# Mining for Peace*

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**Abstract**

We study the feasibility of opening new mines in ethnically diverse countries without escalating the risk of conflict. We propose a theoretical model in which ethnic groups can organize themselves to fight at the national or the local level. Our model yields two key insights. First, peace cannot be guaranteed in the presence of ethnic segregation and spatial resource inequality. Second, once the peace-maximizing policies are implemented, local conflict risks depend on local resource rents and local ethnic groups as well as the country's entire ethnic and mining geography. We validate key concepts from our model using granular spatial data from Sierra Leone and the rest of sub-Saharan Africa and employing a shift-share identification strategy. We then apply these concepts to simulate the potential impact of planned mining projects in Sierra Leone and confirm that projects in the right locations can promote peace. We offer policy recommendations for making the mining industry a facilitator of peace and prosperity.

*Key words*: Civil conflict, natural resources, mining, ethnic diversity.

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## 1. Introduction

Global demand for minerals is rising, presenting development opportunities for resource-rich countries in Africa and beyond. Unfortunately, the exploitation of natural resources has fueled conflicts and caused misery in many ethnically diverse countries (e.g., Berman et al., 2017). Examples include the gold-fueled ethnic conflict in Ituri Province in the east of the Democratic Republic of the Congo (DRC) and the diamond-fueled civil war in Sierra Leone. Hence, it is crucial to develop strategies that allow low- and middle-income countries to mitigate mining-related conflict risks effectively to capitalize on current opportunities. These strategies would also contribute to a stable supply of critical minerals required for the green energy transition.

We present novel theoretical arguments and corroborating empirical evidence suggesting that the spatial distribution of industrial mining sites is a key determinant of mining-related conflict. We argue that the effect of new mines on conflict risks depends on the location of these new mines and the country's entire mining and ethnic geographies (i.e., the location and revenues of existing mines and the spatial distribution of ethnic groups). The link between the local and the national level arises from the possibility that members of a group can form intra-ethnic coalitions at the local or the national level and, therefore, bargain for resource rents at both levels simultaneously. We show that peace cannot be guaranteed in the presence of ethnic segregation and spatial resource inequality. However, mining projects often exist in locations where new mining activities reduce the country's aggregate propensity for conflict – a possibility to which we refer as *mining for peace.* Leveraging this framework, we provide theoretical concepts for quantifying conflict-related externalities of new mines and discuss how policymakers and mining companies could use these concepts, e.g., for the proper pricing of mining licenses or human rights due diligence.

**Theoretical contribution:** Our first contribution is a theoretical model to predict the occurrence and location of conflict events as a function of the observed spatial distributions of natural resource rents and ethnic groups. Our model features a country with an arbitrary distribution of ethnic groups and resource rents across locations. Ethnic groups constitute coalitions that can contest resource rents at the local level (in conflicts that primarily involve their local populations fighting for the local resource rents) or at the national level (in a grand conflict that involves their whole ethnic group fighting for the entire pool of resource rents).[1] The possibility of different intra-ethnic coalitions links the local and the national level. The resulting possibility of conflict at different levels can lead to bargaining failure (as in Morelli and Rohner, 2015).[2]

Following the general suggestion of Roth (2002), we take a mechanism-design approach and study a central planner that prioritizes the implementation of peace at the national level while simultaneously attempting to prevent local conflicts.[3] Thereby, the planner may care about all locations equally or give higher weight to peace in some locations (in line with the literature on ethno-regional favoritism, e.g., Burgess et al., 2015; De Luca et al., 2018; Hodler and Raschky, 2014). To achieve their goal, the planner can redistribute resource rents across ethnic groups and locations under uncertainty of the private conflict costs of the groups involved. The resulting conflict risks metaphorically

[1]The interaction between local and national (or, more generally, systemic) factors is at the center of our methodology and broadly in line with general principles of social network theory. For complementary applications to the economics of conflict, see, e.g., König et al. (2017), Amarasinghe et al. (2020), and Mueller et al. (2022). These applications all abstract from a country's mining geography and conflict-reducing transfers of resource rents. The model of Mueller et al. (2022), however, shares the explicit focus on ethnic geography with our model. Their model differs by assuming full rather than no coordination between co-ethnics in different locations and by focusing on the choice of where to recruit (with direct conflict spillovers) rather than the choice of where to fight. We return to these differences in Section 2.5.

[2]The argument that there needs to be a bargaining failure for conflict to occur goes back to Fearon (1995). Jackson and Morelli (2011) and Blattman (2022) discuss different types of bargaining failures.

[3]For earlier work on conflict outbreak relying on mechanism design, see, e.g., Bester and Wärneryd (2006), Fey and Ramsay (2009), and Hörner et al. (2015). Information asymmetries are the leading force for understanding conflict outbreaks in these approaches. Relatedly, Laurent-Lucchetti et al. (2024) present a model in which free and fair elections can reduce information asymmetries between ethnic groups and, thereby, the risk of conflict. In contrast, conflict typically occurs even without any information asymmetry in our model, while the presence of information asymmetry augments the parameter range for which it does.

represent the least conflictual outcome that could be achieved in bargaining between local and national leaders of ethnic groups in the shadow of conflict. These risks can be seen as lower bounds because they would increase in the presence of additional political economy constraints on efficient bargaining. We are agnostic about how the planner redistributes resource rents, but notice that discriminatory taxation, politically targeted transfers, biased local public goods provision, and unequal employment opportunities are common in many countries.

We first show that the implementation of peace (at the national level and in all locations) via the truthful revelation of such costs is generally impossible in the presence of ethnic segregation and spatial resource inequality, thus linking the occurrence of local conflicts to country-level systemic properties. We then characterize the probability of conflict at each location when the planner implements the (second-best) transfer scheme that guarantees peace at the national level and minimizes local conflict risks based on prior information only. These predictions for local conflict risks are a main difference to Morelli and Rohner (2015), along with the mechanism design framework, the arbitrary number of ethnic groups and locations, and the broader set of potential conflict initiators at the local and the national level.

More generally, our model offers a nuanced narrative on the role of ethnicity in conflicts over natural resources. Instead of assuming that all ethnic groups are inclined to fight for resource rents, there is an endogenous politicization and violent radicalization along ethnic lines. It is the groups that are generally over-represented in resource-rich locations that get politicized and radicalized. Berman et al. (2023) document that these ethnic groups often feel economically deprived and politically excluded. Our model implies that these groups experience "discord" between high local resource rents and comparatively low post-transfer well-being. Members of such discordant groups may thus initiate local conflicts.

Importantly, the model delivers two prominent indices for empirical analysis: the national *peace deficit* and the local *conflict exposure*. The former corresponds to the monetary amount necessary to guarantee peace everywhere, which is our proxy for the country's aggregate propensity for conflict. The latter is a proxy for the relative propensity for conflict at each location.

