results remain stable across specifications, indicating that the baseline findings are not driven by less precisely identified matches.

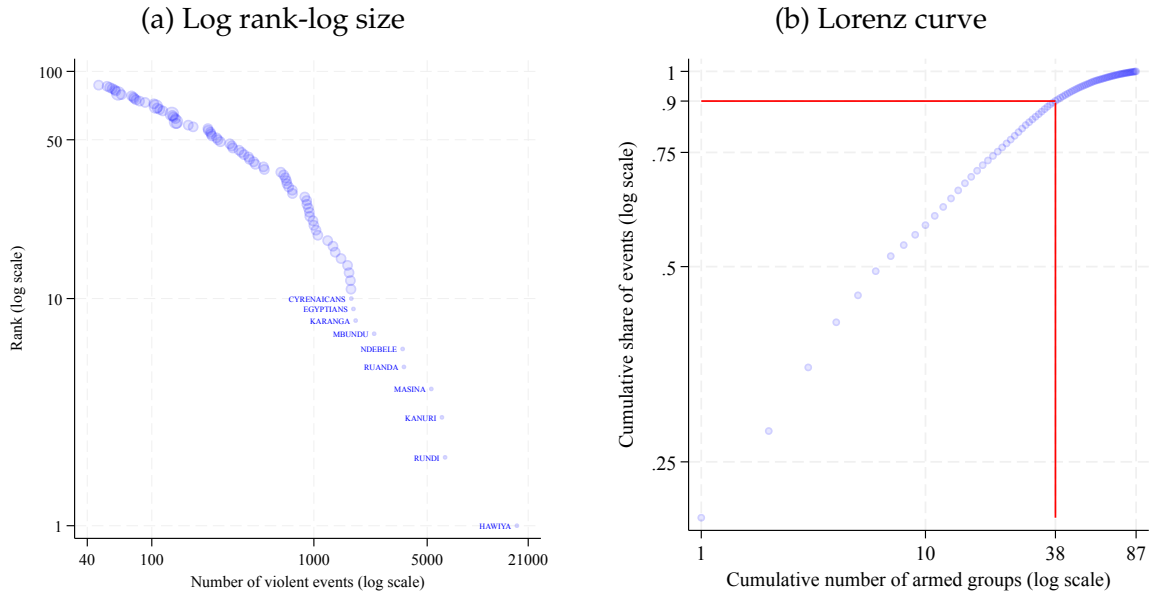
Grade #1: Inference procedure. We first assess how the ethnic affiliation of each group is identified. We assign a Grade A to 133 actors: For these actors, inference is *direct* as it is based on explicit

^{oa.28}The Uppsala Conflict Data Program (UCDP) has recorded ongoing violent conflicts since the 1970s and, together with ACLED, is one of the most popular conflict related databases.

^{oa.29}The EPR Core dataset identifies all politically relevant ethnic groups and their access to state power in every country of the world from 1946 to 2021. It includes annual data on over 800 groups and codes the degree to which their representatives held executive-level state power—from total control of the government to overt political discrimination.

^{oa.30}In fact, 42 armed actors are covered in the ACD2EPR dataset. However, several of them are associated with an ethnic group that is not a Murdock ethnic group. We apply the same methodology used earlier to convert them. For four actors, we could not find a conversion, making comparison impossible. Therefore, out of the 42 actors, we retain only 38 actors for the purpose of the validation exercise.

Figure OA.B3: Violence originating from Murdock ethnic groups



Note: Both panels are based on the sample of step 6, comprising 220 actors in 78335 events. Panel (a) reports the log rank-log size relationship, with the ten major ethnic groups being highlighted. Panel (b) reports a Lorenz curve plotting cumulative counts of ethnic groups (ranked by size) against cumulative share of events.

documentation of the ethnic composition of the group (e.g., leadership or troops). For the remaining 87 actors, we rely on a combination of sources (e.g., leadership ethnicity or the geographic distribution of events) and inference is therefore *indirect*; we assign a Grade B.

Grade #2: Conversion to Murdock classification. We then evaluate how contemporary ethnic group names are mapped to Murdock’s historical classification. For 153 actors, the match is direct and we assign Grade A. For 41 actors, the correspondence is established using the LEDA database (Müller-Crepon et al., 2022), which relies on linguistic proximity across ethnic classifications (Grade B). For the remaining 26 actors, the mapping requires additional external sources or assumptions (Grade C).

Grade #3: Decision rule. Following the inference and conversion procedures, two distinct scenarios arise. First, a single Murdock ethnic group may be unambiguously associated with the actor. In this case, no additional information is required, and we assign Grade A. Second, the procedures may yield multiple candidate Murdock ethnic groups for a given actor. In such cases, we rely on additional external information to identify a unique group. This includes selecting the group with the largest population within the actor’s country, identifying the group most frequently associated with the actor’s events, or leveraging the ethnic affiliation of related actors with established links. As this procedure requires additional assumptions, we assign Grade B.

Construction of the confidence index. Combining the scores across the three dimensions yields 12 possible Grade combinations. We aggregate these combinations into four confidence levels reflecting the overall reliability of the match between each actor and a unique Murdock ethnic group. High-confidence matches (confidence index A), corresponding to combinations “AAA”

and “ABA”, represent 85 actors (38.64%). Matches with good but slightly less precise information (confidence index B), corresponding to “AAB”, “ACA”, “ABB”, and “ACB”, represent 48 actors (21.82%). Matches based on more indirect or less precise information (confidence index C), corresponding to “BAA”, “BBA”, and “BCA”, represent 81 actors (36.82%). Finally, the least reliable matches (confidence index D), corresponding to “BAB”, “BBB”, and “BCB”, represent 6 actors (2.73%). Importantly, the 85 actors in the highest-confidence category alone account for 52.89% of total violent events in the sample. Including actors with a confidence index B raises this share to 78.45%. When an armed group is matched indirectly through association with another group, it inherits the confidence Grade of the referenced armed group.

Robustness test. To assess the sensitivity of our results to match quality, we re-estimate the baseline gravity specification, corresponding to Column 3 of Table 2. For each threshold, we reconstruct origin-destination violence flows after removing events involving actors below the corresponding confidence category. We consider three samples: actors assigned to (i) confidence category A, (ii) categories A and B, and (iii) categories A through C. The results remain quantitatively and qualitatively stable across specifications, indicating that the baseline findings are not driven by less precisely identified matches (Table OA.B7).

Table OA.B7: Robustness of gravity estimates to the quality of ethnic matching

Model	(1)	(2)	(3)
Confidence Index	A	A & B	A, B, & C
log distance	-3.02*** (0.111)	-2.62*** (0.076)	-2.43*** (0.060)
Murdock ethnic border	3.07*** (0.427)	2.60*** (0.261)	2.54*** (0.186)
Political border	-1.89*** (0.178)	-1.56*** (0.136)	-1.71*** (0.111)
Observations	21,472	35,595	51,709
Pseudo R ²	0.579	0.547	0.547

Note: The dependent variable is the share of events in n originating from i . Cross-section over 1997-2023. Estimated with PPML with i and n fixed effects. Column (1) is estimated on a sample of 47 origins attacking a total of 493 destinations, including only matches between actors and Murdock ethnic groups with a confidence index of “A”. Column (2) is estimated on a sample of 60 origins attacking a total of 555 destinations, including matches between actors and Murdock ethnic groups with a confidence index of “A” or “B”. Column (3) is estimated on a sample of 83 origins attacking a total of 622 destinations, including matches between actors and Murdock ethnic groups with a confidence index of “A”, “B” or “C”. * significant at 10%, ** significant at 5%, *** significant at 1%. Standard errors clustered at the origin-destination level.

OA.B.6 Alternative measures of distance

This appendix examines the robustness of our results to alternative measures of distance and spatial interactions. We consider three approaches: constructing a population-weighted CES distance that captures within-region geography (Section OA.B.6.1); accounting for the concentration of violent events near inter-ethnic borders (Section OA.B.6.2); and allowing for spatial dispersion of ethnic

groups using Afrobarometer data (Section OA.B.6.3). Together, these exercises assess the sensitivity of the estimated distance elasticity in the gravity equation of violence.

OA.B.6.1 Effective distance: Construction, estimation, and interpretation

A defect of centroid distance is that it implicitly assumes a uniform population distribution within regions and collapses each pair of regions to a single point-to-point distance. As a result, it ignores that interactions are more likely to arise between proximate and densely populated areas. To address this concern, we consider an alternative measure of distance—the *effective distance* developed by Head and Mayer (2010)—which accounts for (i) the fact that the relevant actors underlying the studied flows are not uniformly distributed inside the geographical units over which flows are aggregated (here, Murdock regions), and (ii) the fact that distances between units should reflect the greater weight of interactions between nearby subunits relative to more distant ones.

Definition of the effective distance. To implement this approach, we divide the African continent into grid cells of 0.5×0.5 decimal degrees (approximately 55×55 km at the equator), for which gridded population data are available.^{oa.31} This yields a total of 17504 grid cells covering the 824 Murdock regions. We then define the *effective distance* between regions i and n , which are respectively composed of sets of grid cells indexed by k and ℓ , as:

$$d_{in}^* = \left[\sum_{k \in i} \sum_{\ell \in n} \left(\frac{\text{pop}_k}{\text{pop}_i} \right) \left(\frac{\text{pop}_\ell}{\text{pop}_n} \right) d_{k\ell}^\theta \right]^{\frac{1}{\theta}}, \quad (\text{OA.B.24})$$

where pop_k and pop_ℓ represent population of grids k and ℓ , respectively, and $d_{k\ell}$ represents the great-circle distance between their centroids when $k \neq \ell$ and the disk-based approximation when $k = \ell$. The weights $\left(\frac{\text{pop}_k}{\text{pop}_i} \right) \left(\frac{\text{pop}_\ell}{\text{pop}_n} \right)$ can be interpreted as the probability that a random interaction between regions i and n takes place between locations k and ℓ . The negative parameter θ represents the distance-decay parameter recovered from the estimated gravity equation of violence.^{oa.32, oa.33} Importantly, the CES form of (OA.B.24) combines all bilateral distances while placing *more weight on shorter distances* (because $\theta < 0$). Another advantage of this alternative measure is that it uses the same formula for internal and external distances of Murdock regions, i.e. using respectively $i = n$ and $i \neq n$ in the definition of d_{in}^* .

Iterative estimation procedure: We estimate the gravity equation of violence (23) using effective distance in place of centroid distance:

$$\mathbb{E} \left(\frac{\text{violence}_{in}}{\text{violence}_n} \right) = \exp \left[\theta \log d_{in}^* + \kappa_e \text{Murdock ethnic border}_{in} + \kappa_p \text{Political border}_{in} + \text{FE}_i^{*o} + \text{FE}_n^{*d} + v_{in} \right]. \quad (\text{OA.B.25})$$

Since the construction of the effective distance d_{in}^* itself depends on θ , the problem has a fixed-point structure that requires an iterative approach. We therefore follow the iterative procedure proposed

^{oa.31}We use population counts from WorldPop, constructed using a top-down unconstrained estimation approach for the year 2000 (Lloyd et al., 2019).

^{oa.32}This parameter corresponds to the term $\left(-\frac{\alpha_1 \gamma}{1-\gamma} \right)$ in the gravity equation (23).

^{oa.33}Head and Mayer (2010) derived this formula relevant for trade flows between *countries* out of a gravity model driving underlying trade between *sub-national* units. Therefore, in their case, trade shares are used as weights, and θ is equal to the distance-decay parameter for trade.

by [Hinz \(2019\)](#). Starting from an initial value $\theta^{(0)}$, we construct the corresponding distance measure $d_{in}^*(\theta^{(0)})$ using (OA.B.24) and estimate equation (OA.B.25), which yields an updated estimate $\theta^{(1)}$. We then recompute $d_{in}^*(\theta^{(1)})$ and re-estimate the equation. This procedure is repeated until convergence, defined by $|\theta^{(t+1)} - \theta^{(t)}| \leq \epsilon$, where $\epsilon = 10^{-6}$.

A concern with estimating equation (OA.B.25) is that d_{in}^* is potentially endogenous. The population weights $\frac{\text{pop}_k}{\text{pop}_i}$ and $\frac{\text{pop}_\ell}{\text{pop}_n}$ may themselves reflect the spatial distribution of violence. While we use population shares measured at the beginning of the sample period, this does not fully address concerns related to historical conflict. If past violence has shaped settlement patterns—through displacement or selective migration away from conflict-prone areas—then population shares may remain correlated with the error term in the gravity equation. As a robustness check, we address this concern using a control-function approach. The excluded shifter in this exercise is a population-*unweighted* version of d_{in}^* , constructed at each iteration of the fixed-point procedure:

$$d_{\text{NO POP},in}^* = \left[\sum_{k \in i} \sum_{\ell \in n} \frac{1}{\#\text{grid}_i} \frac{1}{\#\text{grid}_n} d_{k\ell}^\theta \right]^{1/\theta}, \quad (\text{OA.B.26})$$

where $\#\text{grid}_i$ and $\#\text{grid}_n$ denote the number of grid cells in Murdock regions i and n . This measure depends only on the spatial configuration of grid cells within each region and is therefore orthogonal to the distribution of population. We refer to this measure as *non-population weighted* CES distance. The first-stage regression takes the form:

$$\begin{aligned} \log(d_{in}^*) &= \beta_1 \log(d_{\text{NO POP},in}^*) + \beta_2 \text{Murdock ethnic border}_{in} + \beta_3 \text{Political border}_{in} \\ &+ \text{FE}_i^o + \text{FE}_n^d + u_{in}, \end{aligned} \quad (\text{OA.B.27})$$

with standard errors clustered at the dyad level. The estimated residuals $\hat{u}_{in}$ are then included as an additional regressor in the second-stage PPML estimation of equation (OA.B.25). The rest of the iterative estimation procedure is unchanged.

Results and interpretation. Table OA.B8 reports the results of the iterative PPML estimation of the gravity equation of violence. Column (1) presents the PPML estimates using the effective distance, while Column (4) implements a control-function robustness check for the potential endogeneity of population weights. In the latter, the fixed-point procedure converges to $\hat{\theta} = -2.14$. This parameter value is the one used to build the effective distance in Columns (2) and (3) which report the first stage and reduced form, respectively, once convergence is achieved.

Relative to the baseline specification (col. 3, Table 2), using the effective distance in Column (1) slightly attenuates the estimated distance elasticity. Accounting for endogeneity in Column (4) yields a similar estimate: doubling the distance between two ethnic regions reduces bilateral violence by 77%, compared with 81% when distance is measured between centroids. Turning to borders, the estimated effect of ethnic boundaries increases relative to the baseline specification, while the coefficient on political borders remains stable across specifications. Crossing an ethnic border increases violence by $\exp(3.11) = 22.42$, compared with $\exp(2.52) = 12.43$ in the baseline. In summary, replacing centroid distance with effective distance leaves the estimated elasticity with respect to distance largely unchanged, while increasing the coefficient on ethnic borders. Our theoretical framework provides a natural interpretation of this pattern, as it predicts how alternative distance measures that reweight bilateral interactions translate into changes in reduced-form coefficients. To see this, we first characterize the relationship between effective and centroid distances

across region pairs by assuming:

$$\log(d_{in}^*) = \eta_0 + \eta_1 \log(d_{in}) + \eta_2 \text{Murdock ethnic border}_{in} + \eta_3 \text{Pol border}_{in} + \epsilon_{in}. \quad (\text{OA.B.28})$$

Combining this relation with (OA.B.25) yields the gravity equation of violence estimated with centroid distance:

$$\mathbb{E} \left(\frac{\text{violence}_{in}}{\text{violence}_n} \right) = \exp \left[\theta \eta_0 + \theta \eta_1 \log(d_{in}) + (\theta \eta_2 + \kappa_e) \text{Murdock ethnic border}_{in} + (\theta \eta_3 + \kappa_p) \text{Pol border}_{in} + \text{FE}_i^o + \text{FE}_n^d + v_{in} + \theta \epsilon_{in} \right]. \quad (\text{OA.B.29})$$

This relation maps the effective-distance structural parameters $(\theta, \kappa_e, \kappa_p)$ into the centroid-distance gravity coefficients, conditional on the linking relationship (OA.B.28). If this relationship held exactly, the coefficients in (OA.B.29) would correspond to simple combinations of those in (OA.B.25) and (OA.B.28). In practice, however, the residual ϵ_{in} enters the gravity equation through $\theta \epsilon_{in}$ and does not average out under PPML, so the mapping is not exact. Nonetheless, this decomposition provides a useful guide for interpreting the changes in point estimates when moving from centroid to effective distance.

We therefore assess equation (OA.B.28) empirically by examining the relationship between effective and centroid distances in the data. For all origin-destination pairs in the gravity sample, Figure (OA.B.4) plots centroid distances against effective distances, computed using equation (OA.B.24) with the estimated parameter $\hat{\theta} = -2.14$. Visual inspection indicates that the two measures are highly correlated. Differences are concentrated at short distances, where centroid distance is more prone to mismeasure bilateral proximity. Table (OA.B.9) confirms these patterns based on the estimation of equation (OA.B.28). We find that $\hat{\eta}_1 = 1.02$, indicating that effective and centroid distances are closely aligned, consistent with the stability of the estimated distance elasticity when moving from centroid to effective distance. By contrast, since $\hat{\theta} < 0$ and $\hat{\eta}_2 > 0$, the coefficient on ethnic borders in equation (OA.B.29) is smaller than the one in equation (OA.B.25): $(\hat{\theta} \hat{\eta}_2 + \hat{\kappa}_e) < \hat{\kappa}_e$, implying a larger estimated coefficient on ethnic borders when using effective distance. Overall, the joint pattern—a stable distance elasticity and a stronger ethnic border effect—is a direct implication of how population weighting reshapes bilateral distances across regions, in line with the predictions of the model.

OA.B.6.2 Concentration of violent events around borders

Depetris-Chauvín and Özak (2024) document that a large fraction of conflict events occurs near historical ethnic boundaries. This observation raises the possibility that, in our analysis, centroid-based distances may overstate relevant interaction distances and that observed patterns are primarily driven by local border dynamics. In this appendix, we first examine the spatial distribution of violent events relative to ethnic borders in our estimation sample. We then re-estimate the gravity equation after excluding events located near borders and, more restrictively, after removing contiguous homeland pairs. The resulting estimates remain stable across specifications, showing that the baseline results capture forces operating beyond purely local border interactions.

Panel (a) of Figure OA.B.5 displays the cumulative distribution of distances between violent events and the nearest Murdock ethnic border in our estimation sample. We find that 50% of all events occur within 16 km of the closest ethnic boundary, indicating that a substantial share of violence takes place near borders. Splitting the sample by the median size of Murdock regions (approximately 14 thousand km²), panel (b) shows that 50% of events occur within 9 km and 20 km of the nearest border for regions below and above the median, respectively. We then reconstruct bilateral

Table OA.B8: Estimates of the frictions to violence: IV approach

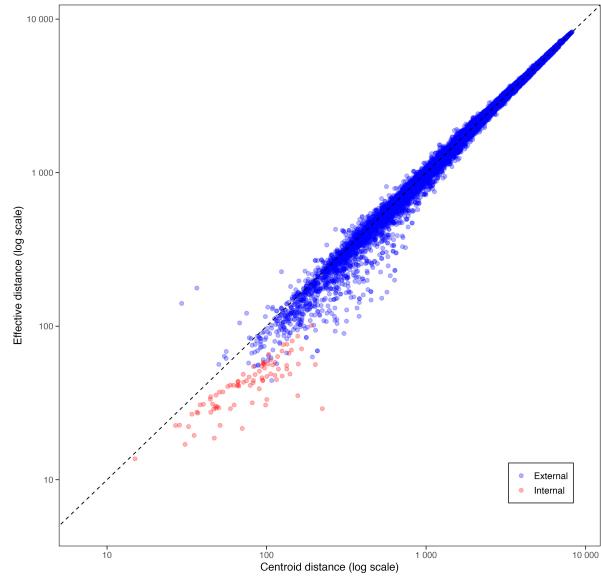
Model	(1) OLS	(2) First stage	(3) Reduced form	(4) Control Function
log distance	-2.13*** (0.121)			-2.14*** (0.054)
Murdock ethnic border	3.11*** (0.265)	-1.04*** (0.099)	4.78*** (0.241)	3.11*** (0.200)
Political border	-1.78*** (0.232)	-0.014* (0.007)	-1.84*** (0.115)	-1.77*** (0.109)
log distance (no pop.)		0.984*** (0.002)	-1.97*** (0.050)	
Resid. 1st-stage				0.113 (0.138)
Observations	54,201	54,201	54,201	54,201
Pseudo R^2	0.542		0.533	0.542

Note: The sample is a cross-section for 1997–2023 with 87 origins and 623 destinations. The dependent variable is the share of violent events in n originating from i , except in column (2). Effective distance is measured using equation (OA.B.24), while population-unweighted distance uses equation (OA.B.26). All specifications include origin and destination fixed effects. Columns (1)–(4) report OLS, first stage, reduced form, and control-function PPML estimates, respectively. Standard errors clustered at the i - n pair level. * 10%, ** 5%, *** 1%.

Table OA.B9: Relation between d_{in}^* and d_{in}

Model	(1)
log centroid distance (d)	1.02*** (0.0004)
Murdock ethnic border	0.518*** (0.006)
Political border	0.032*** (0.001)
Intercept	-0.703*** (0.006)
Observations	54,201
R^2	0.995

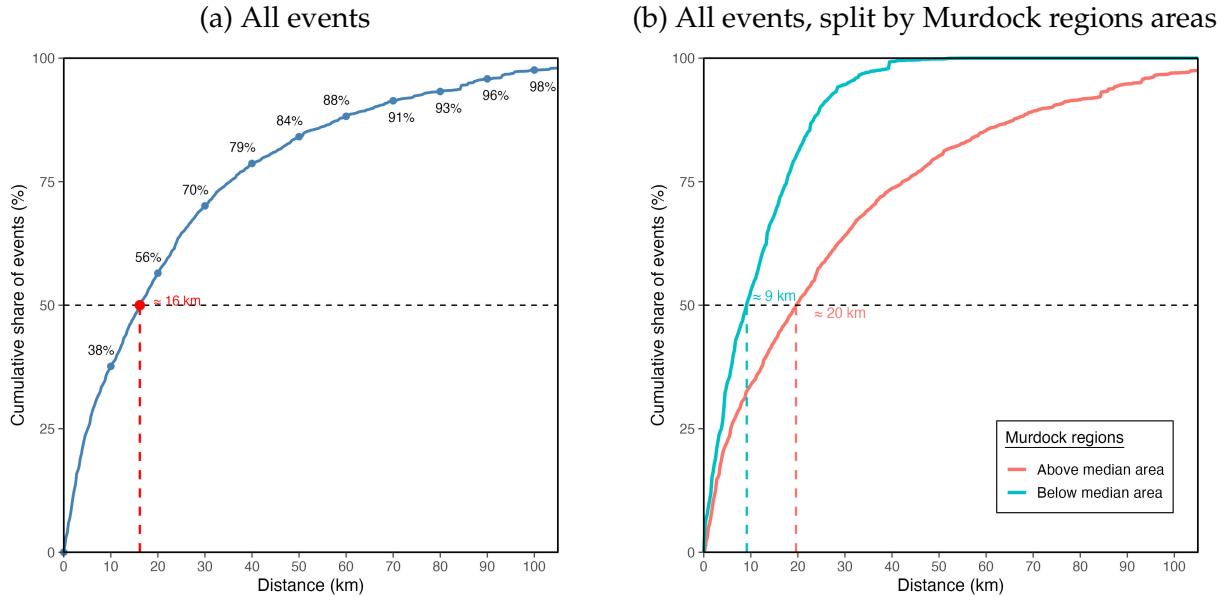
Note: The table reports OLS estimates where the dependent variable is the log of effective distance. The sample consists of a cross-section covering 1997–2023, with 87 origins and 623 destinations, yielding a total of 54,201 observations. Effective distance is computed using equation (OA.B.24) with the estimated parameter $\hat{\theta} = -2.14$. All distances are measured in km. * significant at 10%, ** at 5%, *** at 1%.

Figure OA.B4: Relation between d_{in}^* and d_{in} 

Note: This figure plots effective distance against centroid distance (log scale). Red (blue) dots represent internal (external) distances. Effective distance is computed using equation (OA.B.24) with the estimated parameter $\hat{\theta} = -2.14$. All distances are measured in km.

violence flows after excluding events located within 16 km of the closest ethnic boundary and, in a more stringent specification, within 50 km. We re-estimate the baseline gravity specification on these restricted samples (Columns 1 and 2 of Tables OA.B10). The resulting estimates are close to their baseline counterparts in Table 2. Finally, we exclude all region pairs that share a common ethnic border. The results, reported in Column (3) continue to exhibit a clear and robust gravity pattern of violence.

Figure OA.B5: Cumulative distribution of events by distance to the nearest Murdock border.



Note: Panel (a) reports the cumulative share of events by distance to the nearest Murdock border. Each point indicates the cumulative percentage of events within successive 10 km intervals, and the red dashed line marks the median distance. Panel (b) splits the sample between events occurring in Murdock regions with areas above and below the median (approximately 14 thousand km²). Dashed lines indicate the median distance for each subsample. The sample corresponds to the 78335 violent events obtained at Step 6 of the data construction procedure (Table 1). Distances are expressed in km.

OA.B.6.3 Ethnic dispersion and distance measurement.

In this robustness exercise, we address potential measurement error in our baseline analysis arising from the use of the Murdock map, which abstracts from contemporaneous local ethnic diversity. While the map provides a historically grounded representation of pre-colonial settlement patterns, it does not capture the spatial overlap of ethnic homelands. This may lead to (i) misclassifying local inter-ethnic violence as inter-regional flows, and (ii) overstating bilateral distances, particularly at short ranges. We proceed in three steps. First, we formalize how population dispersion generates measurement error within our framework. Second, we construct a proxy for the spatial distribution of ethnic groups using Afrobarometer data, allowing for overlapping presence on a restricted sample. Third, we re-estimate the gravity equation using this alternative measure.

Step 1: Nature of the problem. The Murdock map, widely used in the literature (e.g. Michalopoulos and Papaioannou, 2013, 2016), does not capture local ethnic diversity, a key determinant of conflict (Esteban and Ray, 2011; Montalvo and Reynal-Querol, 2005; Desmet et al., 2020). It provides

Table OA.B10: Frictions to violence: excluding violence at border

Model	(1)	(2)	(3)
log distance	-2.44*** (0.074)	-2.67*** (0.142)	-2.95*** (0.083)
Murdock ethnic border	2.35*** (0.209)	2.16*** (0.298)	3.66*** (0.224)
Political border	-1.74*** (0.137)	-1.89*** (0.245)	-1.88*** (0.125)
Observations	42,369	13,920	49,042
Pseudo R ²	0.550	0.593	0.553

Note: The dependent variable is the share of violent events in region n originating from region i observed over the 1997-2023 period. Column (1) is estimated on a sample comprising 87 origins attacking a total of 487 destinations, Column (2) on a sample of 80 origins attacking a total of 174 destinations and Column (3) on 87 origins attacking a total of 569 destinations. All columns are PPML estimations with i and n fixed effects and standard errors clustered at the i - n pair level. * significant at 10%, ** significant at 5%, *** significant at 1%.

a *historically grounded* and *non-overlapping* representation of pre-colonial settlement patterns. Deviations from this historical benchmark arise from subsequent migration and urbanization (Alesina et al., 2016), which have led to increased spatial dispersion and local overlap of ethnic groups. Violence itself is also likely to have been a key driver of population movements in Africa, implying that the current spatial distribution of ethnic groups may be endogenous to conflict patterns. In this sense, the Murdock map should be viewed as a proxy for ethnic geography. Nonetheless, recent evidence shows that it contains informative variation that remains predictive in contemporary data (Bahrami-Rad et al., 2021b).

This limitation has direct implications for the empirical specification. In the gravity specification of violence, while origin and destination fixed effects absorb unobserved heterogeneity at the monadic (regional) level, bilateral frictions may nevertheless be measured with error.

Baseline procedure: A central element of our construction of flows of violence is the assignment of each observed armed group g to an ethnic group e , as detailed in Section 3.2. Aggregating across armed groups originating from the same e , formula (20) (omitting non-essential elements) yields the flow of violence perpetrated by fighters originating from e in destination n :

$$\text{violence}_{en} = \sum_{g \in e} \# \text{events}_{gn}, \quad (\text{OA.B.30})$$

where geo-coordinates allow each event to be assigned to a destination region n .

The next step in our baseline procedure consists of associating a geographical origin and therefore a distance with each violence flow. To this end, we map each ethnic group e to a *unique* origin region $i = M(e)$ using the Murdock mapping between ethnicities and non-overlapping regions. We then define the centroid distance $d(M(e), n)$ as the great-circle distance between the centroid of $M(e)$ and n . Finally, the empirical gravity equation consists essentially of regressing violence_{en} on $d(M(e), n)$. The one-to-one mapping $i = M(e)$ allows us to use i interchangeably with e in all baseline equations.

Expected distance under spatial dispersion: When groups are spatially dispersed and locally overlap, our theoretical framework instead motivates constructing the expected distance between fight-

ers from e and destination n :

$$\mathbb{E}[d(e, n)] = \sum_i \text{share}(e, i) d(i, n), \quad (\text{OA.B.31})$$

where $\text{share}(e, i)$ denotes the share of group e located in region i .

As a consequence, $d(M(e), n)$, the measure of distance used in our baseline analysis, is only a proxy for the expected distance $\mathbb{E}[d(e, n)]$. In practice, our one-to-one mapping amounts to replace $\text{share}(e, i)$ with a binary variable equal to one if $i = M(e)$ and zero otherwise. We show below that this approximation leads to measurement error mostly at short distances and then assess how it affects both the estimated distance elasticity and the ethnic-border coefficient.

Step 2: Measuring the spatial distribution of ethnic groups. Capturing the co-presence of ethnic groups beyond their historical homelands would require exhaustive information—either detailed historical data on intra- and inter-country migration across the continent, or a comprehensive, high-resolution snapshot of current ethnic composition for all African countries. To our knowledge, such data do not exist.

We therefore construct a proxy using Afrobarometer survey data^{oa.34}, which provide granular, individual-level information on respondents' place of residence and self-reported ethnic affiliation. Specifically, we measure share of e living in i as $\text{share}(e, i) = \frac{N_{e,i}}{N_e}$, where $N_{e,i}$ denotes the number of Afrobarometer respondents identifying as e and residing in region i , and $N_e = \sum_i N_{e,i}$. Unlike the baseline approach, this allows ethnic groups to be spatially distributed across multiple regions rather than being restricted to a single homeland.

We combine Afrobarometer rounds 3 to 8, covering 39 Sub-Saharan African countries over the period 2005–2022. The raw data comprise 252515 individuals. The data include geo-referenced information on respondents' location and survey questions on self-reported ethnic identity.^{oa.35} Self-reported identities are matched to Murdock ethnic groups using the LEDA database (Müller-Crepon et al., 2022).^{oa.36} The final sample comprises 171150 individuals.^{oa.37}

Given data limitations, the sample is not exhaustive and missing origin-destination pairs may reflect either the absence of ethnic linkages or incomplete coverage. We therefore restrict the analysis to ethnic groups whose Murdock homeland is observed in the Afrobarometer data, ensuring that each allocation is anchored to an observed homeland. This restriction reduces the sample to 437 ethnic groups e and 548 regions i . We then construct a proxy for the expected distance $\mathbb{E}[d(e, n)]$ using the following formula:

$$\check{d}(e, n) = \sum_i \text{share}(e, i) d(i, n) = \sum_i \frac{N_{e,i}}{N_e} d(i, n), \quad (\text{OA.B.32})$$

which we refer to as “ethnicity-weighted distance”.

^{oa.34}<https://www.afrobarometer.org/data/>

^{oa.35} Respondents report their ethnic affiliation through standardized survey questions (e.g., “What is your ethnic community, cultural group, or tribe?”). Importantly, respondents answer this question without being prompted with a pre-defined list. The response is recorded only if it can be matched to the pre-established Afrobarometer coding categories; otherwise, it is left unclassified.

^{oa.36} More precisely, we use the mapping between Afrobarometer reported ethnicities and Murdock ethnic groups provided by the LEDA database, restricting attention to matches established at the most disaggregated level, namely dialects. When the mapping between an Afrobarometer group and a Murdock group is unambiguous, we retain it. When multiple Murdock groups can be associated with a given Afrobarometer group, we assign the one spatially closest to the reported location of the respondent.

^{oa.37} The reduction reflects missing questions in some country-waves, non-response, unmatched categories, coding inconsistencies, and GPS errors.

Step 3: Persistence of ethnic homelands and implications for distance measurement. We begin by assessing how well the Murdock historical homeland predicts the current spatial distribution of ethnic groups. We estimate the following specification, which is analogous to a gravity equation of long-run migration:

$$\text{share}(e, i) = \exp\{\alpha + \beta_1 \text{Homeland}(e, i) + \beta_2 \log d(e, i) + \text{FE}(e) + \text{FE}(i) + \varepsilon(e, i)\},$$

where $\text{Homeland}(e, i)$ is an indicator coding for the condition $M(e) = i$, which is equal to one if region i corresponds to the Murdock homeland of ethnic group e , and zero otherwise, and $d(e, i)$ denotes the centroid distance between region i and the Murdock homeland of group e .^{oa.38}

Table OA.B11: Ethnic Shares and Centroid Distance

Model	(1)
log centroid distance	-1.15*** (0.064)
Homeland	0.728*** (0.095)
Observations	4,255
Pseudo R ²	0.312

Notes: The dependent variable is the share of ethnic group e residing in region i of the Murdock map. The sample consists of 4255 pairs of $(e \times i)$ with strictly positive shares. *Homeland* is an indicator equal to one if i corresponds to the historical homeland $M(e)$ assigned to ethnic group e by the Murdock map, and zero otherwise. *Log centroid distance* is the centroid distance between region i and the historical homeland of group e . Estimated with PPML including two sets of fixed effects, one for e and another for i . Standard errors are clustered at the e and i level. * significant at 10%, ** significant at 5%, *** significant at 1%.

The results point to strong spatial persistence in ethnic settlement patterns (Table OA.B11). Ethnic shares are significantly higher within historical homelands: the estimates imply an increase of 107.2%, corresponding to roughly a doubling relative to non-homeland pairs, or 11 percentage points at sample mean. Distance also plays a central role. A doubling of the centroid distance reduces the ethnic share by about 55%, indicating a pronounced spatial decay away from the homeland. This pattern is consistent with a gravity-type structure of long-run migration, where deviations from the historical allocation are concentrated at short distances.

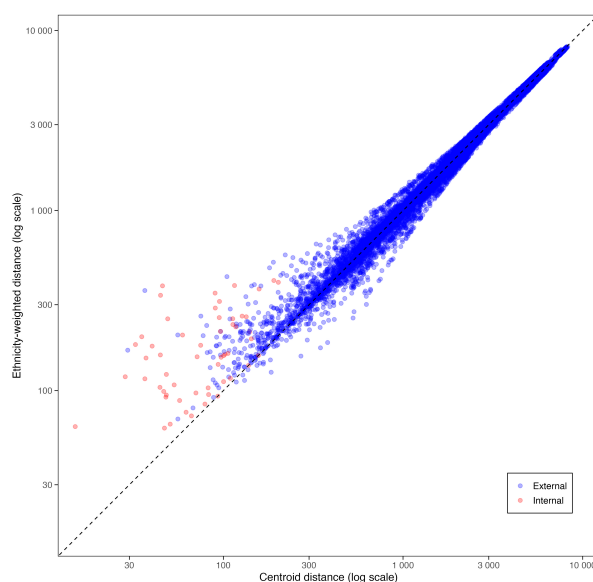
Next, we provide two pieces of evidence on the relationship between our baseline centroid distance and the ethnicity-weighted distance. Table OA.B12 reports estimates from a regression of $\log \check{d}(e, n)$ on $\log d(M(e), n)$ on the subsample relevant for the gravity of violence estimation in the next step. Figure OA.B6 complements this analysis with a visual representation of their relative spatial dispersion. The results show that centroid and ethnicity-weighted distances are nearly proportional: the estimated elasticity is 0.98, and the fit is high ($R^2 = 0.989$). The figure confirms this result, with observations closely aligned along the 45-degree line. Residual differences are limited and

^{oa.38}We run this regression with PPML on positive shares only, since the zeroes could be due to under-representation in the Afrobarometer of some e in some i rather than truly zero migrant.