**Empirical contribution:** Our second contribution is to provide empirical support for our theoretical model. Of course, this model focusing on ethnic tensions over resource rents cannot possibly capture all the relevant aspects of any real-world conflict. Consider the conflict in Ituri Province in the DRC. Ethnic animosities between Hema and Lendu people and control over gold mines are indeed key factors of this conflict, but access to land matters too (e.g., Matthysen and Gobbers, 2022). Or consider the diamond-fuelled civil war in Sierra Leone. Our model captures many relevant aspects of this conflict, but it does not account for the fact that only some, rather than all, armed groups were formed along ethnic lines (as discussed in more detail in Section 3.1).

Given that our model (like any other model) lacks the details to perfectly explain any single conflict, we "just" aim to validate whether a higher national peace deficit and higher local conflict exposure indeed go hand in hand with higher levels of national and local conflict. We do so in two settings. First, we focus on Sierra Leone, for which we can obtain granular data on conflict locations, the location and size of mines, and fine-grained census data on local ethnic diversity. Second, we use a sample of 28 ethnically diverse, resource-rich countries in sub-Saharan Africa. This larger sample comes at the cost of less fine-grained data on local ethnic diversity.

We validate the theoretical predictions on local conflict exposure in different ways. First, following the static nature of the model, we time-average the data over the entire sample period and different sub-periods (characterized by the economic importance of different minerals). Second, we make use of the panel dimension and run standard two-way fixed effects regressions as well as two-stage least squares regressions with a generated instrument based on a shift-share approach that is commonly used in literature to deal with potentially endogenous mining operations (e.g., Bazzi and Blattman, 2014; Berman and Couttenier, 2015; Berman et al., 2017; Dube and Vargas, 2013). These different empirical analyses all show a close relation between the theoretically predicted local conflict exposure and the observed local conflict risks. Results are qualitatively similar in our sub-Saharan African sample.

Given the crucial role of discordant groups in our model, we conduct several tests showing that diversity among these groups is essential to predict local conflict. Most importantly, we take our analysis to the level of ethnic groups within wards and confirm that discordant groups in resource-rich locations are more likely to be involved in conflict than non-discordant groups in resource-rich locations or discordant groups in resource-poor locations.

Turning to the national level, we document a strong correlation between the theoretically derived peace deficit and the observed aggregate propensity for conflict over time in both our samples. Taken together, our empirical analyses suggest that our theoretical model can predict how, conditional on a country's ethnic geography, changes in its mining geography shape the occurrence and location of conflict events.

Our empirical contribution provides further nuance to the literature on the effects of natural resources and ethnic diversity on conflict.[4] In particular, our framework allows us to focus on the systemic component of the local conflict risk that depends on a country's entire ethnic and mining geography while accounting for local determinants of local conflict. Thus, we build a bridge between cross-country studies (e.g., Collier and Hoeffler, 2004) and granular spatial studies (e.g., Adhvaryu et al., 2021; Berman et al., 2017) on natural resources, ethnic diversity, and conflict.

[4] See, e.g., Collier and Hoeffler (2004), Humphreys (2005), Brückner and Ciccone (2010), Dube and Vargas (2013), Bazzi and Blattman (2014), Lei and Michaels (2014), Berman et al. (2017), Hodler et al. (2023) and Shapiro and Vanden Eynde (2023) on the role of natural resource rents; Montalvo and Reynal-Querol (2005), Matuszeski and Schneider (2006), Esteban and Ray (2008), Desmet et al. (2012), Esteban et al. (2012), Esteban et al. (2015), Corvalan and Vargas (2015), Novta (2016), Spolaore and Wacziarg (2016), Desmet et al. (2017), Eberle et al. (2025) and McGuirk and Nunn (2025) on the role of ethnic diversity; and Morelli and Rohner (2015), Adhvaryu et al. (2021) and Gehring et al. (2023) on the interaction between the two.

**Policy contribution:** Our third contribution is to use the theoretical concepts of the national peace deficit and the local conflict exposure to simulate the consequences of new industrial mining projects. We consider all known mineral deposits in Sierra Leone and run counterfactual analyses to predict how the hypothetical development of these deposits would affect the overall risk of conflict and the spatial distribution thereof. For example, we predict that the planned new gold mines on the Baomahun and Nimini deposits would increase the country's aggregate propensity for conflict. Importantly, we also identify alternative (gold) deposits whose development would lower the aggregate propensity for conflict. Hence, we confirm that *mining for peace* is not only a theoretical but also an empirical possibility. We also investigate mine closures and sequential mine openings. We document how mining the "right" deposits first can enlarge the set of other deposits that could be mined for peace. Finally, we predict how different mine openings would affect the spatial distribution of local conflict risks.

We view the changes in local and aggregate conflict risks induced by new mining projects as externalities. We propose that governments and other stakeholders use the concepts of the national peace deficit and the local conflict exposure to conduct cost-benefit analyses when designing mining policies. Explicitly considering the conflict externalities generated by new mines allows for a better assessment of the true costs of mining in specific locations and allows for the proper pricing of mining licenses. Thus, we contribute to a recent literature that discusses policies to mitigate the political resource curse, such as public information campaigns (Armand et al., 2020), foreign corruption regulation (Christensen et al., 2024), and international certification schemes (Binzel et al., 2024). In addition, our framework offers insights for international mining companies, not least because conflict threatens their assets, increases their production and transportation costs, and undermines their "social licenses to operate," which have become common in the mining industry (e.g., Prno and Slocombe, 2012).

The remainder of the paper is structured as follows. Section 2 present our theoretical model. Section 3 introduces our empirical setting and data, and Section 4 provides empirical support for our theoretical concepts. Section 5 discusses external validity in the sample of 28 diverse, resource-rich sub-Saharan African countries. Section 6 applies our theoretical concepts in counterfactual analyses to study how new mining projects would affect conflict. Section 7 concludes and provides policy recommendations for making the mining industry a facilitator of peace and prosperity in diverse low- and middle-income countries.

## 2. Model

In this section, we present and solve our theoretical model on how the spatial distributions of natural resource rents and ethnic groups shape national and local conflict risks. Section 2.1 introduces the setup. Sections 2.2–2.4 solve three versions of the model with slightly different informational environments. Section 2.5 discusses various possible extensions of the model.

### 2.1. Setup

Consider a country inhabited by a continuum of individuals. This population is partitioned into a finite set of ethnic groups $G \subset \mathbb{N}$ and a finite set of locations $L \subset \mathbb{N}$. These locations may represent subnational administrative or political units like wards in Sierra Leone. We denote the mass of individuals in ethnic group $g \in G$ and location $l \in L$ by $m_l^g \geq 0$, with $m_l := \sum_{g \in G} m_l^g$, $m^g := \sum_{l \in L} m_l^g$, and $m := \sum_{g \in G} m^g$.

Mining activities and the associated upstream and downstream services give rise to resource rents. The resource rent in location $l \in L$ is $r_l > 0$, where $r := \sum_{l \in L} r_l$ denotes the aggregate resource rent and $\mathbf{r}$ their $|L|$ dimensional vector. Individuals can form intra-ethnic coalitions at the local or the national level to contest resource rents in local or national conflicts, respectively.