Table OA.B12: $\check{d}(e, n)$ vs $d(M(e), n)$: Regression

Model	(1)
Intercept	0.162*** (0.040)
log centroid distance	0.980*** (0.005)
Homeland	0.697*** (0.065)
Observations	22,825
R ²	0.989

Note: The sample consists of a cross-section of 55×415 pairs of ethnic groups (e) and regions (n) observed over 1997–2023. The dependent variable is the ethnicity-weighted distance $\check{d}(e, n)$. The centroid distance is $d(M(e), n)$, the distance between the historical homeland $M(e)$ of ethnic group e and region n . *Homeland* is an indicator equal to one if region n corresponds to the historical homeland $M(e)$ assigned to ethnic group e by the Murdock map, and zero otherwise. OLS estimates are reported. All distances are measured in km. * significant at 10%, ** significant at 5%, *** significant at 1%.

Figure OA.B6: $\check{d}(e, n)$ vs $d(M(e), n)$: Visualization

Note: The sample consists of a cross-section of 55×415 pairs of ethnic groups (e) and regions (n) observed over 1997–2023. The figure plots the ethnicity-weighted distance $\check{d}(e, n)$ against the centroid distance $d(M(e), n)$, with both axes in log-scale. Red (blue) dots represent internal (external) pairs for which $e = n$ ($e \neq n$). The solid black line is the 45-degree line. All distances are measured in km.

arise primarily at short distances, where ethnic dispersion is more pronounced. Taken together, these results indicate that centroid distance provides a close approximation to ethnicity-weighted distance, with any measurement error being small and concentrated at short spatial scales.

Step 4: Gravity of violence with ethnicity-weighted distance. Finally, we re-estimate the baseline gravity equation of violence (col. 3, Table 2) by replacing centroid distance with ethnicity-weighted distance.^{oa.39} Due to the aforementioned limitations of the Afrobarometer data, the sample is reduced to 55×420 ethnic group–region pairs observed over 1997–2023. Additionally, the PPML gravity estimator excludes five regions that are singletons and therefore do not contribute to identification. The resulting estimation sample consists of a cross-section of 55 origins attacking 415 destinations.

Table OA.B13 reports the estimation results. Column (1) replicates the baseline specification (with centroid distance) on the reduced sample, while Column (2) replaces it with ethnicity-weighted distance. The estimated distance elasticity becomes slightly larger in absolute value relative to Column (1), indicating that the overall spatial gradient of violence is largely unchanged. By contrast, the coefficient on Murdock ethnic border_{*in*} declines relative to the baseline. This pattern reflects how spatial dispersion reshapes effective distances between groups. As shown in Figure OA.B6, ethnicity-weighted distances are systematically smaller than centroid distances, particularly at short ranges, as populations are not concentrated at centroids but distributed across nearby locations. As a result, interactions that appear distant under centroid distance are reclassified as shorter-distance interactions once the spatial distribution of ethnic groups is taken into account. This mechanically steepens the estimated distance gradient and attenuates the ethnic-border coefficient. A natural concern is that ethnic shares may be endogenous to violence, for instance through conflict-induced displacement. To address this issue, we instrument ethnicity-weighted distance with centroid distance using a control-function approach. The results remain unchanged (col. 3, Table OA.B13). Taken together, these results indicate that measurement error in distances primarily affects the decomposition between intra- and inter-regional violence, while leaving the overall spatial decay of violence largely unchanged.

OA.B.7 LLM-assisted identification of violence types

This appendix describes how we use a classification procedure assisted by a large language model (LLM) to exploit the descriptive narratives recorded by ACLED, identify the motives underlying violent events, and test empirically whether the gravity structure is observed across distinct motive categories. The exercise is motivated by the broader theoretical framework. In the baseline setup, violence takes the form of raiding, with fighters appropriating unsecured resources across space. As shown in Appendix D.2, the framework can be extended to accommodate other forms of appropriation, namely territorial control and political control, as well as grievance-driven violence. These extensions share a common theoretical implication: the gravity structure does not hinge on violence being narrowly directed toward looting output. It arises from the spatial allocation of violence across destinations under bilateral frictions and origin-specific opportunity costs.

We proceed in two steps. First, we apply an LLM-assisted classification pipeline to the ACLED narratives to identify events related to resource appropriation, broadly defined to include raiding,

^{oa.39}For each origin i and destination n , we construct the ethnicity-weighted distance between n and the ethnic group e whose historical homeland is i . Formally, $M(e)$ denotes the Murdock homeland of ethnic group e , so $M^{-1}(i)$ denotes the ethnic group assigned to origin homeland i . We compute $\tilde{d}(e, n)$ using equation (OA.B.32). The empirical gravity equation then regresses $\frac{\text{violence}_{in}}{\text{violence}_n}$ on $\log \tilde{d}(M^{-1}(i), n)$, augmented with the two additional bilateral frictions (Murdock ethnic border and political border) measured at the $i \times n$ level.

Table OA.B13: Estimates of the frictions to violence using different measures of distance

Model	(1)	(2)	(3)
log centroid distance	-2.33*** (0.174)		
Murdock ethnic border	2.68*** (0.306)	1.31*** (0.234)	1.25*** (0.236)
Political border	-2.38*** (0.277)	-2.41*** (0.254)	-2.36*** (0.266)
log ethnicity-weighted distance		-2.58*** (0.215)	-2.53*** (0.200)
First-stage residuals			1.33*** (0.415)
Observations	22,825	22,825	22,825
Pseudo R ²	0.584	0.582	0.586

The sample consists of a cross-section of 55 origins attacking 415 destinations over 1997–2023. The dependent variable is the share of violent events in destination n originating from origin i . *Log centroid distance* corresponds to the great-circle distance between the centroids of n and i . The *log ethnicity-weighted distance* corresponds to the distance, weighted by ethnic shares, between the destination n and the ethnic group e whose historical homeland is i . *First-stage residuals* correspond to the residuals from a first-stage regression of *log ethnicity-weighted distance* on *log centroid distance*. * significant at 10%, ** significant at 5%, *** significant at 1%.

territorial control, and political control. Because these motives are not mutually exclusive, an event may be assigned to several categories. Events for which a motive can be inferred but which do not fall into any of these three appropriation categories are grouped into a residual category, “Other motives”. This category may include ethnic, religious, or identity-based grievances, but it should not be interpreted as a direct measure of such motives. Second, we estimate the gravity equation separately across these categories.

Classification procedure. ACLED provides a short narrative for each recorded event describing its main features. We use these narratives to identify violent events related to appropriation—hereafter resource appropriation—using a LLM implemented as a multi-agent pipeline.^{oa.40} After removing duplicated descriptions attached to multiple events, the sample contains 71871 unique narratives.^{oa.41} Not all narratives contain enough information to infer a motive, and informative narratives may map to several, non-exclusive categories. We therefore treat motive identification as a sequence of classification tasks. Applying a single general-purpose prompt to perform all tasks jointly on a large text corpus increases the risk of classification error (Wei et al., 2022; Ji et al., 2023). We instead implement a sequential multi-agent architecture, in which each agent performs a well-defined task along the classification pipeline, following recent work on LLM-based pipelines (Guo et al., 2024; Tran et al., 2025; Fernández-Fuertes, 2025). Figure OA.B7 summarizes the three-stage procedure, detailed below. The resulting labels should not be interpreted as ground truth: they

^{oa.40}Classification is performed using the OpenAI language model GPT-4o mini (version gpt-4o-mini-2024-07-18), with temperature set to zero.

^{oa.41}There are fewer narratives than events in the estimation sample (78335 events at Step 6 in Table 1) because ACLED sometimes assigns identical or generic descriptions to several observations.

are text-based proxies for event motives, generated by a deterministic pre-specified classification pipeline.

Step 1: Usability screening of narratives.

The first agent in the pipeline processes the full set of ACLED event narratives (hereafter, notes) and determines whether each note is usable for analysis. A note is classified as non-usable when its content does not describe a conflict-related event. This includes notes that consist solely of external references or links, notes that refer to other data sources (e.g., “See original data”), as well as sentences that are unrelated to politics or conflict. Notes satisfying these conditions are excluded from subsequent analysis. This initial filtering stage restricts the sample to interpretable narratives, ensuring that subsequent classification is conducted only where motive inference is feasible. Table OA.B14 reports illustrative examples of excluded notes, which typically contain only geographic information (e.g., “town is called Gbalamuya”), vague statements unrelated to a violent act (e.g., “RRR left the city”), or placeholders and source-related content (e.g., “Comes from OLA source”). In total, only 29 unique narratives are removed at this stage, indicating the high descriptive quality of ACLED narratives in our sample.

Step 2: Motive inferability screening.

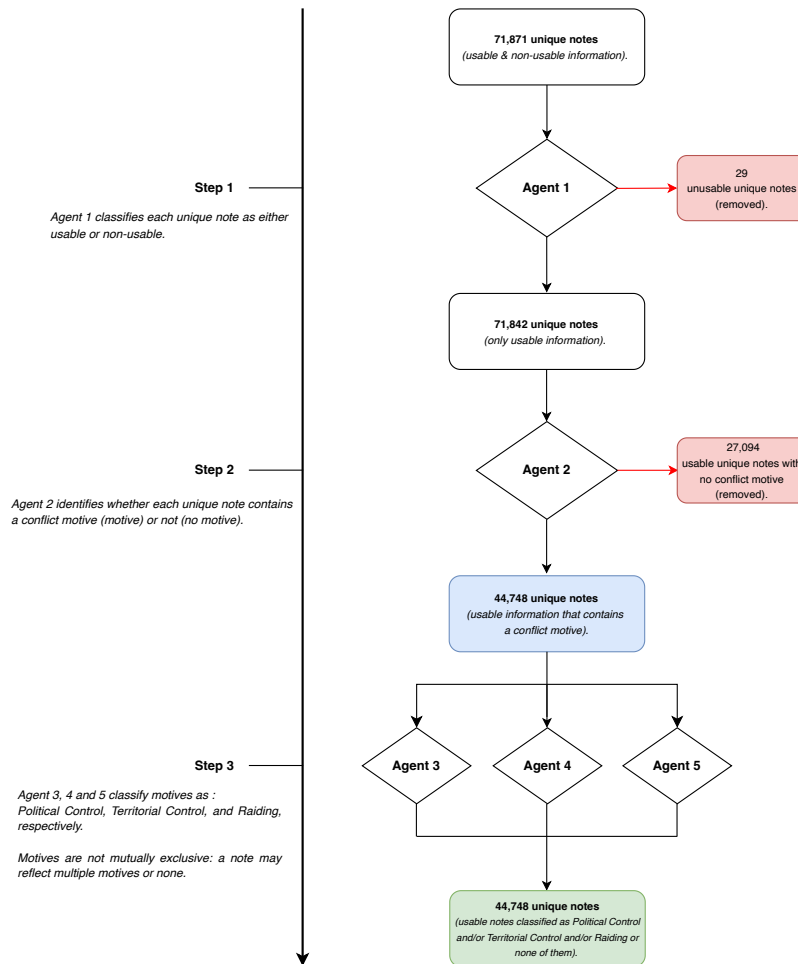
The second agent in the pipeline operates exclusively on the sample retained after Step 1 and assesses whether a motive can be inferred from the information contained in the note. Notes whose descriptions lack sufficient contextual detail to infer intent or purpose are classified as “No motive,” indicating that the available text does not support motive attribution. In total, 27094 notes are classified as such. These notes typically describe violent events using general factual information without providing insight into the underlying motivation. Examples are reported in Table OA.B14. Most notes categorized as “No motive” focus solely on the actors involved (e.g., “1 civilian was killed during clashes between FRPI and FARDC in and around Gety. Another was injured.”), or the location of the incident (e.g., “22 October. Military forces clashed with Ambazonian Separatists in Bambui”). This second-stage screening restricts the sample to narratives for which motive classification is feasible, ensuring that subsequent agents operate only on notes that contain sufficient information to infer a motive.

Step 3: Motive classification.

The third stage is applied to notes retained after Steps 1 and 2, i.e., narratives that are both interpretable and contain sufficient information to infer a conflict-related motive (44748 notes). We deploy three classification agents (Agents 3–5) that identify political control, territorial control, and raiding, respectively. The choice of these categories follows directly from the extended theoretical framework in Appendix D.2 and is consistent with the conflict literature. Accordingly, we distinguish three forms of appropriation that differ in the degree of control they require: raiding captures one-off extraction without sustained control; territorial control allows repeated extraction through control of space; and political control extends this logic to taxation and coercion (Sánchez de la Sierra, 2020).

Operationally, each agent independently evaluates whether a given note reflects its assigned motive. Because these categories are not mutually exclusive, a note may be classified under one, two, or all three dimensions. Notes that are classified as involving a conflict-related motive but are not assigned to any of the three appropriation categories are grouped into a residual category, “Other motives”, which captures non-appropriation or residual motives; illustrative examples include ethnic, religious, or identity-based grievances. Examples are reported in Tables OA.B15 and OA.B16. The following prompts are used:

Figure OA.B7: Multi-Agent Architecture for ACLED Note Classification



Note: This figure illustrates the sequential multi-agent LLM pipeline used to process ACLED event notes. Agents are organized in a top-down sequence. Agent 1 filters out unusable notes, and Agent 2 assesses whether the narrative contains sufficient information to infer a motive. Notes that pass both stages are then processed by three specialized classification agents, which identify the presence of Political Control (Agent 3), Territorial Control (Agent 4), and Raiding motives (Agent 5). These categories are not mutually exclusive. This staged architecture restricts classification to informative narratives, reduces computational costs, and limits classification errors.

Table OA.B14: Examples of ACLED Event Notes Removed in Step 1 and Step 2

Information type	Description
Step 1: Unusable info.	
Location	<i>"town is called Gbalamuya", "13km W of Malanje", "Hills just outside Bujumbura"</i>
Placeholders	<i>"See original data", "Comes from OLA source", "Date is date report published"</i>
Generic	<i>"RRR left the city", "stationed"</i>
Step 2: No motive info.	
Only actors and location	<i>"3 civilians were wounded in mortar attacks by the FNL";</i> <i>- 25 October. Boko Haram killed two people in Amchide.;</i> <i>- "22 October. Military forces clashed with Ambazonian Separatists in Bambui";</i> <i>- "05 January. ADF elements attacked Nyaleke, killing 5 civilians." ;</i> <i>On 20 September 2019, in Nyaleke, FARDC have clashed with ADF. No further details available..</i>

Note: The table reports illustrative ACLED event notes by classification category. "Unusable info." and "No motive info." refer to notes excluded at Steps 1 and 2, respectively. Examples are illustrative and not exhaustive.

Prompt for "raiding": *Violence primarily aimed at extracting, seizing or gaining control of local resources such as but not limited to food, livestock, cash, goods, land, vehicles, arms, ammunitions or other private property from civilians or rival groups, including looting, pillaging, raiding, extortion.*

Prompt for "territorial control": *Violence primarily aimed to capture, hold, defend, or expand geographic areas or strategic locations (villages, towns, road-blockage, checkpoints, supply routes, borders) from civilians, rival groups or governments.*

Prompt for "political control": *Violence primary perpetrated to gain control of political authority, to levy taxes, to attack, destabilize or replace existing authority, to establish or maintain dominance within a society or a government.*

Empirical results. Among the 44748 retained notes, 72% are classified as involving resource appropriation. Mapping these classified notes back to ACLED events, resource-appropriation motives account for 73% of events with an inferable motive. In terms of specific motives, 63% of notes are associated with at least a political control motive, while 26% are linked to at least a territorial control or raiding motive. The greater prevalence of political control reflects both its broader definition—encompassing several forms of political coercion—and its frequent overlap with other motives. More than half of the notes classified as involving political control are also associated with either territorial control or raiding. Although a comprehensive decomposition of the residual category "Other motives" is beyond the scope of the paper, illustrative examples appear linked to ethnic grievances or religious tensions; these examples should be read as descriptive, not as a classification of the residual category as a whole (see Table OA.B16).

We next examine how this classification maps into the gravity estimation sample. Restricting attention to events for which a conflict motive can be identified yields 48541 out of 78335 distinct events (62%). This sample consists of 86 origins and 580 destinations. Further restricting

Table OA.B15: Examples of ACLED Event Notes Categorized as “Resource Appropriation” in Step

3

Information type	Description
Raiding	- July. Al Shabaab militants looted livestock from the local population in Tayeeglow. - A rebel force, aboard about 30 to 40 armed vehicles, on Tuesday attacked the citizens of the area and looted their properties,’ the paper quoted Ali Kairan, commissioner of Habila locality, as saying. The Government of Sudan retaliated in reaction to this which caused the battle in the same area between rebels and government troops - 02 September. Boko Haram militants abducted a woman and looted from civilians in Zelevet, Mokolo.
Territorial cont.	- SPLA rebels captured a strategic crossroad at the town of Lafon - 50 soldiers were reportedly killed as well as 7 rebels. - Unita has taken by force 1/4 of the areas it handed over to the state in early 1998. The capture of Luau opens diamond supply lines to Zambia. On government strategy, Dos Santos is most concerned with depriving Unita of their rear bases in Congo-K and B. - ADLF rebels overpower Zaire armed forces causing them to retreat from Kwango river bridge a strategically important bridge on the way to Kinshasa.
Political cont.	- Looting: On 27 December 2022, presumed JNIM militants taxed harvest in the village of Sakati (Say, Tillaberi). - After gaining control of Aw Diinle on 15/03, al Shabaab regains control of the town after a offensive and clash. Seven pro-government forces killed. - On 26 October 2021, Al Shabaab militants attacked AMISOM UPDF and government security forces (SNA) in the Barawe Airstrip and Biyamalow village neighborhoods in Baraaawe town (Baraaawe, Lower Shabelle). The militants claimed killing several soldiers in Biyamalow. Unknown number of fatalities coded as 3.