In case of local or national conflict, a fraction of the corresponding resources is used to fight or destroyed in the conflict, while the rest is preserved. The groups' forecasts of these preserved fractions (perhaps mediated by psychological factors such as pride and entitlement) determine their valuations of the spoils of victory. As such fractions are difficult to assess due to unpredictable conflict dynamics of winners and losers, we think of them as subjective, thus random and privately known. We denote by $v_l^g \in [0,1]$ the fraction of the local resource rent $r_l$ that the local representatives of group $g \in G$ believe to be preserved in case of a conflict they win in location $l \in L$ (their local valuation). Similarly, we denote by $v^g$ the fraction of the national resource rent $r$ that the national representatives of group $g \in G$ believe to be preserved in case of a national conflict they win (their national valuation). The groups' subjective valuations of victory are then represented by a $|G| \times (|L|+1)$ dimensional matrix $\mathbf{v}$ with $v_l^g$ and $v^g$ as typical elements.

In case of conflict in location $l \in L$, the expected aggregate payoff of the local members of ethnic group $g \in G$ is thus $r_l v_l^g s_l^g$, where $s_l^g \in [0,1]$ denotes the expected share of preserved local resource rent conquered by them. Similarly, in case of national conflict, the expected aggregate payoff of members of ethnic group $g \in G$ in the whole country is $r v^g s^g$, where $s^g \in [0,1]$ denotes the expected share of preserved aggregate resource rent conquered by them. In line with the literature, we think of $s_l^g$ and $s^g$ as winning probabilities in winner-take-all conflicts, so that naturally $\sum_{g\in G} s_l^g = 1$ for each $l \in L$ and $\sum_{g\in G} s^g = 1$. The distribution of these winning probabilities is represented by a $|G| \times (|L|+1)$ dimensional matrix $\mathbf{s}$ with $s_l^g$ and $s^g$ as typical elements.

In the theoretical literature on conflict, winning probabilities are typically determined by the strategic interaction of the competing groups in conflict, where both group sizes and mobilization motives matter in determining the relative strength of a group. These motives are complex and jointly determined by, among others, the salience of ethnic identity, the complementarity of labor and capital in collective action, and the incentives of leaders and followers (e.g., Atkin et al., 2021; Esteban and Ray, 2008; Jackson and Morelli, 2007).

In our model, we abstract from such complex motives and simply assume that the winning probabilities are determined by the different groups' population shares in the relevant context. That is, $s_l^g = m_l^g/m_l$ and $s^g = m^g/m$.[5]

The focus of our analysis is instead on the promotion of peace via transfers of resource rents across ethnic groups and locations. For this purpose, we consider a planner who can redistribute resource rents to implement peace both at the local and the national level. As discussed in the Introduction, the planner could metaphorically represent the efficient bargaining between leaders of ethnic groups in the shadow of conflict.[6] The focus on resource rents implies that the planner can transfer the income generated by the resource endowments but not the endowments themselves. In this setting, the transfer received by a group determines the group's payoff under peace: specifically, the aggregate payoff for members of ethnic group $g \in G$ in location $l \in L$ in case of peace at location $l$ is their transfer $t_l^g \geq 0$, while the aggregate payoff of the whole ethnic population of group $g \in G$ in case of peace at the national level is their aggregate transfer $t^g := \sum_{l \in L} t_l^g$. A system of transfers is denoted by a $|G| \times |L|$ dimensional matrix $\mathbf{t}$ with $t_l^g$ as a typical element.

The first and foremost objective of the planner is to avoid the outbreak of a national conflict, e.g., because the consequences of national conflict are particularly uncertain and potentially detrimental for both the political leadership and the country's population. The planner's secondary objective is to sustain peace in many locations. Thereby, the planner assigns a priority weight $w_l \in (0, 1)$ to each location $l \in L$, with $\sum_{l \in L} w_l = 1$. These weights allow for the possibility that the planner cares more about peace in regions with

[5]These assumptions imply that we abstract from modeling fighting efforts and that all groups are equally efficient in converting population mass into military strength. The assumption $s_l^g = m_l^g/m_l$ also implies that national governments (and national militias) do not intervene in local conflicts. We discuss in Section 2.5 how results would change if we loosened these assumptions.

[6]The resulting conflict risks metaphorically represent the least conflictual outcomes that could be achieved with bargaining and transfers when local and national conflicts are simultaneous threats. In the presence of additional constraints on efficient bargaining due to political economy factors external to our model, the resulting conflict risks would necessarily be higher.

active mines or certain ethnic compositions. The literature on ethno-regional favoritism (e.g., Burgess et al., 2015; De Luca et al., 2018; Hodler and Raschky, 2014) suggests that these latter regions may be those with a high share of co-ethnics of the country's political leaders. We assume the planner maximizes the weighted sum of the peace probabilities $p_l \in [0,1]$ across all locations,

$$\max_{\mathbf{t}} \sum_{l \in L} w_l p_l, \tag{1}$$

subject to guaranteeing peace at the national level, a budget constraint, and informational frictions.[7] We call such objective *peace-maximizing*. We will carry this objective across all stages of our theoretical inquiry in slightly different forms, adapted to the specific informational structure.

In our model, the crucial friction for peace is that transfers represent the status-quo income of the groups (their peace payoff) and thus cannot be conditioned on the local or national nature of the conflict threat. Instead, the transfers should prevent conflict at both levels simultaneously, as ethnic coalitions may mobilize at either the local or the national level after the transfers are determined.[8] In addition to this commitment friction on the part of the groups, the planner has two fundamental constraints for promoting peace. The first is the limited budget for redistribution, which is determined by the aggregate value of the resource rents. The second is the limited information about the groups' perceptions of the wastefulness of conflict, as quantified by $v^g$ and $v_l^g$, which are privately known by the groups.

[7]The linear specification of the planner's objective is consistent with Von Neumann–Morgenstern representation of the planner's preferences in the form of expected utility, where the weight $w_l$ represents the difference between the utility of peace and the utility of conflict in location $l$.

[8]If groups were ex-ante committed to a type of conflict – with ethnic coalitions mobilizing either at the local or national level – conflict could always be prevented via an opportune transfer system that redistributes the peace surplus by rewarding coalitions proportionally to their strength. This, however, fails to occur in our model in which groups can choose to mobilize either at the local or national level after they learn their status-quo incomes. For related approaches where, despite efficient bargaining and transfers, conflict occurs due to commitment frictions, see Ray (2009) and Morelli and Rohner (2015).

In our analysis, we consider three alternative ways the planner may approach this informational constraint. In Section 2.2, we study the conditions under which the planner can guarantee peace at the national level and all locations – thus achieving the unconstrained maximum of the planner's objective (1) – for any possible realization of $\mathbf{v}$ and, therefore, in the absence of any reliable knowledge on $\mathbf{v}$. This exercise delivers a restrictive condition for peace implementation (the *peace condition*), the set of groups that initiate conflict (the *discordant groups*), and the amount of additional funds necessary to pacify the country (the *peace deficit*).

In Section 2.3, we inquire whether the constrained maximum of (1) can be reached via a system of transfers that incentivizes the groups to truthfully reveal their private information on $v_l^g$ and $v^g$. We find that such a transfer system fails to exist whenever the peace condition is violated, thus suggesting a general impossibility.

In Section 2.4, we study the constrained maximum of (1) based on prior information only (rather than revealed information). As a result of this analysis, we obtain the probability of conflict at each location.

### 2.2. Peace-guaranteeing transfers

In this section, we inquire whether the planner can achieve the unconstrained maximum of the peace-maximizing objective (1) in the absence of reliable knowledge and, therefore, for any beliefs about preserved local and national resources $\mathbf{v}$.

As in all our model specifications, the planner will attempt to do so by appropriately redistributing resource rents. We, therefore, introduce some terminology that will be carried on in subsequent sections. First, given $\mathbf{r}$, we say that a system of transfers $\mathbf{t}$ is *budget feasible* if $\sum_{g \in G} t^g \leq r$. This condition requires the planner's intervention to be purely redistributive and does not allow for extra income. Second, given $\mathbf{r}$ and $\mathbf{s}$, we say that a system of transfers $\mathbf{t}$ *guarantees peace everywhere* if, for every possible $\mathbf{v}$, it does so simultaneously at the national level and in each location, i.e.,

$$t^g \geq s^g r v^g \text{ and } t_l^g \geq s_l^g r_l v_l^g \text{ for each } g \in G \text{ and } l \in L.$$

These conditions are very restrictive as they must hold even for the most demanding case of non-destructive conflicts (i.e., $v_l^g = v^g = 1$). They can be seen as the ideal goal of a planner who, fearing the chaotic consequences of conflict, aims at guaranteeing peace at every level and every location under any foreseeable contingency.

Our first result characterizes the *peace condition*, i.e., the narrow set of configurations of **r** and **s** that can guarantee peace everywhere in a budget-feasible manner.[9]

Proposition 1. *Given* $\boldsymbol{r}$ *and* $\boldsymbol{s}$, *there exists a system of transfers* $\boldsymbol{t}$ *that guarantees peace everywhere and is budget feasible if and only if*

$$1 = \sum_{l \in L} (r_l/r)(s_l^g/s^g) \text{ for each } g \in G. \tag{2}$$

Given that the winning probabilities take the form $s_l^g = m_l^g/m_l$ and $s^g = m^g/m$ for all $l \in L$ and $g \in G$, the peace condition (2) can be rewritten as

$$1 = \sum_{l \in L} (r_l/r)[(m_l^g/m_l)/(m^g/m)] \quad \text{or} \quad 1 = \sum_{l \in L} [(r_l/m_l)/(r/m)](m_l^g/m^g).$$

Hence, it holds in two special cases: First, it holds if there is no ethnic segregation, i.e., if $m_l^g/m_l = m^g/m$ for all $l \in L$ and $g \in G$, as understood from the first equality. Second, it holds if there is no inequality in per capita resource rents across locations, i.e., if $r_l/m_l = r/m$ for all $l \in L$, as understood from the second equality. However, in the presence of ethnic segregation and

[9] Online Appendix A contains the proofs of all propositions.

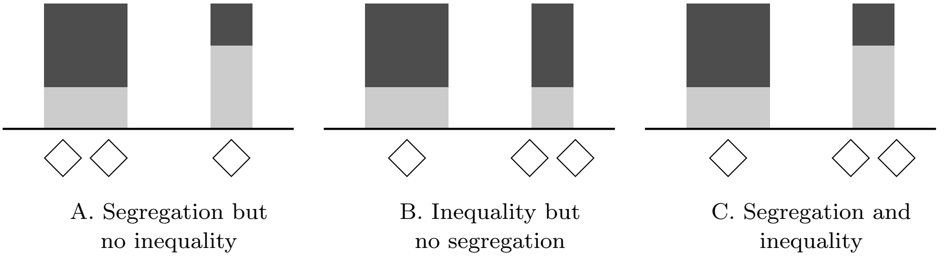



FIGURE 1. Illustration of peace condition. Each graph represents a different country where the horizontal axis represents different locations $l \in L = \{1, 2\}$ and each tone of gray indicates a different ethnic group $g \in G = \{1, 2\}$. The size of the gray rectangular areas above the horizontal axis indicates the population mass $m_l^g$ of each group $g \in G$ in each location $l \in L$. The diamonds below the horizontal axis indicate the resource rent $r_l$ at each location $l \in L$.

spatial resource inequality, the peace condition (2) does not generally hold. Hence, peace is typically not guaranteed.

Figure 1 illustrates these insights with simple examples. Panel A shows a country with no spatial resource inequality. There, a peace-guaranteeing, budget-feasible transfer scheme exists because per-capita resource rents are identical across locations. Panel B shows a country with no ethnic segregation. There, such a transfer scheme exists because each group's population share is identical across locations. In contrast, peace cannot typically be guaranteed in countries with both ethnic segregation and spatial resource inequality, like the country shown in Panel C.[10]

We now take a closer look at why conflict emerges. Importantly, conflict may only be initiated by groups belonging to the set

$$G^* = \{g \in G : 1 < \sum_{l \in L} (r_l/r)(s_l^g/s^g)\}. \tag{3}$$

The definition of this set can be easily understood in relation to the peace condition (2). Intuitively, if peace is guaranteed at the national level for every

[10]For the case with two locations and two ethnic groups, peace is guaranteed if and only if there is no inequality *or* no ethnic segregation. With more groups or more locations instead, this is only a sufficient condition.

$\mathbf{v}$, the aggregate transfers to groups must equal their maximum claims at the national level, $t^g = s^g r$. Then, the groups that may initiate local conflict are the ones that are over-represented in resource-rich locations. The reason is that they are short of transfers from the constraint at the national level:

$$rs^g = t^g = \sum_{l \in L} t_l^g < \sum_{l \in L} r_l s_l^g.$$

Hence, they may experience discord between the resource rents accruing in the locations where they predominantly live and their comparatively low post-transfer well-being. We, therefore, call the groups in set $G^*$ *discordant groups*. All other groups $g \notin G^*$ are over-represented in resource-poor locations. Hence, their total transfers $t^g = s^g r$ are more than sufficient to ensure they do not initiate conflict in any location, $t_l^g \geq s_l^g r_l$.

To see an example of the logic of discordant groups, consider again Figure 1. There, the set of discordant groups is empty in panels A and B. In panel C, which we already identified as the only case of conflict, the group depicted in light gray is a discordant group as it is over-represented in the resource-rich location on the right. The other group, instead, depicted in dark gray, is non-discordant as it is under-represented in this location.