Note: The table reports illustrative ACLED event notes by classification category “Political control”, “Territorial control” and “Raiding”. Examples are illustrative and not exhaustive.

Table OA.B16: Examples of ACLED Event Notes Categorized as “Other Motives” in Step 3

Information type	Description
Ethnic grievances	- “On 20 June 2020, a Ngumino ethnic militia clashed with Mayi-Mayi Ebu Ela rebels in Kalingi (Mwenga, Sud-Kivu) over land conflicts and cattle herding. Two Ngumino and 1 Ebu Ela militiamen died in the clash.”; - ‘Six Banyamulenge [ethnic Tutsis living in eastern Democratic Republic of Congo] were killed and four others wounded in an ambush perpetrated by Mayi Mayi [DR-Congo tribal warriors] and FDD [Burundian Hutu Forces for the Defence of Democracy] ‘rebel forces’.”; - “On 6 August 2021, SPLM-IO forces killed a Zande civilian in Tambura town (Tambura county, Western Equatoria state), amid heightened political, military, and ethnic tensions in the area.”
Religious conflicts	- “Al Shabaab forces reportedly launched an attack on Ma-reerey village of Afgoi district with the reported intent of desecrating a religious Sheikh’s tomb (Ahlu-sunna wal Jamaa). In a heavy exchange of fire two persons were killed.”; - “Property destruction: Fighters from the Islamist MU-JAO group destroyed a religious building in Douentza arguing that it was non-Islamic.”; - “At least 49 dead (including a priest and 38 people who had been abducted), and dozens wounded when armed men entered the Church of Our Lady of Fatima as people were gathered inside for a religious ceremony. They opened fire and threw grenades (...).”

Note: The table reports illustrative ACLED event notes by classification category “Other motives”, which includes events whose motives fall outside the three appropriation categories. Examples are illustrative and not exhaustive.

to resource-appropriation events leaves 35603 events, with 86 origins and 555 destinations.^{oa.42} Table OA.B17 shows that the estimated coefficients are close to the baseline. In particular, the distance elasticity is virtually unchanged, while the coefficients on ethnic border decline slightly. The estimated coefficients on political border are unaffected. We also estimate the model on the residual “Other motives” sample (Table OA.B18). If the estimated spatial gradient were driven only by events classified as resource appropriation, one would expect a substantially weaker gradient in this residual subsample. This is not what we find. The distance elasticity remains close to the baseline, and the coefficients on borders are of comparable magnitude. We interpret this pattern as evidence that the main gravity estimates are not mechanically driven by the appropriation-labeled subset alone. It is consistent with the theoretical extensions developed in Appendix D.2.

Table OA.B17: Estimates of the frictions to violence (“Resource appropriation” sample)

Model	(1)	(2)	(3)	(4)
log distance	-2.68*** (0.050)	-2.91*** (0.057)	-2.44*** (0.065)	-2.49*** (0.089)
Murdock ethnic border		2.27*** (0.188)	2.36*** (0.182)	
Political border			-1.72*** (0.120)	
Murdock ethnic border: contiguity				1.96*** (0.193)
Murdock ethnic border: no contiguity				2.55*** (0.222)
Political border: contiguity				-1.24*** (0.105)
Political border: no contiguity				-2.99*** (0.202)
Observations	47,730	47,730	47,730	47,730
Pseudo R ²	0.525	0.533	0.554	0.559

Note: The dependent variable is the share of events in n originating from i . Cross-section over 1997–2023. Estimated with PPML with i and n fixed effects. Columns (1)–(4) are estimated on a sample of 86 origins attacking a total of 555 destinations, including only events that are classified as “resource appropriation”. * significant at 10%, ** significant at 5%, and *** significant at 1%. Standard errors clustered at the origin-dest pair level.

Overall, these results suggest that the estimated spatial gradient is not confined to events classified as appropriation-related. Because motive labels are inferred from ACLED narratives and the “Other motives” category is residual, we interpret this exercise as a robustness partition rather than as direct evidence on the full set of non-economic motives for violence.

OA.B.8 Event aggregation, geo-precision, and destination definition

In this appendix, we provide additional details on the aggregation of geocoded events into Murdock destination regions. We then consider alternative aggregation rules, including destination definitions based on finer administrative units, and re-estimate the gravity equation accordingly. We show that the results remain quantitatively stable across these alternative specifications.

^{oa.42}The only origin excluded is “KRAN”, for which the associated ACLED event notes do not contain sufficient information to assign a motive.

Table OA.B18: Estimates of the frictions to violence (“Other motives” sample)

Model	(1)	(2)	(3)	(4)
log distance	-2.66*** (0.056)	-2.93*** (0.068)	-2.42*** (0.079)	-2.35*** (0.106)
Murdock ethnic border		2.34*** (0.223)	2.36*** (0.216)	
Political border			-1.72*** (0.149)	
Murdock ethnic border: contiguity				1.86*** (0.229)
Murdock ethnic border: no contiguity				2.37*** (0.273)
Political border: contiguity				-1.28*** (0.129)
Political border: no contiguity				-3.40*** (0.283)
Observations	38,760	38,760	38,760	38,760
Pseudo R ²	0.530	0.539	0.558	0.567

Note: The dependent variable is the share of events in n originating from i . Cross-section over 1997–2023. Estimated with PPML with i and n fixed effects. Columns (1)–(4) are estimated on a sample of 85 origins attacking a total of 456 destinations, including only events that are classified as “Other motives”. * significant at 10%, ** significant at 5%, and *** significant at 1%. Standard errors clustered at the origin–dest pair level.

In Step 1 of our data-construction procedure, we apply a *geographic filter* that restricts the baseline sample to violent events with the most precise ACLED geo-precision code, level 1 (out of three possible precision levels). This restriction removes around-one third of all events (Table 1) and reflects a deliberate trade-off: we prioritize measurement precision over coverage in order to minimize destination misclassification. Although estimation is ultimately conducted at the regional level, precise event coordinates remain essential, as lower-precision ACLED events may correspond to broad or ambiguous locations—such as border areas, forests, or provincial capitals—thereby increasing the risk of incorrectly assigning destinations (Table OA.B19). As a robustness exercise, we progressively relax this filter by re-estimating the baseline gravity equation of violence (col. 3, Table 2) including events with geo-precision levels 1–2 and then 1–3. These alternative specifications increase violence coverage while testing whether broader inclusion alters the point estimates or reduces statistical precision. We find that the estimated gravity pattern remains quantitatively unchanged across specifications (Table OA.B20, col. 1 and 2).

We now assess the implications of the loss of spatial information induced by aggregation at the level of Murdock regions. To do so, we reconstruct bilateral flows of violence while retaining origins as Murdock homelands, which proxy for actors’ recruitment bases, but redefine destinations using Admin-1 and Admin-2 administrative regions.^{oa.43} Admin-1 regions (roughly states or provinces) provide spatial granularity broadly comparable to Murdock homelands, while Admin-2 regions (districts) offer a finer partition, albeit with incomplete coverage, reducing the sample by approximately 3.4%. Each ACLED event is reassigned to its corresponding administrative destination. Among the 771 Admin-1 regions and 6188 Admin-2 regions in the data, 638 and 2967, respectively, record at least one violent event.

^{oa.43} Administrative boundaries follow the GADM database (<https://gadm.org/index.html>).

Using these alternative destination definitions, we re-estimate the baseline gravity specification (col. 3 of Table 2). Results are reported in Table OA.B20, Columns (3) and (4). The estimated distance elasticity remains stable across specifications. In the baseline, doubling bilateral distance reduces violence by 81%; under Admin-1 and Admin-2 definitions, the corresponding declines are 77% and 73%, respectively. By contrast, the estimated ethnic-border effect becomes more attenuated, while the political-border effect strengthens substantially under finer destination definitions. Overall, these patterns indicate that the core gravity structure is not an artifact of destination aggregation at the Murdock level. Rather, the principal spatial decay of violence remains highly robust, while finer geographic partitions primarily affect the relative decomposition of bilateral frictions.

Table OA.B19: Geo-precision codes for ACLED events

Geo-precision	Description
1	Event located in a specific place within a town/city (e.g., a neighborhood or market).
2	Event known to have occurred in a named town or city, but the specific site is unknown. Geocoded to the town/city centroid.
3	Only a larger region is reported. Geocoded to the closest natural location mentioned (e.g., “border area”, “forest”, “sea”); if none, use the provincial capital.

Source: Definitions of geo-precision codes are from [ACLED \(2023\)](#).

Table OA.B20: Estimates of the frictions to violence: robustness to geo-precision and destination units

Model	(1)	(2)	(3)	(4)
Sample	Geo-precision 1& 2	1 to 3	Destination definition Admin-1	Admin-2
log distance	-2.49*** (0.060)	-2.50*** (0.060)	-2.09*** (0.059)	-1.90*** (0.037)
Murdock ethnic border	2.50*** (0.168)	2.50*** (0.169)	1.73*** (0.174)	1.50*** (0.093)
Political border	-1.58*** (0.109)	-1.57*** (0.109)	-2.46*** (0.136)	-3.07*** (0.105)
Observations	56,115	56,202	55,506	252,195
Pseudo R ²	0.550	0.550	0.597	0.622

Note: The dependent variable is the share of events in region n originating from region i . Cross-section over 1997–2023. All specifications are estimated using PPML with origin (i) and destination (n) fixed effects. Column (1) is estimated on the sample with geo-precision levels 1–2, comprising 87 origins and 645 destinations. Column (2) extends the sample to geo-precision levels 1–3, with 87 origins and 646 destinations. Column (3) uses Murdock regions as origins and Admin-1 regions as destinations, with 87 origins and 638 destinations. Column (4) uses Murdock regions as origins and Admin-2 regions as destinations, with 85 origins and 2967 destinations. Standard errors are clustered at the origin–destination pair level. * significant at 10%, ** significant at 5%, and *** significant at 1%.

OA.B.9 Panel regressions

The baseline estimates for the gravity of violence (Table 2) collapse the time dimension by aggregating events over 1997–2023 to estimate cross-sectional regressions. This raises the concern, discussed in the main text, that temporal diffusion of violence (“domino effect”) could be misinterpreted as spatial dependence.

To address this concern, we conduct two robustness exercises that retain the time dimension of the data. First, we reconstruct bilateral flows at the yearly level from 1997 to 2023 and estimate a pooled yearly version of the gravity equation with origin-by-year and destination-by-year fixed effects. This specification thus flexibly controls for time-varying local shocks at both origin and destination. The results, displayed in Table OA.B21, are quantitatively close to the baseline cross-sectional estimates. Second, we estimate the gravity equation separately for each year. Figure OA.B8 shows that the estimated yearly distance elasticities are stable over time and, in most years, not statistically different from the baseline cross-sectional estimate (from the main text) at conventional significance levels. Differences in precision over time reflect variation in sample size across years. Similar patterns hold for the coefficients on the other frictions (not reported, but available upon request).

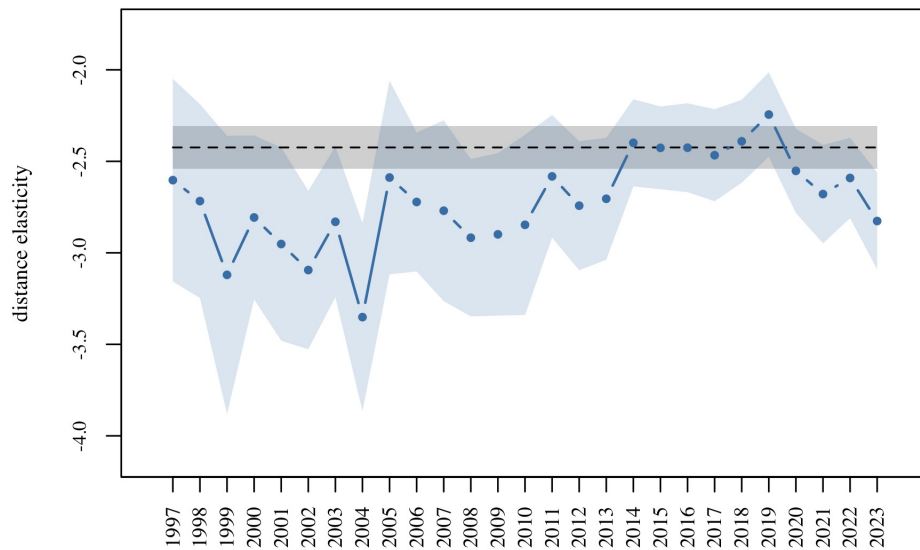
Taken together, these results suggest that the spatial gradient identified in the cross section is not merely an artifact of pooling years, although they do not rule out persistent spatio-temporal diffusion of violence. Rather, the gradient reflects stable spatial interactions consistent with the equilibrium structure of the model.

Table OA.B21: Estimates of the frictions to violence (pooled yearly data)

Model	(1)	(2)	(3)	(4)
log distance	-2.78*** (0.051)	-3.12*** (0.054)	-2.62*** (0.058)	-2.75*** (0.073)
Murdock ethnic border		2.39*** (0.204)	2.46*** (0.168)	
Political border			-1.77*** (0.113)	
Murdock ethnic border: contiguity				2.10*** (0.172)
Murdock ethnic border: no contiguity				2.82*** (0.206)
Political border: contiguity				-1.24*** (0.099)
Political border: no contiguity				-3.46*** (0.175)
Observations	279,460	279,460	279,460	279,460
Pseudo R ²	0.561	0.570	0.587	0.594

Note: Dependent variable is the share of events in n originating from i in year t . Panel over 1997–2023. Estimated by PPML with (i, t) and (n, t) fixed effects. Columns (1)–(4) are estimated on the sample of 87 origins attacking a total of 623 destinations. * significant at 10%, ** significant at 5%, and *** significant at 1%.. Standard errors clustered at the origin-destination pair level.

Figure OA.B8: Yearly variation of the distance elasticity of violence $_{int}$



Note: The figure reports the estimated distance coefficients from yearly regressions estimated with origin and destination fixed effects (which are therefore allowed to vary across years). Standard errors are clustered at the origin-destination pair level. The black dashed line shows the value of this coefficient for the cross-section of data summed over the whole period, as in the main text. The grey shaded area reports the confidence interval around this coefficient. It is estimated via PPML with i and n fixed effects and standard errors clustered at the origin-destination pair level. The blue dots and line segments report the yearly estimates, while the light-blue shaded area reports their confidence intervals. All coefficients are significant at the 1% level. Bounds represent the confidence interval at the 95% level.

OA.C Supplementary material for section 5 (model inversion)

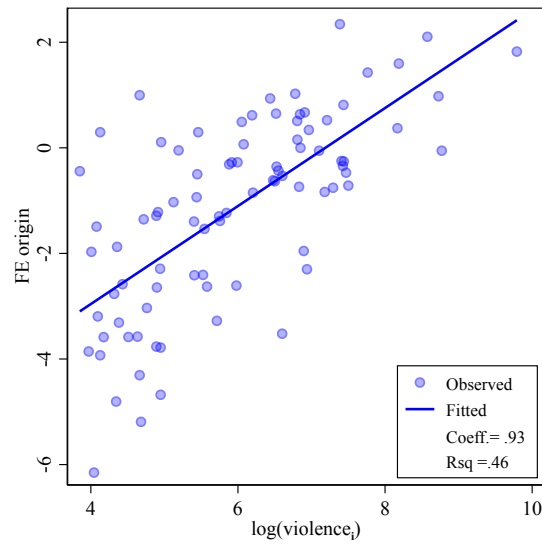
This section provides supplementary material related to our inversion procedure in Section 5.

OA.C.1 Material for steps 1, 2 and 6

Calibrating reference fighting capacity: the Zaghawa case. ACLED reports 944 violent events originating from the Zaghawa, our reference group. We associate the Zaghawa with the following armed groups: the Justice and Equality Movement, the Sudan Liberation Movement/Army and its Abdul Wahid al-Nur and Minnawi factions, and the Sudan Revolutionary Front. Because the Justice and Equality Movement and the listed Sudan Liberation Movement/Army factions are members of the Sudan Revolutionary Front, a coalition formed in 2011, separately adding their forces to those reported for the coalition would lead to double-counting. We therefore assign 37500 fighters to the Zaghawa, corresponding to the average reported number of soldiers in the Sudan Revolutionary Front for the years in which this information is available—2011, 2013, 2014, and 2015—(UCDP). The Forces of Freedom and Change is also assigned to the Zaghawa ethnic group in our actor classification. We exclude it from the fighter count, however, because it was a political coalition created in 2019 to coordinate opposition to Omar al-Bashir and negotiate power sharing, and our sources indicate that it had no military force of its own. Consistent with equation (4), we set the reference fighting capacity equal to the Zaghawa violence-to-fighter ratio, $\hat{\psi}_1 = 944/37500 = 0.02517$.

Cross-validation of recovered productivity and origin effects. In Figure OA.C9, we plot the estimated $\widehat{FE}_i^o$ against the observed (logged) number of violent events originating from i . Table OA.C22 reports the estimation results of equation (33) for OLS in column (1), first stage in column (2), reduced form version of the regression in column (3), and 2SLS in column (4). To cross-validate the method to recover productivity $\widehat{A}_i$, in Figure OA.C10 we plot (logged) $\widehat{A}_i$ against observed (logged) nighttime light.

Figure OA.C9: Gravity fixed effects and observed violence



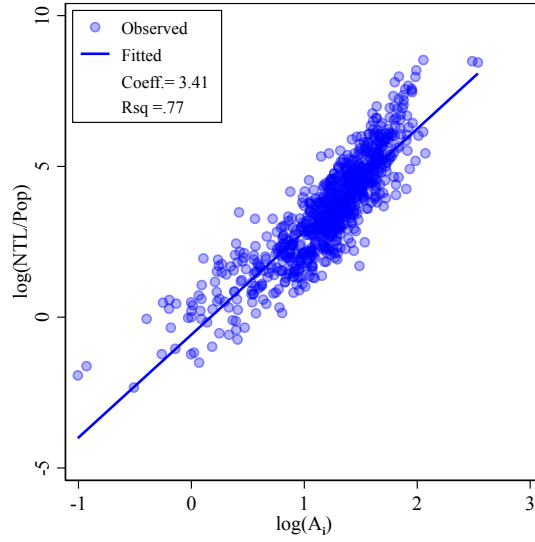
Note: The x-axis displays the observed (logged) number of violent events perpetrated by the 87 origins of violence. The y-axis reports their origin fixed effects, as recovered from the estimation of equation (23), replicating Column 3 of Table 2.

Table OA.C22: Determinants of $\widehat{FE}_i^o$

	(1) OLS $\widehat{FE}_i^o$	(2) First stage $\log\left(\frac{\text{light}_i}{\text{light}_1}\right)$	(3) Reduced form $\widehat{FE}_i^o$	(4) 2SLS $\widehat{FE}_i^o$
Dep. Var.				
$\log\left(\frac{\text{light}_i}{\text{light}_1}\right)$	-0.391*** (0.061)			-0.490*** (0.080)
$\log\left(\frac{\overline{\text{Price}}_i}{\overline{\text{Price}}_1}\right)$		21.110*** (2.057)	-10.342*** (1.648)	
R-squared	0.264	0.552	0.225	
Observations	87	86	86	86
First-stage F-statistic				105

Note: This Table presents the OLS regression (Column 1), the first stage (Column 2), the reduced form version of the regression (Column 3), and the IV estimate of Equation (33) (Column 4). $\widehat{FE}_i^o$ are estimated using Equation (23). $\log\left(\frac{\text{light}_i}{\text{light}_1}\right)$ corresponds to the log of the nighttime light per capital normalized by the value associated to the reference group. $\log\left(\frac{\overline{\text{Price}}_i}{\overline{\text{Price}}_1}\right)$ corresponds to the log average world prices of the 5 most suitable crops normalized by the value of the reference group. The ethnic group Ifora is not included in columns 2 to 4 because the log ratio of prices is undefined for this group due to the underlying crop suitability being equal to zero. * Significant at 10%, ** significant at 5%, *** significant at 1%.

Figure OA.C10: Estimated productivity $\hat{A}_i$ and nighttime lights



Note: The x-axis displays the (logged) productivity $\hat{A}_i$ recovered from the equation (38) for the 824 ethnic regions. The y-axis reports the (logged) nighttime lights per capita.

OA.C.2 Material for step 5: Gravity of trade flows in Africa

In this section we estimate a gravity equation of bilateral trade between African countries over the 1970–2018 period to recover reduced-form trade-friction coefficients used to calibrate $(1 - \sigma) \log \tau_{in}$ (Step 5 in the inversion procedure).

No data are available for trade flows at the detailed geographical level used for measuring bilateral violence. Our approach is therefore to apply coefficients obtained for bilateral trade equation estimated at the national level. We estimate the following country-level gravity equation using the data compiled by [Head and Mayer \(2021\)](#) for the 1970–2018 period:

$$\mathbb{E}(X_{odt}) = \exp [\mu_1 \log \text{distance}_{od} + \mu_2 \text{Political border}_{od} + \mu_3 \text{RTA}_{odt} + \text{FE}_{ot} + \text{FE}_{dt}], \quad (\text{OA.C.33})$$

where X_{odt} is the bilateral trade flow from origin country o to destination country d in year t . The independent variables are the log of the bilateral distance between o and d , a binary variable that equals one if o and d are different countries, and another binary variable that equals one if o and d are part of the same regional trade agreement.^{oa.44} Estimation is carried out using the HDFE PPML estimator including origin $\times$ year and destination $\times$ year fixed effects, and clustering by dyad. Table OA.C23 displays the estimates. The first column displays the traditional gravity setup that only considers international trade flows, for the whole panel. The coefficients on distance and RTA are of similar magnitudes when compared with the vast literature estimating those frictions (see [Head and Mayer \(2014\)](#) for a meta-analysis of those frictions). Column (2) focuses on intra-African trade, and shows that the absolute value of coefficient rises: distance is more detrimental to African trade, but RTAs have a larger positive influence. Those patterns are repeated in columns (3) and (4) which include self-trade for each of the countries and years. Crossing a national border reduces trade drastically in general, but even more in Africa. Another approach to allow for African-specific

^{oa.44}See the appendix of [Head and Mayer \(2021\)](#) for details of how flows internal to a country are constructed.

Table OA.C23: Gravity estimates of frictions for Africa

Model	(1)	(2)	(3)	(4)	(5)	(6)
log distance (All)	-1.30*** (0.029)	-2.11*** (0.116)	-1.12*** (0.030)	-1.76*** (0.112)		
RTA (All)	0.349*** (0.053)	0.746*** (0.172)	0.856*** (0.044)	1.18*** (0.137)		
Border (All)			-3.45*** (0.080)	-4.21*** (0.186)		
log distance (not Afr)					-1.12*** (0.030)	
RTA (not Afr)					0.734*** (0.046)	0.504*** (0.035)
Border (not Afr)					-3.14*** (0.084)	
log distance (Afr)					-0.845*** (0.038)	
RTA (Afr)					1.71*** (0.133)	1.07*** (0.132)
Border (Afr)					-5.34*** (0.158)	
Observations	743,245	46,025	752,491	48,528	752,491	750,212
Squared Correlation	0.686	0.979	0.938	0.998	0.941	0.985
Only Africa:	No	Yes	No	Yes	No	No
With self-trade:	No	No	Yes	Yes	Yes	Yes

Note: All regressions are estimated using PPML. The first five columns include origin-year and destination-year fixed effects, while column (6) adds country-pair fixed effect. Columns (2) and (4) restrict the sample to African countries, the remaining columns do not. Columns (1) and (2) do not include self-trade, the others do.

* Significant at 10%, ** significant at 5%, *** significant at 1%.

frictions is to interact those three frictions with intra-African and non-intra-African dummies. This allows for country-year fixed effects to be better estimated since all countries are included in the regression. The strong effects of African border crossing and RTAs are maintained, but distance effects are now more similar. Column (6) adds dyadic fixed effects to the regression leaving only the time-varying RTA coefficient to be identified: Again, RTAs are revealed to have a stronger effect inside Africa.

Results displayed in column 5 are used to calibrate the μ s in equation (37); the trade elasticity $1 - \sigma$ is calibrated separately from [Head and Mayer \(2014\)](#).

OA.C.3 Non-targeted moments.

To assess whether the recovered state-capacity measure $\hat{s}_n$ captures variation in state presence, we conduct two external validation exercises. These exercises use independent data sources that are not targeted by the inversion procedure.

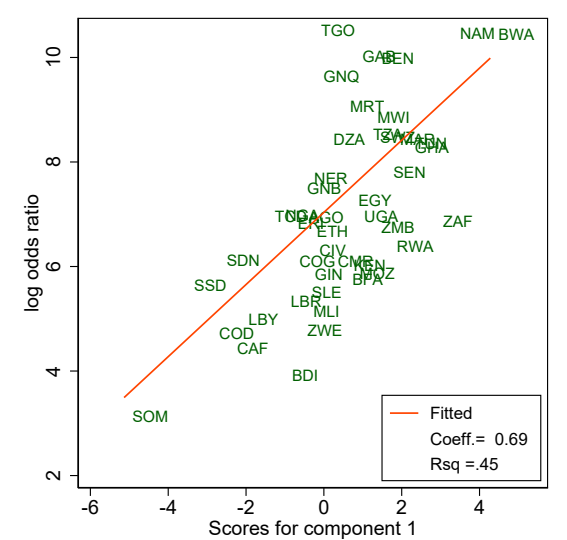
First, we examine cross-country variation. We aggregate $\hat{s}_n$ across Murdock homelands using population weights and transform the resulting country-level measure into log-odds. We then relate this measure to the first principal component of four country-level indicators: government effectiveness, political stability, and regulatory quality from the Worldwide Governance Indicators ([World Bank, 2025](#)), and territorial control from V-Dem ([Coppedge et al., 2026](#)). Each indicator is averaged over the sample period before constructing the principal component. This component summarizes common variation in institutional quality and territorial reach, rather than relying on a single proxy for state capacity. Figure [OA.C11](#) reports the corresponding bivariate relationship. The coefficient is 0.69 and the R-squared is 0.45, indicating that the country average of $\hat{s}_n$ is systematically higher in countries with stronger institutions. Botswana, Namibia, and South Africa lie near the top of the distribution, whereas Somalia, South Sudan, and the Central African Republic are among the countries with the lowest recovered values.

Second, we focus on within-country variations in $\hat{s}_n$. We examine whether $\hat{s}_n$ is also related to local perceptions of state institutions. We use Afrobarometer rounds 3–8 and retain approximately 222,000 geocoded respondents with valid, non-missing answers to the question on trust in the police. In each round, respondents are asked how much they trust the police, on a four-point scale ranging from “not at all” to “a lot”.^{oa.45} We define an indicator equal to one when the respondent reports trusting the police “somewhat” or “a lot”, and zero when the respondent reports trusting the police “not at all” or “just a little”. Using the GPS coordinates in Afrobarometer, we assign each respondent to a Murdock ethnic homeland and compute, for each homeland, the share of respondents who report trust in police.

At the level of Murdock ethnic homelands, we compare this local trust measure to the log odds of $\hat{s}_n$. To focus on within-country variation, we partial out country fixed effects from both variables and weight observations by the number of Afrobarometer respondents in each homeland. This specification asks whether, within the same country, ethnic homelands with higher recovered state capacity are also those where respondents express greater trust in police. Figure [OA.C12](#) reports the resulting partial-regression plot. The relationship is positive and statistically significant. Although this exercise is not causal, it provides a useful subnational validation check: the spatial variation recovered from the model is positively associated with independent survey-based evidence on local trust in police. Since the Afrobarometer measure is not used in the inversion, this relationship provides an additional untargeted moment supporting the interpretation of $\hat{s}_n$ as a measure of local state presence.

^{oa.45}The exact question is: “How much do you trust each of the following, or haven’t you heard enough about them to say: The Police?” The four substantive answers are “not at all”, “just a little”, “somewhat”, and “a lot”. We exclude non-substantive responses such as “don’t know”, “refused”, and missing values.

Figure OA.C11: s_n and institutional quality across African countries



Note: The vertical axis is the log-odds ratio of the population-weighted country-level average of the recovered $\hat{s}_n$. The horizontal axis is the first principal component of government effectiveness, political stability, and regulatory quality from the Worldwide Governance Indicators (World Bank, 2025), together with territorial control from V-Dem (Coppedge et al., 2026). Countries are labeled by ISO codes. The orange line reports the linear fit. The sample consists of 45 countries.

Figure OA.C12: s_n and trust in police across Murdock homelands.



Note: The figure reports the residualized relationship between trust in police and the log-odds ratio of the recovered $\hat{s}_n$. Both variables are residualized with respect to country fixed effects. Observations are weighted by the number of Afrobarometer respondents used to compute trust in police within each Murdock homeland. The fitted line corresponds to the weighted linear fit between the residualized variables. The sample consists of 463 Murdock regions.

Finally, we could not identify a suitable external validation exercise for fighting capacities ψ_i . This is a genuine data limitation rather than a neglected robustness check: systematic information on the combat effectiveness, manpower, equipment, territorial control, financing, and operational capacity of armed groups in Africa is extremely difficult to obtain in a comparable, open-source format and at the spatial scale required by our inversion. Existing information is often qualitative and available only for the largest and most visible organizations.

OA.D Supplementary material for section 6 (counterfactuals)

OA.D.1 Calibration of violence spillovers

Destruction spillover. Equation (39) specifies the destruction spillover. Accordingly, the set of structural parameters to be calibrated consists of the semi-elasticity of TFP to violence ε_1 and of the vector of baseline productivity $\bar{A}$. The calibration procedure thus consists in estimating the empirical counterpart of (39), such that:

$$\log A_n = -\varepsilon_1 \times \text{violence}_n + \text{residual}_{1,n}, \quad (\text{OA.D.34})$$

where A_n is recovered from Step 6 of the model inversion procedure (page 31) and violence_n represents the total violence as observed in the data.

An endogeneity concern arises from potential reverse causation going from productivity to violence: Indeed, a change in A_n affects local income per-capita w_n , which in turn can influence violence_n ; this causal path is, in essence, linked to the *rapacity* effect. We address this issue by building a model-consistent shifter of violence_n . For this purpose, we incorporate the spatial weights defined in equation (24) into equation (25) to express monadic violence exerted in n as:

$$\log(\text{violence}_n) = \log(1 - s_n) + \log w_n + \log \sum_i \frac{\xi_{in}^{-\frac{\gamma}{1-\gamma}} \left(\frac{\psi_i L_i}{Y_i} \right)^{\frac{1}{1-\gamma}} \bar{L}_n}{\sum_k \xi_{kn}^{-\frac{\gamma}{1-\gamma}} \left(\frac{\psi_k L_k}{Y_k} \right)^{\frac{\gamma}{1-\gamma}}}. \quad (\text{OA.D.35})$$

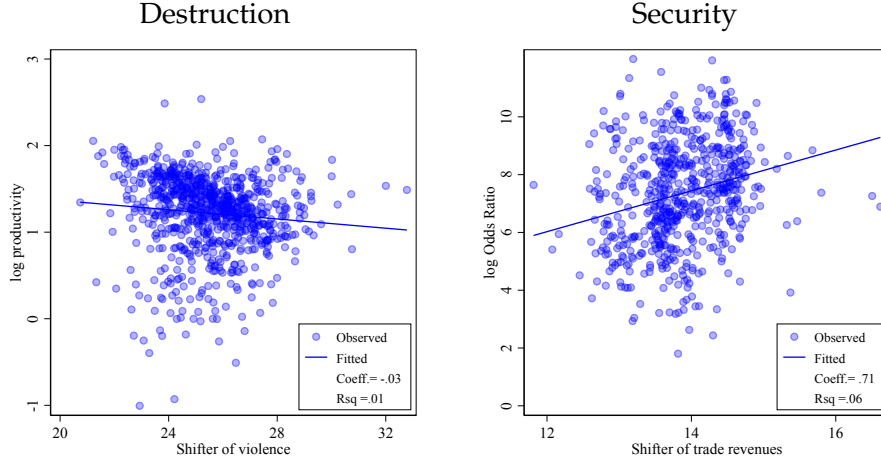
To satisfy the exclusion restriction, we need to choose a shifter of violence_n that is independent of productivities and incomes. In this regard, the first two terms on the right-hand side of the previous equation are unsuitable, as they both depend on local income w_n , indirectly through the security spillover for the first term, and directly for the second term. A natural choice is the third term, which corresponds to the SPV component (see page 25) augmented with $\log \bar{L}_n$. After removing its dependence on endogenous incomes and replacing labor endowments with observed population, we obtain an implementable SPV-based shifter of violence_n :

$$\widetilde{\text{SPV}}_n \equiv \log \sum_i \frac{\xi_{in}^{-\frac{\gamma}{1-\gamma}} (\psi_i \text{pop}_i)^{\frac{1}{1-\gamma}} \text{pop}_n}{\sum_k \left(\frac{\psi_k \text{pop}_k}{\xi_{kn}} \right)^{\frac{\gamma}{1-\gamma}}}. \quad (\text{OA.D.36})$$

We perform a 2SLS estimation of (OA.D.34) using $\widetilde{\text{SPV}}_n$ as the instrument. The semi-elasticity of TFP to violence is estimated to be $-\varepsilon_1 = -0.000439$ with a standard error of 0.00017 and a first-stage F-statistic equal to 35. This elasticity has a direct quantitative interpretation: an increase of one hundred ACLED events leads to a reduction in local TFP by 4.4%. The corresponding reduced form relationship between the IV and the dependent variable is depicted in the left panel of Figure OA.D13. Lastly, comparing equations (39) and (OA.D.34) reveals that the structural interpretation of the error term is $\text{residual}_{1,n} = \log \bar{A}_n$. This relationship enables us to recover the

baseline productivity level in the destruction spillover.

Figure OA.D13: Reduced form evidence of violence spillovers



Security spillover. We adopt a similar approach to calibrate the elasticity ε_2 and the baseline state capacity parameter $\bar{s}_n$ in the security spillover equation (40). This equation can be reformulated into the following econometric specification:

$$\log \frac{s_n}{1 - s_n} = \varepsilon_2 \times \log \frac{Y_n}{P_n} + \text{residual}_{2,n}, \quad (\text{OA.D.37})$$

where s_n is the state capacity parameter recovered from Step 3 of the model inversion procedure (equation 35), $\text{residual}_{2,n}$ absorbs the baseline log-odds of state capacity and regional income is proxied by nighttime lights: $\text{light}_n^\lambda \times \text{pop}_n$. Regions with $s_n = 1$ receive no incoming violence by construction and are excluded from the estimation sample, as the log-odds is undefined at this boundary. To estimate this equation, we need to instrument income so as to address potential reverse causation from state capacity on income (through violence and the destruction spillover). We construct the following model-consistent shifter of n 's trade revenues:

$$\widetilde{\text{MP}}_n \equiv \log \sum_k \frac{\tau_{nk}^{1-\sigma} \bar{L}_k}{\sum_\ell \tau_{\ell k}^{1-\sigma}}, \quad (\text{OA.D.38})$$

which corresponds to a Market Potential based on equation (16), after removing all dependencies on income, productivity, and state capacity, and adapting the countries' subscripts such that n is the supplier of goods.

Equation (OA.D.37) is estimated using $\widetilde{\text{MP}}_n$ as the instrument. The 2SLS estimate of the elasticity of state capacity to income is equal to $\varepsilon_2 = 0.499$ with a standard error of 0.086 and a first-stage F-statistic equal to 286. The right panel of Figure OA.D13 illustrates the reduced form relationship. Comparing equations (40) and (OA.D.37) reveals that the structural interpretation of the residual is $\text{residual}_{2,n} = \log \frac{\bar{s}_n}{1 - \bar{s}_n}$. This relationship allows to recover the vector of baseline state capacity $\bar{\mathbf{s}}$.