We conclude this section by defining a measure of the general tendency for conflict in a country. We call this measure the *peace deficit*, as it quantifies the amount of additional funds that would allow the planner to guarantee peace everywhere. By Proposition 1 and the related discussion of discordant groups, it is straightforward that the peace deficit can be written as

$$\Delta := \sum_{g \in G} \max \left\{ \sum_{l \in L} r_l s_l^g - r s^g, 0 \right\} = \sum_{g \in G^*} \left( \sum_{l \in L} r_l s_l^g - r s^g \right). \tag{4}$$

Intuitively, the set of discordant groups is empty and $\Delta = 0$ if the peace condition holds, while this set is non-empty and $\Delta > 0$ otherwise. In our empirical applications, we will use the peace deficit $\Delta$ to measure a country's aggregate propensity for conflict.

### 2.3. Peace-implementing mechanism

In this section, we discuss whether the constrained maximum of the peace-maximizing objective (1) can be reached via a system of transfers that incentivizes the groups to truthfully reveal their private information on $v_l^g$ and $v^g$.

The desirability of such information revelation is straightforward. Having established that it is (generally impossible) to guarantee peace for every possible realization of $\mathbf{v}$, we now consider whether the planner can promote peace for at least some of these realizations. More specifically, conflict could always be prevented if known to be very destructive, e.g., if $v_l^g \approx 0$ and $v^g \approx 0$ for all $g$ and $l$, as relatively low transfers would be sufficient to guarantee that all groups opt for peace. Thus, if the planner could identify such realizations of $\mathbf{v}$, it could at least guarantee peace in contingencies where conflict is particularly wasteful. However, this is not immediate as the perceived wastefulness of conflict – as measured by $v_l^g$ and $v^g$ – is private information of the groups, and groups may not have an incentive to communicate this truthfully to the planner.

Taking a mechanism design approach, we focus on the scenario in which the members of group $g \in G$ inhabiting each location $l \in L$ are required to reveal their perceived preserved fraction $v_l^g \in [0, 1]$ to the planner via a corresponding message $\mu_l^g \in [0, 1]$, while the national representatives of group $g$ are required to reveal $v^g \in [0, 1]$ via $\mu^g \in [0, 1]$. In this context, a mechanism is a function $T$ that maps each profile of messages $\mu := (\mu_l^g, \mu^g)$ into the corresponding transfer system $t_l^g = T_l^g(\mu)$ for each $l \in L$ and $g \in G$, where $t^g = \sum_{l \in L} T_l^g(\mu)$.[11] Given the transfer system is implemented, all groups act upon their transfer and their perceived preserved fractions $v_l^g$ and $v^g$. Hence, there is conflict outbreak at

[11]The extension to stochastic mechanisms – mapping message profiles into probability distributions over transfer systems – is omitted for ease of exposition but straightforward, leading to the same impossibility conclusions below.

location $l \in L$ if and only if $t_l^{g'} < s_l^{g'} r_l v_l^{g'}$ for some $g' \in G$, and national conflict outbreak if and only if $t^{g'} < s^{g'} r v^{g'}$ for some $g' \in G$.

We consider two desirable properties a mechanism should satisfy for every given profile of preserved fractions $\mathbf{v}$. Adapting (1) to the present setting, we say that a mechanism is *peace-maximizing* if it implements peace at the national level and, given that this is guaranteed, implements peace at the local level for the highest ($w_l$-weighted) number of locations. Borrowing a conventional idea from the literature, we say that a mechanism is *incentive compatible* if the national and local representatives of each group have a weak incentive to truthfully reveal their private information to the planner whenever peace is implemented by such revelation in the relevant (national or local) context. We are now ready to state our next result:

Proposition 2. *Given $\boldsymbol{r}$ and $\boldsymbol{s}$, there exists a mechanism that is peace-maximizing and incentive compatible if and only if the peace condition (2) holds.*

Proposition 1 has shown that peace can be guaranteed in the absence of information revelation only in the narrow set of cases satisfying the peace condition (2). Now, Proposition 2 shows that peace implementation is limited to the identical set of cases. Communication of private information thus fails to promote peace whenever relevant, making Proposition 2 effectively an *impossibility result*. We conclude that informational frictions make conflict generally unavoidable even when it is so wasteful that (in principle) there are enough transfers to convince all groups to sustain peace. The intuition for the impossibility of truthful revelation is that local groups may have an incentive to pretend being short of transfers when they are not. This pretense is to the advantage of the group's representatives in the location that claims the shortage of transfers, but against the interest of the remaining group members who face an increased exposure to conflict outbreaks in other locations. Note that, as peace is prioritized at the national level, the transfers to each group are fixed in aggregate, and information is used to determine how they should be distributed across the group's local representatives. At its core, the impossibility of truthful revelation is thus a collective-action problem within groups.

### 2.4. Constrained optimization and local conflict exposure

In this section, we study the planner's constrained optimization of the peace-maximizing objective (1) based on prior information only (rather than no information or revealed information, as in the previous two sections). As a result, we will obtain the probability of conflict at each location under the implementation of the optimal (second-best) transfer system.

In line with our general assumptions on the planner's objective (1) and constraints, we assume that – for each resource distribution $\mathbf{r}$ and group strength distribution $\mathbf{s}$ that violate the peace condition (2) – the planner chooses the transfer scheme $\mathbf{t}$ to maximize the expected ($w_l$-weighted) number of peaceful locations subject to ensuring peace at the national level:

$$\max_{\mathbf{t}} \sum_{l \in L} w_l p_l(\mathbf{t}_l, \mathbf{s}_l, r_l) \text{ s.t. } t^g = s^g r \text{ for each } g \in G.$$

The probability of peace at each location $l \in L$, $p_l(\mathbf{t}_l, \mathbf{s}_l, r_l)$, is determined by the commonly-known prior distribution of perceived fractions of preserved resources at the local level, $v_l^1, \ldots, v_l^{|G|}$, which for simplicity we assume to be independent across locations. For tractability, we also assume that these fractions are independently and identically distributed within locations, according to a cumulative distribution function $\Phi : [0, 1] \to [0, 1]$.[12] Again, we assume that group $g \in G$ at location $l \in L$ acts upon the perceived fraction $v_l^g$ and thus refrains from starting local conflict if and only if $t_l^g \geq s_l^g r_l v_l^g$. As peace has to be sustained unanimously, the probability of peace at location $l \in L$ can

[12]These independence assumptions are necessary to obtain closed-form solutions that we can bring to the data. We will empirically confirm that these solutions are helpful to predict the occurrence of local conflict events. However, the lack of generality (due to these assumptions) may limit the normative value of the second-best transfer scheme.

thus be written as

$$p_l(\mathbf{t}_l, \mathbf{s}_l, r_l) = \prod_{g \in G} \Phi(\min\{t_l^g/(s_l^g r_l), 1\})$$

and the corresponding probability of conflict as $c_l(\mathbf{t}_l, \mathbf{s}_l, r_l) = 1 - p_l(\mathbf{t}_l, \mathbf{s}_l, r_l)$. We propose that $\Phi$ should be increasing, differentiable, and concave, implying a decreasing density function. Such density functions capture the idea that preserved fractions are hard to predict but that highly wasteful events are comparatively more likely – perhaps due to the infamous reputation of ethnic conflicts. The power form $\Phi(x) = x^\alpha$ with $\alpha \in (0, 1)$ satisfies these properties and, for $\alpha$ sufficiently small, turns out to be particularly convenient to obtain an explicit solution.