OA.D.2 Resolution procedure for the numerical simulations

Section 5 provides the steps used to estimate and “invert” the model. Supplemented with the calibration of the security and destruction spillovers detailed in Appendix OA.D.1, we recover all parameters needed for simulating the factual equilibrium. Omitting hats to simplify notation, the set of structural parameters is:

$$\Theta = \{ \gamma, \sigma, \bar{s}_n, \bar{A}_n, \psi_i, \text{pop}_i, \tau_{in}, \xi_{in} \}.$$

Model without destruction and security spillovers. We first consider the version of the model without destruction and security spillovers, corresponding to $\epsilon_1 = 0$ and $\epsilon_2 = 0$ in equations (39) and (40). This corresponds to the framework analyzed in Section 2.4. In this setting, the equilibrium wage vector is characterized by equation (18) and solved numerically through the fixed-point iteration:

$$\tilde{w}_i = \sum_{n=1}^N \beta_{in}(\mathbf{w}) w_n \frac{\text{pop}_n}{\text{pop}_i}, \quad (\text{OA.D.39})$$

where $\beta_{in}(\cdot)$ is the non-linear function defined in equation (19).

The numerical procedure is as follows:

Wage (inner) loop steps:

Step 0: Use $w_i = \frac{A_i}{A_1}$ as values for initializing the procedure.

Step 1: With the vector of w_i (normalized such that $w_1 = 1$) obtained from the previous iteration, compute the RHS of equation (OA.D.39). The LHS of equation (OA.D.39) yields a new vector $\tilde{w}_i$ (also normalized by $\tilde{w}_1$).

Step 2: Use a dampening factor δ to compute the new vector of wages as $\delta w_i + (1 - \delta) \tilde{w}_i$.

The reference group used for the normalization of wages in the inner loop coincides with the one used to normalize productivity in Step 6 of the inversion procedure. We use the Fon ethnic group, whose homeland is located in Benin, as the normalization reference. The Fon are a large group that is not victimized in the data and therefore has $s_n = 1$, a boundary outcome of the inversion in equation (35) rather than an imposed normalization. As a result, the group does not experience violence in the counterfactual simulations, ensuring that its productivity remains normalized at $A_n = 1$.

Steps 1 and 2 are repeated until the vector of wages converges within a specified tolerance level. The fixed-point iteration on equation (OA.D.39) is sufficient for computing the *factual* equilibrium, i.e. the equilibrium values of endogenous variables at baseline values of Θ . Once equipped with the equilibrium wage vector $\mathbf{w}$, we compute the regional income $Y_n = w_n \text{pop}_n$; then, equation (11) gives the optimal number of fighters as $l_{in} = \text{violence}_{in} / \hat{\psi}_i$ for active origins; we set $l_{in} = 0$ for inactive origins ($\hat{\psi}_i = 0$). The remaining endogenous variables can be derived immediately from the equations in Section 2.4. Counterfactual equilibria are computed analogously. Following a perturbation of one or several structural parameters in Θ , the fixed-point algorithm is solved again and the resulting equilibrium outcomes are compared to their factual counterparts.

Model augmented with destruction and security spillovers. We now consider the model augmented with destruction and security spillovers. Their associated elasticities, ϵ_1 and ϵ_2 , are non-zero and calibrated in Appendix OA.D.1. Once productivity and state capacity depend on equi-

librium violence, solving for the wage vector remains necessary but is no longer sufficient to characterize equilibrium. Productivity affects wages through equation (19), while violence feeds back into productivity and state capacity through equations (39) and (40).

Accordingly, we implement a nested fixed-point procedure with three layers. The inner loop solves for the equilibrium wage vector $\mathbf{w}$, given productivity $\mathbf{A}$ and state capacity $\mathbf{s}$ vectors (as described above). The middle loop takes the resulting $\mathbf{w}$ vector from the inner loop to determine the equilibrium state capacity vector $\mathbf{s}$, while the outer loop takes the equilibrium $\mathbf{s}$ and finds $\mathbf{A}$:

State capacity (middle) loop steps:

Step 1: Use the value of w_n obtained from the inner loop to compute nominal income $Y_n = w_n \text{pop}_n$ and the CES price index P_n from equation (2). Insert real income Y_n/P_n in the RHS of equation (40). The LHS of equation (40) yields a new log-odds ratio from which a new vector $\tilde{s}_n$ is recovered.

Step 2: Use a dampening factor δ to compute the new vector of state capacities as $\delta s_n + (1 - \delta)\tilde{s}_n$.

Steps 1 and 2 are repeated until the state-capacity vector converges within a specified tolerance level.

Productivity (outer) loop steps:

Step 1: Use the vector of s_n (obtained from the middle loop) and w_n (from the inner loop) in equation (25) in order to compute the RHS of equation (39). The LHS of equation (39) yields a new vector $\tilde{A}_n$.

Step 2: Use a dampening factor δ to compute the new vector of productivities as $\delta A_n + (1 - \delta)\tilde{A}_n$.

The overall simulation procedure stops once the productivity vector $\mathbf{A}$ converges within the specified tolerance level. The resulting fixed point jointly determines equilibrium wages, violence, productivity, and state capacity under the full general-equilibrium structure of the model.

OA.D.3 Factual equilibrium

Table OA.D24 reports a number of important statistics predicted by the model in the initial (factual) equilibrium. For each panel, the three rows report three spatial categories: i) flows that occur within the same ethnic region; ii) within the same country (but between different ethnic regions); and iii) across different countries. The two first columns show the model's predictions for trade and violence, respectively, while the last column reports the observed figures for violence. Finally, panel (a) reports the shares (in percentage) of total trade and violence that take place within each of the three categories. Panel (b) reports the shares of those flows across destinations.

OA.D.4 Counterfactual 1: A rise in the Kanuri region's productivity

This appendix provides additional material to the first counterfactual on the consequences of a 10% increase in the baseline productivity ($\bar{A}_n$ in equation 39) of the Kanuri region.

Contribution of each margin. In the first exercise, we run five types of counterfactuals, gradually incorporating the rich interactions that our model captures between the trade/production part of the economy and the violent part of this world. Results are displayed in Table OA.D25.

Table OA.D24: Factual equilibrium: some statistics

Panel (a)	Total trade	Total violence	
	Pred.	Pred.	Obs
same ethnic region	31.19	21.15	26.79
same country	62.27	49.85	46.37
different countries	6.55	28.99	26.84

Panel (b)	π_{in}	$\frac{\text{violence}_{in}}{\text{violence}_n}$	
	Pred.	Pred.	Obs
same ethnic region	15.10	6.52	6.52
same country	76.54	57.29	57.31
different countries	8.63	36.46	36.45

Note: All figures represent percentage points. Columns 1 and 2 report the levels of trade and violence that the model predicts to take place in the factual equilibrium in each of the categories. Column 3 reports observed violence. Panel (a) reports shares of total trade and violence that take place within each of the three categories. Panel (b) reports shares across destinations n , averaged separately by column.

Scenario 1: Trade-only adjustment with fixed fighting allocation. In this scenario, the allocation of labor between production and fighting is held constant. This has consequences for the equilibrium characterization that differs in several respects from the system of equations reported in Section 2.4. First, the labor market clearing condition (15) is still valid but L_i and l_i are now exogenously set. Second, in absence of free occupation choice, production and fighting incomes—given by the two endogenous variables w_i^P and w_i^F , respectively—are not necessarily equalized in equilibrium and equation (13) is not verified anymore. Therefore, the wage dependence of the trade share in (16) and fighting probability in (17) must be adjusted accordingly. Finally, total income is now equal to $Y_i = w_i^F \times l_i + w_i^P \times L_i$. Combining these elements together, we obtain the set of equations that characterizes the trade-only equilibrium:

$$w_i^P L_i = \sum_{n=1}^N \frac{\tau_{in}^{-(\sigma-1)} \left(\frac{A_i}{w_i^P} \right)^{\sigma-1}}{\sum_{k=1}^N \tau_{kn}^{-(\sigma-1)} \left(\frac{A_k}{w_k^P} \right)^{\sigma-1}} s_n Y_n, \quad (\text{OA.D.40})$$

$$w_i^F l_i = \sum_{n=1}^N \frac{\tilde{\varsigma}_{in}^{-\frac{\gamma}{1-\gamma}} \left(\frac{\psi_i}{w_i^F} \right)^{\frac{\gamma}{1-\gamma}}}{\sum_{k=1}^N \tilde{\varsigma}_{kn}^{-\frac{\gamma}{1-\gamma}} \left(\frac{\psi_k}{w_k^F} \right)^{\frac{\gamma}{1-\gamma}}} (1 - s_n) Y_n, \quad (\text{OA.D.41})$$

$$Y_i = w_i^F \times l_i + w_i^P \times L_i. \quad (\text{OA.D.42})$$

This system of $3 \times N$ equations has $3 \times N$ unknowns, represented by the vector $\{w_i^P, w_i^F, Y_i\}_{1 \leq i \leq N}$. Under this trade-only adjustment, the allocation of labor between production and fighting is held fixed, so the scenario shuts down the endogenous violence-reallocation margin and isolates the trade response to the productivity shock. Scenario 1 in Table OA.D25 reports the simulation results of the previous relations for three different geographic zones: the Kanuri region, their neighbors (i.e. regions within 1000km), and the rest of Africa (i.e. regions within 1000-2000km). Because of the endogenous redirection of trade flows, an exogenous 10% increase in TFP translates into a less

than proportional increase in income and welfare.^{oa.46}

Scenario 2: Spillover-free. This scenario allows the endogenous reallocation of the labor force between producers and fighters, which renders violence endogenous in the first column, while keeping the two spillover channels (on A_n and s_n) muted. The rise of TFP in the Kanuri region has two main effects on violence received by the Kanuri: there is a fall in internal violence because w_i rises in equation (11) (Kanuri groups are more attracted to production, and exert less violence, including locally), compensated by an increase in Y_n (caused by w_n), which attracts violence from everywhere (including locally). The second effect dominates resulting in an increase in received violence. However, the reallocation of the population to production in the Kanuri region (with the number of fighters dropping by around 7%) boosts output and reduces the locally perceived price index. This is reflected in the (modest) increase of 0.12 percentage points of income and welfare gains compared to the “Trade-only” scenario. The neighboring regions experience a decrease in their incoming violence (mostly from the Kanuri region), but a slight increase in their fighters’ share of population (mostly attracted by increased Kanuri income). Overall, these effects offset each other in terms of income and welfare.

Scenario 3: Security-inclusive. In this scenario, we unleash the security spillover, in which increased income shrinks the unsecured share of that income ($1 - s_n$ decreases by almost 4%). The main consequence of adding this channel is a 3% decrease in incoming violence in the Kanuri region compared to the status quo. This contributes to a slight increase in local welfare with respect to the previous scenario.

Scenario 4: Damage-inclusive. In this scenario, we replace the security spillover with the damage spillover channel, where violence retroactively affects productive activity. Compared to the “Spillover-free” scenario, the increased violence received by the Kanuri region now reduces TFP by around 0.5 percentage points. As a consequence, local income and welfare do increase, but by a smaller amount than when spillovers are deactivated. Interestingly, the TFP of nearby regions also rises as they experience a reduction in violence. Therefore, their consumers also benefit from the productivity increase in the Kanuri region. This spatial diffusion of the TFP shock happens entirely through the reduction in violence, which is a novel feature of our model.

Scenario 5: Full general equilibrium with security and damage spillovers. In the final scenario, both security and damage spillovers are allowed to operate. Their joint effect magnifies the response to the productivity shock. Incoming violence falls substantially in the Kanuri region, which further amplifies the initial productivity increase and raises welfare gains by almost 40% relative to the spillover-free scenario ($11.82/8.53 = 1.39$). The mechanism is cumulative: the security channel lowers incentives for violence; lower violence reduces destruction; reduced destruction raises productivity; higher productivity increases income and further strengthens security. These feedback loops between security and damage spillovers are a distinctive feature of the framework and capture one mechanism behind the conflict trap emphasized in the literature (for a survey, see [Rohner and Thoenig, 2021](#)).

Welfare changes. Figure [OA.D14](#) provides a decomposition of welfare effects in the “Full-GE” scenario, where all channels are active. The decomposition follows equation (42), and plots the

^{oa.46}This can be seen by rearranging the goods market clearing equation (16) to isolate nominal wages in i , such that $w_i = A_i^{(\sigma-1)/\sigma} L_i^{-1/\sigma} (MP_i)^{1/\sigma}$ where the Market Potential is defined by $MP_i = \sum_{n=1}^N \tau_{in}^{-(\sigma-1)} s_n w_n L_n P_n^{\sigma-1}$. The proportionality factor to a first order is therefore $\frac{(\sigma-1)}{\sigma} < 1$.

Table OA.D25: Aggregate results across CF scenarios

Scenario	Zone	Avg. % Change in					
		violence_n	$1 - s_n$	l_n	TFP (A_n)	Income	Welfare
1:Trade-only	shock	0	0	0	10	8.25	8.41
	close to shock	0	0	0	0	0.01	0.02
	other	0	0	0	0	0.00	0.00
2:Spillover-free	shock	0.66	0	-7.46	10	8.37	8.53
	close to shock	-2.91	0	0.8	0	0.01	0.02
	other	-0.39	0	0.15	0	0.00	0.00
3:Security-inclusive	shock	-3.33	-3.96	-8.6	10	8.36	8.56
	close to shock	-2.92	-0.01	0.71	0	0.01	0.02
	other	-0.39	0	0.14	0	0.00	0.00
4:Damage-inclusive	shock	0.6	0	-6.73	9.5	7.97	8.14
	close to shock	-2.78	0	0.75	0.06	0.07	0.09
	other	-0.39	0	0.22	0.01	0.01	0.01
5:Full-GE	shock	-4.5	-5.36	-11.16	13.78	11.52	11.82
	close to shock	-3.94	-0.08	0.79	0.09	0.10	0.13
	other	-0.54	-0.01	0.26	0.01	0.02	0.02

Note: Numbers represent average percent changes. "Shock" = Kanuri Region; "close to shock" = Regions within 1000km from Kanuri; "other" = Regions within 1000km-2000km from Kanuri. The shock is a 10% increase in the baseline TFP ($\bar{A}_n$ in equation 39) in the Kanuri region. violence_n is the total violence in n . $1 - s_n$ stands for the (opposite of) state capacity in n . l_n the number of fighters in n . TFP (A_n) is the productivity in n . Total "Income" of a region is defined in equation (14). "Welfare" refers to the secured per-capita real wage as defined in equation (41).

three elements of the overall welfare change in percentage points against the distance from the shock in kilometers (up to 1000 kms, since it is very clear from the last row of the last column of Table OA.D25 that welfare changes are quite negligible beyond that range). Total welfare change tends to fall sharply with distance from the original shock, as expected, with some nearby regions still experiencing overall gains around 1 to 2%. As is most visible for the Kanuri region, welfare change mostly comes from the increase in TFP. Indeed, the self-trade channel even acts as a negative contribution, reflecting the shift towards local varieties in the new equilibrium. The rise in s_n has a *direct* but marginal contribution to welfare, due to all regions having initial s_n values close to 1 (including the Kanuri region). However, its indirect effect through the feedback loops highlighted above is critical for welfare, as these interactions between the two spillovers substantially increase the overall TFP compared to the “Damage-inclusive” scenario, where s_n is constant. Figure OA.D15 compares the overall welfare gains in our model to the gains from trade formula of Arkolakis et al. (2012) (ACR). In panel (a), scenarios 1 and 2 are reported. Since these scenarios lack spillover channels, welfare changes align exactly with the ACR formula, except for the Kanuri region, which shows significant gains coming from the direct TFP shock. Panel (b) illustrates scenario 5, where our spillover channels introduce notable deviations from the ACR formula, even for regions without direct TFP gains. This deviation is attributed to the indirect benefits of reduced violence. The statistic of change in self-trade relevant in the traditional trade model is not sufficient anymore in our model which accounts for endogenous violence.

Geography of violence. Figures OA.D16 and OA.D17 provide further details regarding the impact of the productivity shock on the geography of violence between the Kanuri and neighboring regions (all figures are for the “Full-GE” scenario). The gravity of violence equation (11) yields the following decomposition:

$$\Delta \log \text{violence}_{in} = -\frac{\gamma}{1-\gamma} \Delta \log \xi_{in} - \frac{1}{1-\gamma} \Delta \log w_i + \Delta \log w_n + \Delta \log(1 - s_n) - \Delta \log \text{MRV}_n, \quad (\text{OA.D.43})$$

with

$$\text{MRV}_n = \xi_{in}^{-\frac{\gamma}{1-\gamma}} \left(\frac{\psi_i}{w_i} \right)^{\frac{\gamma}{1-\gamma}} + \sum_{k \neq i} \xi_{kn}^{-\frac{\gamma}{1-\gamma}} \left(\frac{\psi_k}{w_k} \right)^{\frac{\gamma}{1-\gamma}},$$

which can be used to study the impact of any shock on each bilateral flow of violence. Here, we analyze the consequences of the 10% productivity increase in the Kanuri region on (i) total violence taking place in the Kanuri region (due to changes in internal as well as in incoming violence), and (ii) violence flowing to other regions. The analysis relies on the theoretical channels discussed in Section 2.3.

As noted above, the increase in Kanuri’s productivity leads to a rise in their local wage (see footnote oa.46 for details). A higher wage decreases violence perpetrated by $i = \text{Kanuri}$ (*opportunity cost* channel) and increases violence targeting $n = \text{Kanuri}$ (*rapacity* channel). Additionally, there is a decline in $(1 - s_n)$ due to security spillovers, which reduces violence targeting Kanuri (*state capacity* channel).

- (i) What is the consequence for Kanuri’s internal violence? For $i = n$, the changes in wage act in opposite direction such that the *rapacity* and *opportunity cost* channels tend to offset each other. Inspection of equation (OA.D.43) reveals that cancellation is exact in the limit when violence is very local (see also footnote 33) and only the *state capacity* channel matters. This logic is at work in panel (a) of Figure OA.D16, where internal Kanuri violence falls by a little

more than 5%. In panel (b), we see the other side of the coin: the increased income of the Kanuri incentivizes rapacity, leading neighboring groups to deploy more fighters to the Kanuri region to seize that additional income. This mechanism is reinforced by the fact that the Kanuri perpetrate less violence, thereby reducing MRV_n and competition in the appropriation market. Overall, the decrease in internal violence outweighs the increase in inward violence, resulting in a net reduction in the total level of violence in the Kanuri region by slightly more than 4% (the black circle in panel (c) of Figure OA.D16, also visible in first column and first row of “Full-GE” scenario in Table OA.D25).

- (ii) What happens to violence perpetrated in other regions? Equation (OA.D.43) highlights how competition in the appropriation market, as captured by MRV_n , shapes the spatial reshuffling of violence. Returning to Figure OA.D16(a), we observe that, initially, the rise in Kanuri’s wage reduces its violence towards every other region. However, this effect is not uniformly distributed: a spatial gradient is visible. In regions very far from the Kanuri region, only the $-\frac{1}{1-\gamma}\Delta \log w_i$ term in equation (OA.D.43) is active since $\xi_{in}^{-\frac{\gamma}{1-\gamma}}$ approaches 0 in MRV_n . Conversely, as a region n gets closer to the Kanuri region, the countervailing term involving w_i in MRV_n becomes stronger, dampening the violence-reducing effect of Kanuri’s TFP increase. A related spatial gradient is visible in panel (b): because the Kanuri group is less active in regions close to it, those regions receive more attacks from other region in Africa. This substitution effect is driven by the change in MRV_n . In panel (c) the net effect is revealed to be violence-reducing for those regions surrounding the positive TFP shock.

Figure OA.D17 maps the three violence responses shown in Figure OA.D16, with blue indicating declines, red increases, and the Kanuri region marked by the green triangle. Panel (a) shows a broad contraction in Kanuri-perpetrated violence, strongest near the homeland. Panel (b) shows that the offsetting rapacity response is much more localized: violence from other regions rises mainly in and around the Kanuri homeland, consistent with the MRV_n driven substitution mechanism. Panel (c) shows that the net effect remains negative across the affected area, providing the spatial counterpart to the violence-reducing effect described in point (ii).

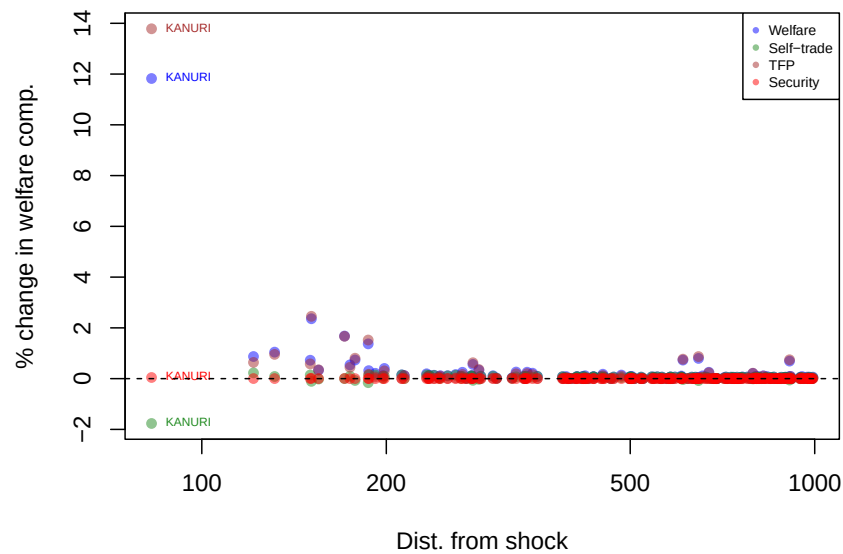
OA.D.5 Counterfactual 2: Sahelexit

We provide here additional material to the counterfactual on the consequences of the “Sahelexit.”

Context. In Figure OA.D18, panel (a), the gray areas depict the 243 ethnic regions primarily affiliated with a pre-exit CEDEAO member country. Among those, Sahelxit regions, namely the ones located within Burkina Faso, Mali or Niger, are shaded in dark gray. CEDEAO, overall, exhibits a high propensity for violence, hosting 26 origins of violence (panel b) and 195 destinations of violence (panel c). With a total of 18543 events originating from the zone, the vast majority of which (17083) affect the region itself. Table OA.D26 summarizes the bilateral flows of violence related to the zone. Most incidents are concentrated along the borders between Mali and Burkina Faso, as well as Mali and Niger. Notable hotspots of violence are also observed in Nigeria, Sierra Leone, and Liberia. The zone hosts two of the most violent origins in our sample: the Kanuri ethnic group, involved in 6166 events (4791 within CEDEAO) and the Masina ethnic group, responsible for 5300 events (all within CEDEAO).

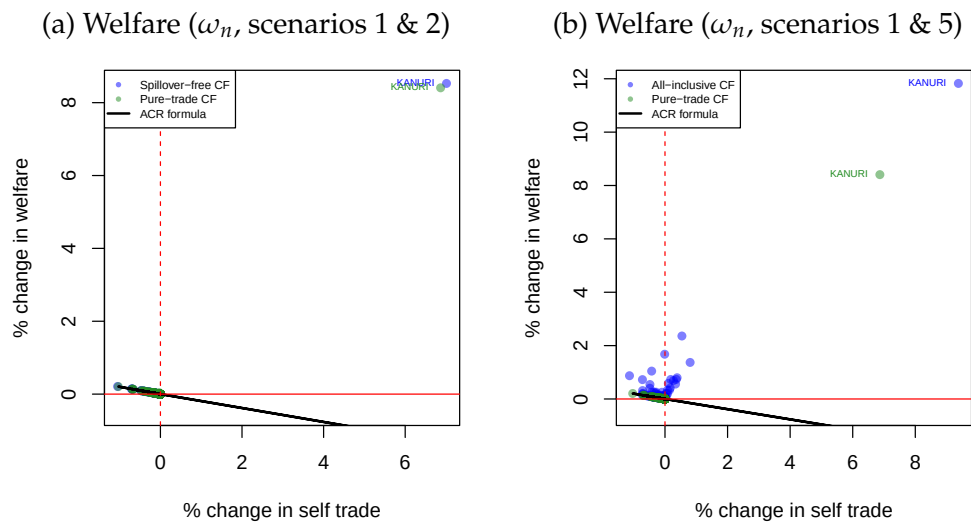
Additional results. Table OA.D27 provides a number of summary results regarding bilateral trade and bilateral violence changes due to the simulated policy experiment. The three rows detail results according to three categories of destinations: those breaking away from CEDEAO; those

Figure OA.D14: Welfare change decomposition after a 10% productivity increase in the Kanuri region



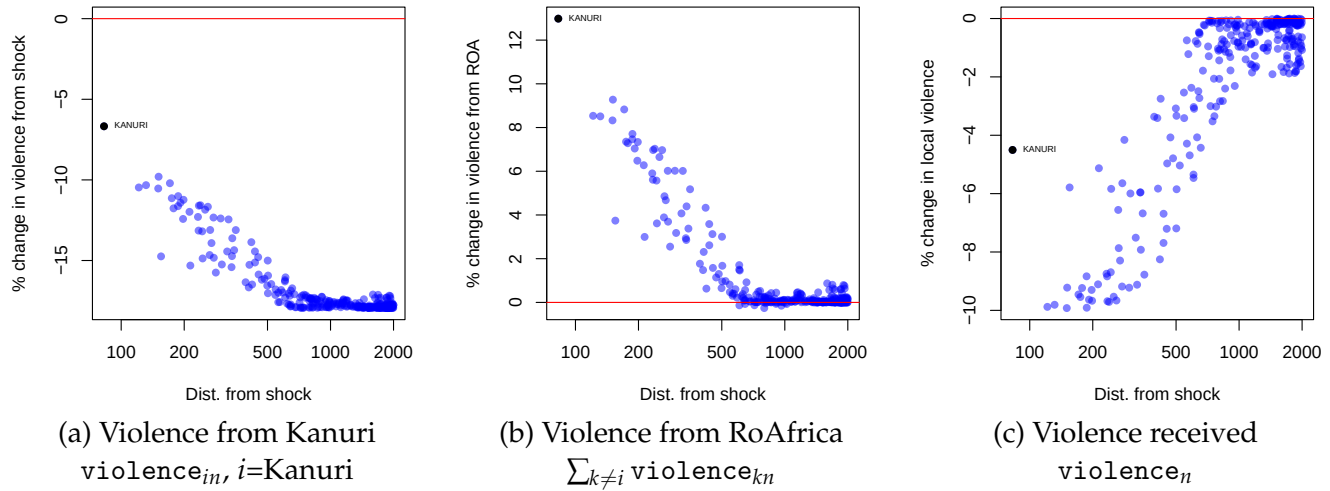
Note: The x -axis displays the distance from the 10% increase in productivity in the Kanuri region. The y -axis reports the overall welfare change in percentage points. All figures come from the “Full-GE” scenario.

Figure OA.D15: Welfare after a 10% productivity increase in the Kanuri region



Note: For all scenarios (1 and 2 in panel a; 1 and 5 in panel b), we compare the overall welfare gains in our model to the formula from [Arkolakis et al. \(2012\)](#). The x -axis displays the change in self trade (in percentage point). The y -axis reports the overall welfare change (in percentage points).

Figure OA.D16: Change in violence after a 10% productivity increase in the Kanuri region



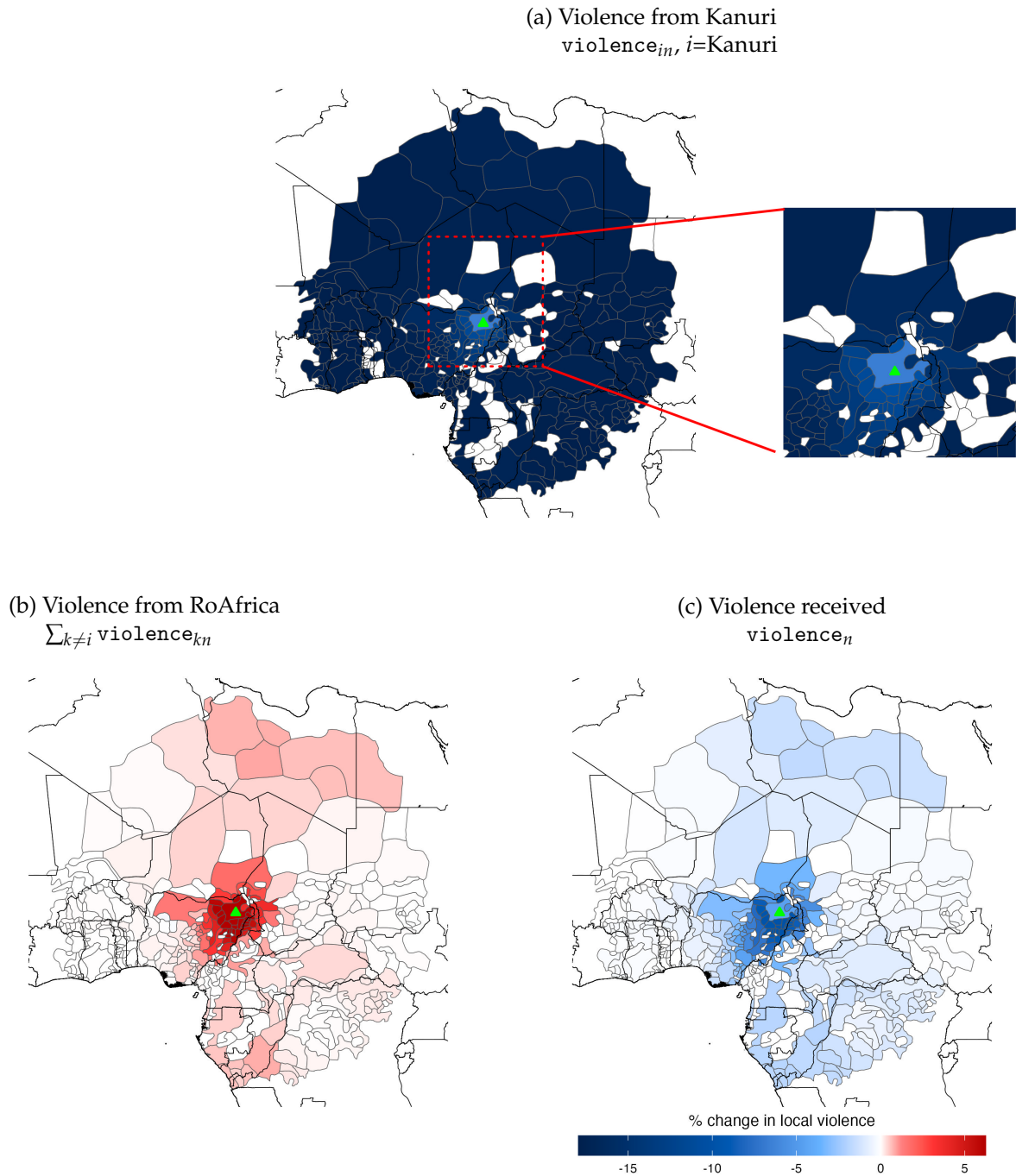
Note: The x -axis displays the distance from the 10% increase in productivity in the Kanuri region. The y -axis reports the overall violence change in percentage points. All figures come from the “Full-GE” scenario. In panel (a), the flows of violence from Kanuri are reported. In panel (b), the flows of violence from all African regions are reported. In panel (c), the flows of violence received by region n are reported.

Table OA.D26: Summary of violence in CEDEAO region

Dest. → Origin ↓	Sahelxit	CEDEAO / Sahelxit	Rest of Africa	Total violence produced by origin
Sahelxit	6313 (97.29%)	105 (1.62%)	71 (1.09%)	6489 (100%)
CEDEAO / Sahelxit	1079 (8.95%)	9586 (79.53%)	1389 (11.52%)	12054 (100%)
Rest of Africa	462 (0.67%)	44 (0.06%)	68190 (99.26%)	68696 (100%)

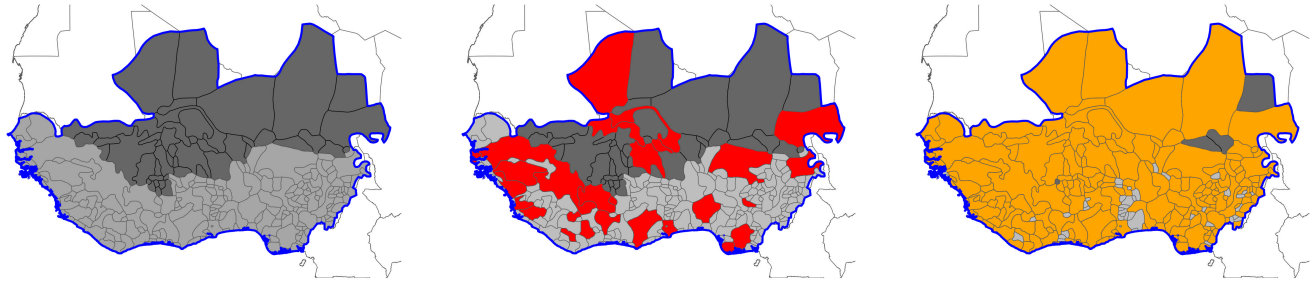
Note: This Table presents a summary of the violence occurring in the CEDEAO region, considering three blocs of actors: armed groups located in the Sahelxit region (col. 2), armed groups located in the CEDEAO region after the Sahelxit (col. 3), and armed groups located in the rest of Africa (col. 4). Percentages represent the number of events from a specific origin $\times$ destination pair (e.g., Sahelxit actors attacking Sahelxit actors) relative to the total number of violent events produced by the considered origin (e.g., Sahelxit actors).

Figure OA.D17: Spatial distribution of the change in violence after a 10% productivity increase in the Kanuri region



Note: All figures come from the “Full-GE” scenario. Red indicates increases and blue indicates declines. In panel (a), the flows of violence from Kanuri are reported. In panel (b), the flows of violence from all African regions are reported. In panel (c), the flows of violence received by region n are reported. The green triangle represents the Kanuri region.

Figure OA.D18: Geography of violence in Sahel and neighbouring countries



(a) Sahel exiters and CEDEAO

(b) 26 Origins of violence

(c) 195 Destinations of violence

Note: In panel (a), the light gray areas depict the 243 ethnic regions primarily affiliated with a pre-exit CEDEAO member country. Sahelexit regions are shaded in dark gray. Panel (b) depicts the origins of violence, and panel (c) shows the destinations of violence.

staying in CEDEAO; and the other regions in Africa. The four columns on the left of this table examine changes in violence over origins, and the four to the right report changes in bilateral trade shares. Table OA.D28 reports the changes in the main monadic variables (total violence, insecurity, number of fighters, TFP, income and welfare) for the same three categories of regions. In both tables, the results are computed for the version of the model accounting for both security and damage spillovers.

- (i) Due to the increase in trade frictions, trade is redirected away from the pairs of regions where the RTA link is shut down. For the most affected regions (Sahelexit), the reallocation of trade is local (within the region itself) or with other Sahelexit regions. The rest of CEDEAO regions also see their local trade increase. In the rest of Africa, most of the action is an increase in imports from Sahelexit regions, which stems from those regions becoming poorer and therefore more competitive in exporting to the rest of Africa. This can be seen in the first row of Table OA.D28, where income in Sahelexit regions drops.
- (ii) For Sahelexit regions, the end of the RTA with the rest of CEDEAO represents a significant loss of economic opportunities. The implication for violence is that looting becomes relatively more attractive as an occupation, drawing more individuals into fighting. Table OA.D28 shows that the number of fighters goes up. As a result, Sahelexit regions increase their fighting activities across all regions (Table OA.D27): violence increases internally, towards other Sahelexit regions, and towards the rest of CEDEAO and the rest of Africa. Conversely, as Sahelexit regions become poorer, their attractiveness for rapacity decreases, leading to a reduction in violence targeting them from the rest of CEDEAO and Africa.

Table OA.D27: Aggregate results of Sahelexit: dyadic effects

Scenario	Zones Origin → Destination ↓	Avg. % change in violence_{in}				Avg. % change in π_{in}			
		Local	Rest of :			Local	Rest of :		
			sahelexit	CEDEAO	Africa		sahelexit	CEDEAO	Africa
Full-GE	sahelexit	1.15	1.42	-0.58	-0.83	9.65	8.74	-81.03	4.27
	rest of CEDEAO	0.14	2.14	0.14	-0.12	1.40	-81.01	1.26	0.67
	other	-0.07	2.08	0.07	-0.18	-0.11	4.26	0.55	-0.04

Note: Numbers represent average percent changes. The average is taken over the ethnic regions inside a destination zone.