We are now ready to state our result. We thereby focus on interior solutions, i.e., configurations of $\mathbf{r}$ and $\mathbf{s}$ such that, given the optimal transfer scheme is in place, each discordant group has a positive probability of initiating conflict in each location.[13]

PROPOSITION 3. *Let $\Phi(x) = x^\alpha$ with $\alpha \in (0, 1/|G^*|)$. If the optimal system of transfers $\boldsymbol{t}^*$ is implemented and the solution interior, the probability of conflict at each location $l \in L$ is*

$$c_l(\boldsymbol{t}_l^*, \boldsymbol{s}_l, r_l) = 1 - \frac{(w_l)^{|G^*|\alpha/(1-\alpha|G^*|)} e_l(\boldsymbol{t}_l^*, \boldsymbol{s}_l, r_l)^{-|G^*|\alpha/[1-|G^*|\alpha]}}{\left[\sum_{l' \in L} (w_{l'})^{1/(1-\alpha|G^*|)} e_{l'}(\boldsymbol{t}_{l'}^*, \boldsymbol{s}_{l'}, r_{l'})^{-|G^*|\alpha/[1-|G^*|\alpha]}\right]^{|G^*|\alpha}},$$

*where*

$$e_l(\boldsymbol{t}_l^*, \boldsymbol{s}_l, r_l) := (r_l/r) \left[\prod_{g \in G^*} (s_l^g/s^g)\right]^{1/|G^*|}. \qquad (5)$$

[13] The focus on interior solutions is necessary for tractability and to get a closed-form solution that we can bring to the data. Given the arbitrary number of groups and locations (and corresponding parameters) in this model, the possibilities for different configurations of corner solutions are infinite.

Proposition 3 delivers the principal testable prediction of our model. In particular, we expect a high correlation between the theoretically predicted local conflict risk $c_l$ and the observed frequency of local conflict events. This conflict risk $c_l$ is decreasing in the priority weight $w_l$ that the planner assigns to location $l$ and increasing in $e_l$, which we call the *local conflict exposure*. The priority weights may well capture local determinants of local conflict, such as the presence of active mines or the share of co-ethnics of the country's political leaders. These weights are likely mediated by the preferences of who is in power and thus, at least partly, subjective. In contrast, the local conflict exposure $e_l$ captures the more systemic (and, arguably, more nuanced) effects of the country's entire ethnic and mining geography on local conflict, which are the main focus of our analysis and, from our perspective, more objectively quantifiable. In our empirical analysis, we will thus focus on the local conflict exposure $e_l$ while controlling for some known local determinants of local conflict.[14]

We now briefly discuss the determinants and structure of the local conflict exposure $e_l$. By its definition (5), the local conflict exposure – and, therefore, the corresponding conflict risk – depends on the interplay of two complementary forces. The first is the relative presence of contestable resources, $r_l/r$. The second is the geometric mean of the discordant groups' relative population shares, $D_{l,G^*} := \left[\prod_{g\in G^*}(s_l^g/s^g)\right]^{1/|G^*|}$, which can be interpreted as a measure of local ethnic diversity quantifying the discordant groups' over-representation in the location.[15] As this measure depends on the population shares of

[14]The local conflict exposure $e_l$ is not a probability, as it abstracts from average effects on a country's propensity for conflict across locations. Nevertheless, the local conflict exposure is perfectly valid and practically convenient to understand within-country variation in the relative propensity for conflict. Average effects are instead captured by the denominator of $c_l$ (which is a measure of the dispersion of the distribution of the priority weights and the local conflict exposures) or, more conveniently, by the peace deficit $\Delta$, which has the added advantages of being independent of the unknown priority weights, the independence assumptions of this section, and our focus on interior solutions.

[15]The interpretation of $D_{l,G^*}$ as a measure of ethnic diversity follows from the application of (the inverse of) the principle of transfers in inequality measurement to fractionalization measures, as $D_{l,G^*}$ increases whenever population is marginally transferred from a locally larger to a locally smaller discordant ethnic group.

discordant groups only, it captures these groups' *endogenous radicalization* and the *bargaining failure* resulting from their claims at various levels of spatial aggregation. The complementarity of these forces is captured by the multiplicative form of the conflict exposure index: $e_l = (r_l/r)D_{l,G^*}$.

We will empirically validate our conflict prediction (5) below. However, it is worth highlighting already that this prediction can account for several prominent stylized facts in the literature: First, conflict events often occur in resource-rich locations (e.g., Berman et al., 2017). Second, conflict events often occur in ethnically diverse locations of segregated countries (e.g., Corvalan and Vargas, 2015; Eberle et al., 2025; Matuszeski and Schneider, 2006). Third, ethnic groups in resource-rich locations often feel economically deprived and politically excluded (Berman et al., 2023). Our prediction systematizes these stylized facts and emphasizes their complementarities, which is essential for understanding the systemic effects of mining.

### 2.5. Extensions

*2.5.1. Heterogeneous fighting efficiency.* Our model assumes that all ethnic groups are equally efficient in converting population mass into military strength. In the real world, groups with privileged access to resources, such as those with prominent roles in the national government or those overrepresented in resource-rich regions, may be militarily stronger than similarly sized groups with worse access to resources.

It is straightforward to extend the model by allowing for heterogeneity in the efficiency with which different groups convert population mass into military strength. The effects on the results would depend on the exact scenario under consideration. Let us first consider ethnic favoritism in the form of the members of a particular ethnic group having better access to governmental resources and thus superior fighting efficiency everywhere. This higher efficiency would scale up the group's winning probability in both the national conflict and every local conflict by a common parameter. In this scenario, the set of discordant groups would remain unaffected and the peace deficit would increase if and only if the favored group was discordant, i.e., over-represented in resource-rich locations.

As a second scenario, let us assume that the fighting efficiency of an ethnic group increases in its proximity to natural resources. Assuming proximity to local resources matters for local conflict, while proximity to all resources matters for national conflict, this would leave local winning probabilities unchanged while drastically inflating the national winning probabilities of groups over-represented in resource-rich locations. In this scenario, the peace deficit would shrink compared to our baseline model, suggesting a lower aggregate propensity for conflict. The reason is that national and local claims would realign, such that less additional funding would be necessary to guarantee peace everywhere.

*2.5.2. Timing and the role of national governments in local conflicts.* Our model assumes that the ethnic groups' winning probabilities in a local conflict depend only on their local population (or local military strength). While this assumption seems fairly realistic in the immediate aftermath of the onset of a local conflict (i.e., in the short run), one may expect national governments and maybe national militias to intervene at some point (i.e., in the medium-to-long run).