Table OA.D28: Aggregate results of Sahelexit: monadic effects

Scenario	Zone	Avg. % Change in					
		violence_n	$1 - s_n$	l_n	TFP (A_n)	Income	Welfare
Full-GE	sahelexit	1.18	0.87	1.25	-0.10	-0.81	-1.77
	rest of CEDEAO	0.29	0.12	0.09	-0.00	0.01	-0.25
	other	0.27	-0.00	-0.33	-0.00	0.11	0.00

Note: Numbers represent average percent changes.

Table OA.D29: Full-GE CF: decomposition of bilateral violence ($n \in \text{Sahelexit}$)

Origin group	Count	Average	Average $\Delta \log$					
			violence_{in}	$\zeta_{in}^{-\frac{\gamma}{1-\gamma}}$	$w_i^{-\frac{1}{1-\gamma}}$	$(1 - s_n)$	w_n	MRV_n^{-1}
Rest of CEDEAO	840	0.69	-0.58	0	0.04	0.87	-0.81	-0.69
Rest of sahelexit	246	24.40	1.41	0	2.03	0.86	-0.80	-0.68
Local	6	358.90	1.14	0	2.03	1.09	-1.12	-0.86
All	1092	8.00	-0.13	0	0.50	0.87	-0.81	-0.69

Note: The destination group is fixed to regions inside the Sahelexit zone; rows report origin groups in CEDEAO. Numbers in the last five columns represent average percentage-point changes.

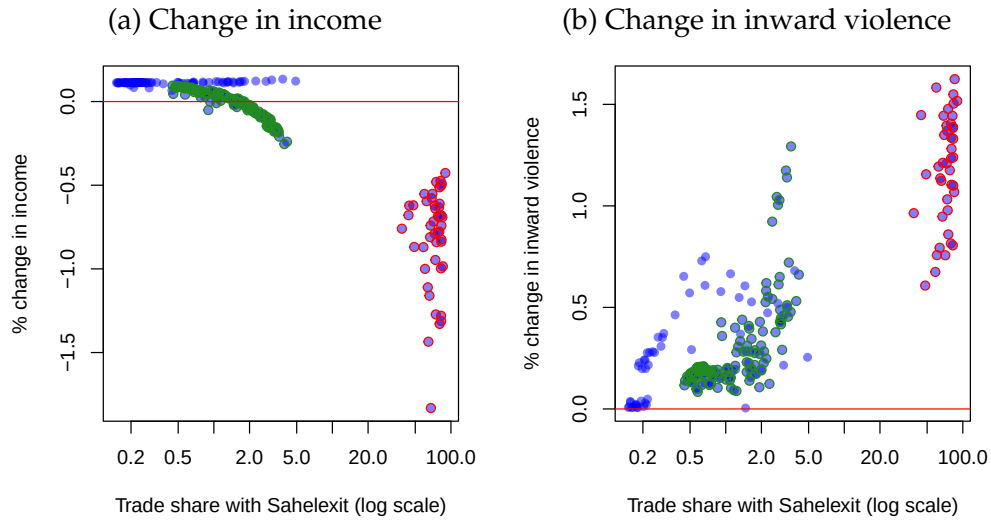
To further understand the reshuffling of violent flows, it is useful to quantify the different elements of the decomposition outlined in equation (OA.D.43). This is done in Table OA.D29, which focuses on bilateral flows of violence received by Sahelexit regions from all the CEDEAO. It is decomposed into three categories of origins: rest of CEDEAO (first row); other Sahelexit regions (second row); self (third row). We discuss in details only the first case but the same logic applies to the other two.

- (iii) Violence originating from the rest of CEDEAO towards Sahelexit regions decreases. This is because the fall in w_n makes looting in those destinations less attractive (*rapacity* effect). The MRV_n term acts similarly, reflecting that the larger number of internal fighters in Sahelexit regions intensifies competition for income appropriation. These pacifying forces are partially counterbalanced by the rise in $1 - s_n$ (*state-capacity* channel), since poorer Sahelexit regions have greater difficulty protecting their income from looting. Overall, the pacifying effects dominate for this flow of violence. However, as shown in the second and third rows of Table OA.D29, the balance of effects shifts when considering violence originating from Sahelexit regions themselves, where the fall in origin wages lowers the opportunity cost of fighting and outweighs the previously mentioned pacifying effects.

Figures OA.D19 and OA.D20 illustrate the changes in income and violence across ethnic regions in West Africa. Although significant inter-regional heterogeneity persists even after accounting for exposure to the Sahelexit trade shock, visual inspection confirms the patterns observed in the aggregate sample. Sahelexit reduces income in regions that break away from CEDEAO. Lower income reduces the opportunity cost of fighting in these regions, leading them to exert more violence across destinations, while other regions exert less. In net, violence increases in almost all regions in West Africa.

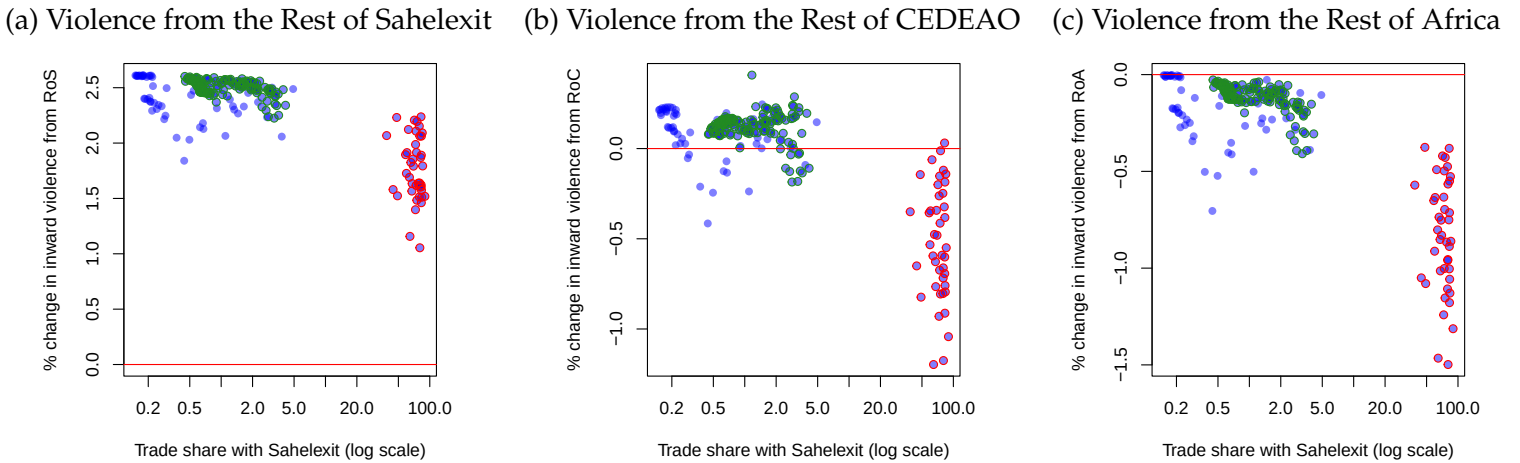
Figure OA.D21 maps the corresponding change in local violence, violence_n , and thus provides a geographical representation of the inward-violence response shown in Figure OA.D20. Red indicates increases in violence, while blue indicates decreases. The increase is concentrated in and

Figure OA.D19: Income Loss and Violence after Sahelexit



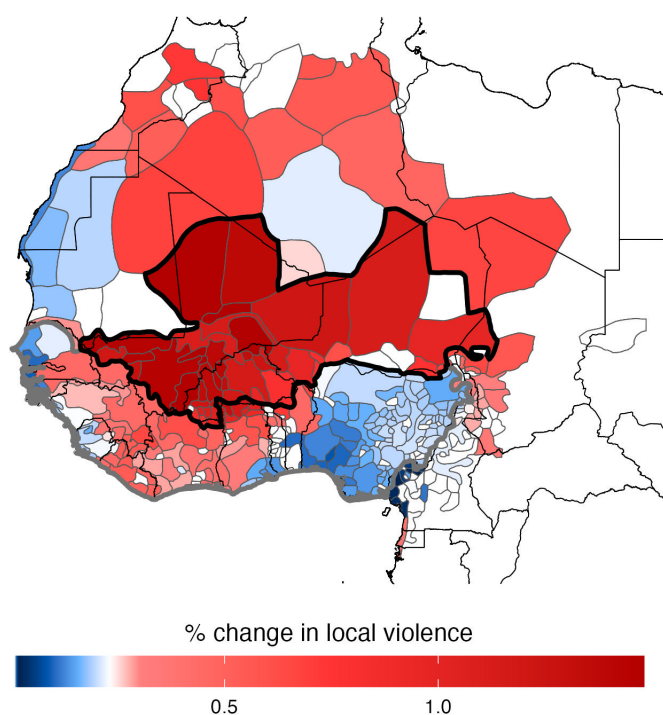
Note: The x-axis displays the trade share with Sahelexit (log scale). In panel (a), the y-axis reports the % change in income. In panel (b), the y-axis reports the % change in inward violence.

Figure OA.D20: Reshuffling of Violence after Sahelexit



Note: In all panels, the x-axis displays the trade share with Sahelexit (log scale). In panel (a), the y-axis reports the % change in inward violence from the Rest of Sahelexit regions. In panel (b), the y-axis reports the % change in inward violence from the Rest of CEDEAO regions. In panel (c), the y-axis reports the % change in inward violence from the Rest of Africa.

Figure OA.D21: Spatial distribution of the change in local violence after Sahelexit



Note: All figures come from the “Full-GE” scenario. The map reports the percentage change in local violence received by each region n ($violence_n$) following Sahelexit; red denotes an increase and blue a decrease. The regions inside the gray line correspond to the 243 ethnic regions primarily affiliated with a pre-exit CEDEAO member country, and the regions inside the thick black line correspond to the Sahelexit regions. This map is the spatial counterpart of the inward-violence flows reported in Figure [OA.D20](#).

around the Sahelexit regions, within the gray line, and among their close partners in the broader CEDEAO bloc, within the thick black line. These regions are the most exposed to the loss of preferential trade access: as income declines, the supply of fighters increases, thereby raising local violence. The effect is spatially uneven: increases are concentrated among regions most exposed to Sahelexit, and attenuate as exposure to the shock falls. The map summarizes the aggregate local-violence response; it should not be read as implying that each component in Figure OA.D20 is monotone in exposure.

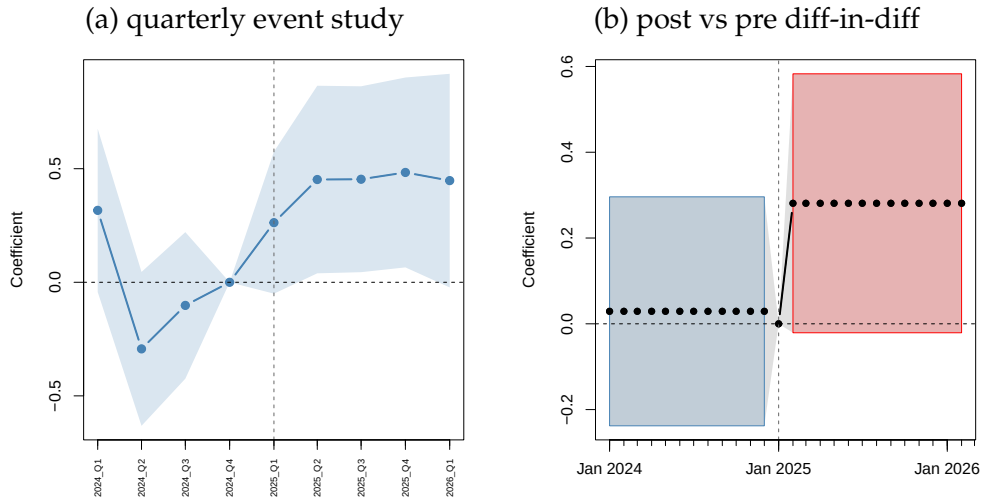
Predicting actual violence. To provide an external consistency check on the Sahelexit counterfactual, we collected the most recent data from ACLED at the monthly level and geo-coded its destinations and origins using the same procedure and the same set of groups as in our baseline data.^{oa.47} Given the short post-withdrawal window and the large set of potential confounders around Sahelexit, the empirical exercises below should be interpreted as descriptive consistency checks, not as causal validation of the mechanism.

Figure OA.D22 reports two regressions on observed monadic violence before and after Sahelxit became effective in January 2025. Panel (a) reports results from an event study comparing violence received by Sahelexit ethnic regions vs the rest of CEDEAO. The equation estimated is

$$\text{violence}_{nq} = \sum_{q=2024Q1}^{2026Q1} \beta_q \times S_n + FE_n + FE_q + \epsilon_{nq},$$

with q denoting a quarter from 2024Q1 to 2026Q1, and S_n being a dummy variable for Sahelexit regions (the control group consists of the rest of CEDEAO regions). The figure reports coefficients β_q by quarter in order to smooth high-frequency volatility. Standard errors are clustered by ethnic group. The blue ribbon around point estimates is the 90% confidence interval, with a reference period chosen as 2024-Q4. The estimates are noisy, but the point estimates rise after the exit of those regions from CEDEAO.

Figure OA.D22: Sahelexit and monadic violence



Panel (b) of the same figure shows a simpler diff-in-diff with same dependent variable and fixed effects, but replacing quarter coefficients with pre-treatment and post-treatment dummies (January

^{oa.47}The “Compatibility” dataset was downloaded from <https://acleddata.com/> on May 5, 2026.

Table OA.D30: Aggregate results of Sahelexit scenarios: dyadic effects

Destination ↓ Origin →	Avg. % change in violence _{in}			
	<u>Data</u>		<u>Counterf.</u>	
	sahelexit	rest of CEDEAO	sahelexit	rest of CEDEAO
sahelexit	97.50	-33.33	1.41	-0.58
rest of CEDEAO	57.16	105.16	2.14	0.14

Note: Numbers represent average percent changes. The average is taken over the ethnic regions inside a destination zone. The first two columns report changes in actual data between the pre-shock period (January–December 2024) and the post-shock period (January 2025–March 2026). The last two columns report simulated changes between the factual and counterfactual equilibria.

2025 being the reference). Again statistical significance is on the weak side, but the pre-treatment effect is close to 0, whereas the post-treatment violence is 28% higher than the reference month. In our counterfactual exercise, the same diff-in-diff regression also yields a positive coefficient, although much smaller, at slightly less than 1% (which reflects the difference between the first and second rows of the first column of table OA.D28).

Hence, the observed changes in relative monadic violence have the same sign as the simulated responses, although the magnitudes are much larger in the data. Table OA.D30 shows that this pattern extends to dyadic predictions. The model predicts that Sahelexit regions exert more outward violence, both locally and in the rest of CEDEAO. This is to be expected if the labor allocation force towards looters is stronger than the reduced attractiveness of Sahelexit spoils due to lower trade (and therefore income) with the rest of CEDEAO. For looters in the rest of CEDEAO a spatial reallocation occurs: because Sahelexit regions lose more income than the rest of CEDEAO, it becomes less attractive to loot ethnic regions in Mali, Burkina Faso and Niger, compared to the ones in the rest of CEDEAO. The data responses have the same signs as the simulated responses, but their magnitudes are substantially larger.

OA.E Bootstrap procedure

Bootstrap inference. Our estimation, inversion, and counterfactual exercises use the event-level ACLED sample obtained after Step 6 of Table 1. This sample depends on the set of non-state armed groups retained in the data construction and on the destinations in which violence is observed. We treat the destination as the resampling cluster because an important source of measurement uncertainty in ACLED is territorial. ACLED is built from local, regional, national, and international media reports, complemented by reports from NGOs, international organizations, governments, conflict parties, and local partners (ACLED, 2023). The precision and exhaustiveness of these sources are unlikely to be uniform across space: violent events are typically better covered in cities and accessible areas than in remote locations where media access, verification capacity, and source density are weaker.^{oa.48} A destination-cluster bootstrap is therefore designed to capture variation in the geographical composition of observed violence, rather than treating all events as independently and identically sampled observations. Sampling variation in these destinations affects the estimated bilateral violence elasticities and fixed effects. Because these estimated parameters subsequently enter the structural inversion and the counterfactual equilibrium calculations, uncer-

^{oa.48}This is consistent with ACLED's discussion of source heterogeneity and access constraints; see also Weidmann (2016) on spatial reporting bias in media-based conflict event data.

tainty originating in the gravity estimation propagates to the recovered structural parameters and counterfactual outcomes. To quantify this uncertainty, we implement the following destination-cluster bootstrap, drawing with replacement from the set of violent destinations in the event-level database obtained after Step 6 of Table 1:

1. Resampling destination clusters. Starting from the event-level bilateral database obtained after Step 6 of Table 1, we draw with replacement from the set of violent Murdock destinations. Whenever a destination is selected, all events occurring within that Murdock region are included in the bootstrap sample. The number of destination draws is fixed at the number of violent destinations in the baseline estimation sample (= 623), while the total number of events varies with the size of the selected destination clusters.

2. Reference-origin admissibility. Because the Zaghawa remains the reference origin in the inversion procedure, we retain only bootstrap replications in which the Zaghawa is represented as an origin of violence and remains in the largest connected set after the connected set is recomputed. These restrictions ensure that the reference scale is well defined in each retained replication and allow meaningful comparisons of the estimated coefficients across replications.

3. Estimation, inversion, and counterfactuals. Using the resulting bootstrap sample, we construct the cross-sectional gravity database by aggregating violent events over time at the Murdock origin–destination level. We then recompute the violence shares ($\text{violence}_{in}/\text{violence}_n$), identify the largest connected set, and retain only the violent origins that belong to it. We re-estimate the gravity coefficients reported in Table 2, together with the fixed effects required by the inversion procedure. Using these draw-specific estimates, we rerun the structural inversion and solve the corresponding counterfactual equilibria reported in Table 5.

4. Computing standard errors. We retain a bootstrap replication only if the recovered economy is economically admissible, the Zaghawa origin is represented as an origin of violence and remains in the largest connected set, and the fixed-point algorithms used for the baseline and counterfactual equilibria converge. Bootstrap standard errors are computed as standard deviations across retained replications. We retain the first 100 bootstrap replications that successfully complete the inversion and both counterfactual exercises. These 100 retained replications are obtained after 188 bootstrap draw attempts.