To account for this possibility, we could again assume that groups with prominent roles in the national government have higher military strength in local conflicts (as in Section 2.5.1). Alternatively, we could assume that each group's local winning probability $s_l^g$ is a linear combination of its local population share $m_l^g/m_l$ and its national population share $m^g/m$, with weight $\pi \in [0, 1)$ determining the relative importance of the latter. Emphasizing the temporal interpretation, $\pi$ could be seen as a time-preference parameter indicating the relative importance of the long run as opposed to the short run in a group's decision to initiate conflict. Within this generalized framework, our baseline model coincides with a focus on the short run: $\pi = 0$. Increasing $\pi$ would leave most qualitative results unchanged while mechanically reducing the peace deficit, since local and national winning probabilities would converge and national and local claims consequently realign. Hence, by implicitly assuming $\pi = 0$, we focus on the setting most suitable for highlighting conflicts that occur because of the tensions arising from the groups' possibility to fight at the national and the local level.

*2.5.3. Intra-ethnic coordination and spatial conflict dynamics.* In our model, ethnic groups strategically choose where to initiate a fight, but the groups' local representatives initiate local conflicts without coordination and independently of their national representatives. This lack of intra-ethnic coordination implies that spatial correlation in conflict patterns mainly results from the spatial concentration of resource rents and the relative presence of discordant groups. In contrast, Mueller et al. (2022) propose a model where ethnic groups are fully coordinated (acting as a single player) and strategically choose where to recruit across locations. Recruitment in one location mechanically translates into violent attacks in other locations, with the ferocity of these attacks declining with the spatial distance. Within our model, if groups were fully coordinated, there would be peace everywhere, as the groups' national representatives would discipline their local representatives into accepting a peaceful split of national resources proportional to population shares. A richer model could combine elements of the spillover effects and coordinated choice (of where to recruit) from Mueller et al. (2022), with the pacifying transfers and the uncoordinated choice (of where to fight) from our model. Such a model could significantly improve our understanding of spatial conflict dynamics in ethnically segregated countries, but would crucially require a more nuanced representation of modes and degrees of coordination between local and national representatives of ethnic groups.

*2.5.4. Inter-ethnic coalitions.* In our model, coalitions can only be formed among co-ethnics, which is consistent with prominent theoretical arguments by Esteban and Ray (2008) and Caselli and Coleman (2013). Nevertheless, it is important to consider how results would change if we allowed for a wider set of coalitions, including inter-ethnic coalitions. The main consequences are clear. Augmenting the set of admissible coalitions would render conflict more likely, as the potentially incompatible claims to be accommodated via the same transfer system would increase, thereby strengthening the impossibility results in Propositions 1 and 2. Moreover, it would weaken the predictive capacity of our model with respect to the occurrence of local conflicts.

*2.5.5. Mining booms and migration.* Mining booms often attract migrants from other parts of the country. Our model is static and thus abstracts from migration. Nevertheless, it can help us to understand the consequences of migration from resource-poor to resource-rich regions. These consequences depend on how migration changes the spatial distribution of ethnic groups. If all individuals from resource-poor regions were equally likely to migrate to any of the resource-rich regions, then ethnic segregation would likely decrease, leading to a lower peace deficit and, hence, a lower aggregate propensity for conflict. In contrast, if migration were mainly about individuals of minority groups in resource-poor regions moving to resource-rich regions dominated by their co-ethnics, then migration could increase ethnic segregation and the aggregate propensity for conflict. Neither of these scenarios seems to apply to Sierra Leone, where the different groups' local population shares are relatively stable over time (as shown below).

## 3. Setting and data

In this section, we provide background information about Sierra Leone and introduce our granular spatial data from Sierra Leone and our main variables. In Section 5 and Appendix D, we introduce less granular spatial data for a sample of 28 sub-Saharan African countries.

### 3.1. Sierra Leone

The Sierra Leonean civil war started in 1991 when the Revolutionary United Front (RUF) invaded out of neighboring Liberia. The government of Sierra

Leone and the Sierra Leone Army (SLA) were unable to react decisively, and the conflict spread over the entire country. Outright battles between the SLA and the RUF were the exception. Instead, the primary targets of violence were civilians and, in the case of RUF, some local chiefs. Local ethnic militias, consisting of traditional hunters and civilians, emerged to defend local communities against the RUF and, sometimes, the SLA (Hoffman, 2007; Reno, 2003). These local ethnic militias loosely cooperated as Civil Defense Forces (CDF). Like the RUF and the SLA, the CDF also committed atrocities and human rights abuses. A UN intervention led by the United Kingdom ended the civil war in 2002. In total, more than 50,000 people were killed in this war (Bellows and Miguel, 2006; Kaldor and Vincent, 2006).

Diamonds played a crucial role in financing organized armed groups (Bellows and Miguel, 2009). All industrial mining operations came to a halt after the beginning of the civil war, but diamonds could easily be mined with forced labor and little capital and could be illicitly exported.

Despite the politicization of ethnic identities and the ethnicization of political processes in post-independence Sierra Leone (Kandeh, 1992), ethnic identities were not of first-order importance in the civil war (Bellows and Miguel, 2006). The RUF had an ethnically diverse background. Their attacks, however, had an ethnic and local component insofar as they collaborated with co-opted candidates for local chieftaincy in contested locations (Raleigh and De Bruijne, 2017). In contrast, the militias that became part of the CDF had very direct links to ethnic groups (Hoffman, 2007; Reno, 2003). The largest of these local ethnic militias was the ethnic Mende-based Kamajors (Bellows and Miguel, 2009; Hoffman, 2007). Another important local ethnic militia was the ethnic Kono-based Donsos (Hoffman, 2007), who defended local communities in the diamond-rich Kono district.[16] Humphreys and Weinstein (2006) study the

[16] Agence France Presse reported on June 17, 1998: "[A] newly formed militia made up of some 400 local hunters called Donsos said it had rescued some 3,000 civilians when it liberated 36 villages in the eastern Kono district." In our conflict data (discussed below), we find that 47.6% of the conflicts involving the Kamajors took place in wards in which the Mende are the largest ethnic group, and 100% of the conflicts initiated by the Donsos took place in wards where the Kono are the largest ethnic group.

effect of ethnic-alignment between armed groups and local population on abuse intensity during the civil war. They find a negative relation, which becomes statistically insignificant once they control for armed group-fixed effects.

The importance of diamonds (especially artisanally mined ones) has constantly decreased since the end of the civil war. The resurgence of industrial mining operations in bauxite, diamonds, iron, and rutile has dramatically shifted the mining geography and export portfolio of Sierra Leone over the last two decades. This portfolio is now dominated by bauxite and iron exports. Overall, the mining sector accounted for 65% of Sierra Leone's exports in 2018 and a large share of its government revenues (around 10% in recent years).[17] Currently, most mineral production results from six industrial mining sites, with two gold mines being planned but not yet completed. In addition, there are known deposits of other precious metals, including limonite and nickel (according to the mining data introduced below).

### 3.2. Data

The main reason for focusing on Sierra Leone is that we can obtain granular, i.e., spatially disaggregated, data on the distribution of ethnic groups, the location and size of mines, and conflict events. Another advantage, which we leverage below, is that different minerals are mined in different parts of Sierra Leone and that the relative importance of these minerals has changed multiple times over the last two decades.

We construct a panel dataset with 107 Sierra Leonean (electoral) wards as the cross-sectional dimension and 22 years as the temporal dimension. Most wards coincide with historical chiefdoms, which are the local government units involved in selling public land to develop mines, or encompass multiple smaller chiefdoms. Wards are the lowest level of spatial aggregation for which we can obtain census information on the population shares of the different ethnic

[17] See https://www.investinginsierraleone.com/natural-resources/.

groups.[18] The average ward has an area of 670 $km^2$ (i.e., less than a quarter of the area of the $0.5 \times 0.5$ decimal degree grid cells commonly used in conflict studies). Our sample period starts in 1997 (as the conflict data is unavailable for earlier years) and ends in 2018 (as we have no access to some of the mining data for later years).

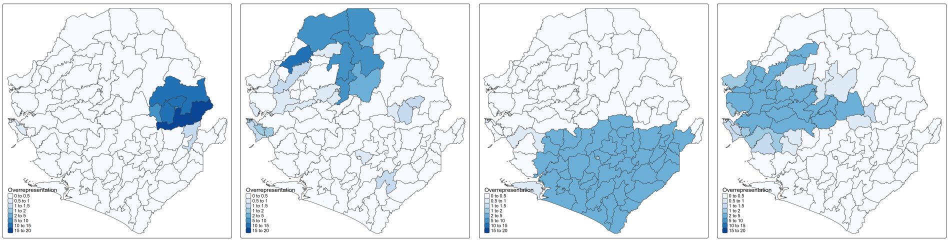
In what follows, we first discuss the ethnicity and natural resource data that we use to compute the two theoretical concepts we aim to empirically validate: the predicted local conflict exposure and the peace deficit. We then discuss the data on conflict events used in these validation exercises. Summary statistics are provided in Online Appendix Tables C.1 and C.2.

*3.2.1. Ethnic geography and local over-representation.* To compute the predicted local conflict exposure $e_l$ and the peace deficit $\Delta$, we need information on the population share $s_l^g$ of each ethnic group $g$ in each ward $l$. We obtain this information from the 2004 Housing and Population Census of Sierra Leone (Ruggles et al., 2025). The census provides information on the ethnic affiliation of each tenth household in Sierra Leone at the level of wards.

The four most populous groups are the Mende (with a country-level population share of 32.9%), the Temne (32.2%), the Limba (8.3%), and the Kono (4.5%). Our sample includes eight more groups with a population share of more than 1%. We assume that the spatial distribution of ethnic groups remains unchanged during our sample period, as such fine-grained data on the spatial distribution of ethnic groups is mostly unavailable for other years.[19] This assumption, however, is appealing given our interest in how the propensity for conflict changes in response to changes in the country's mining geography (rather than in response to changes in its ethnic geography).

[18]We use the shape file of chiefdoms provided by Acemoglu et al. (2014) to build a shape file representing the boundaries of the wards reported in the 2004 Population and Housing Census of Sierra Leone.

[19]Below we show that the ethnic groups' local population shares are relatively stable between 2004 and 2015, which are the years for which we have data.



(A) Kono (B) Limba (C) Mende (D) Temne

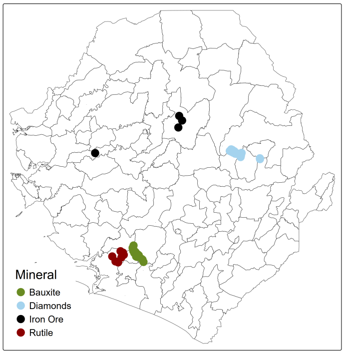
FIGURE 2. Local over-representation of the four largest ethnic groups. Panels A–D plot the local over-representation ($s_l^g/s^g$) across wards for the four most populous ethnic groups.

The ethnic groups' local over-representation $s_l^g/s^g$, i.e., the ratios of the population share of each group in each ward relative to the group's national population share, play a key role in our theoretical model. Figure 2 plots the local over-representation of the four most populous ethnic groups across wards.[20] We see considerable spatial variation in their local over-representation. The Kono are concentrated in the east of the country, the Limba mainly in the north, the Mende in the south, and the Temne in the west and the center.

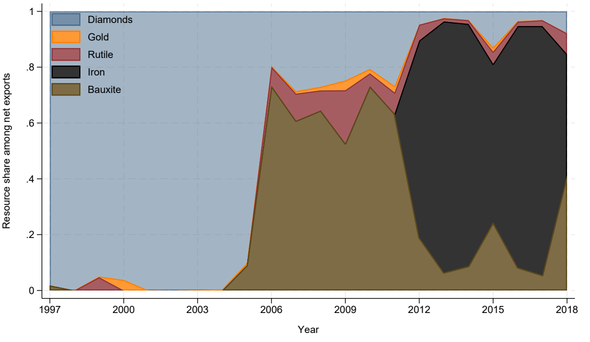
*3.2.2. Mines and local resource rents.* To build a time-varying measure of the resource rents $r_l$ in each ward $l$, we use data on the location and size of industrial mines, which we will complement with data on artisanal and small-scale mining in an important robustness test, as well as data on the importance of the corresponding minerals over time.

We use two spatial datasets on industrial mines. The first is the Raw Material Data (RMD, S&P Global Market Intelligence, 2025). The RMD provides information on global mining activities since 1980, including the (approximate) location, name, owner, primary commodity, and the years in which a mine is active. It lacks discovery dates, and its information on the amounts extracted is incomplete. The second dataset is the global dataset of mining areas produced by Maus et al. (2020). They leverage recent satellite

[20]Online Appendix Figure C.1 plots the local over-representation of the remaining eight groups with a national population share of more than 1%.




(A) Locations of mining areas




(B) Share of net exports of different minerals

FIGURE 3. Mining locations and the relative importance of different minerals. Panel A plots the locations of all industrial mining areas reported in Maus et al. (2020), with different colors indicating different minerals. Panel B plots the net exports from each mineral as a share of the total net exports from the five main minerals.

images and machine learning techniques to identify the actual mining areas within close proximity of the sometimes imprecise mining locations reported in the RMD. We match the two datasets so that we have information on the primary commodity of each industrial mine (from RMD) as well as the location and shapes (polygons) of the corresponding mining areas (from Maus et al., 2020).[21] Panel A of Figure 3 shows the resulting spatial distribution of industrial mining areas, with different colors indicating different main minerals extracted. We see that diamonds are exclusively mined in the east of the country, bauxite and rutile in the south-west, and iron primarily north of the center.

We measure the (time-varying) importance of the different minerals for Sierra Leone based on their net exports. For this purpose, we use the export and import data from United Nations Statistics Division (2025) and compute the value of net exports in current prices for each mineral and year (thereby setting negative values to zero). Panel B of Figure 3 shows each mineral's net exports as a share of the total net exports from the five main minerals. We see

[21]Some mines consist of multiple mining areas close to one another. We verify the existence of each industrial mine using Google Earth and auxiliary data (see Online Appendix B.1).

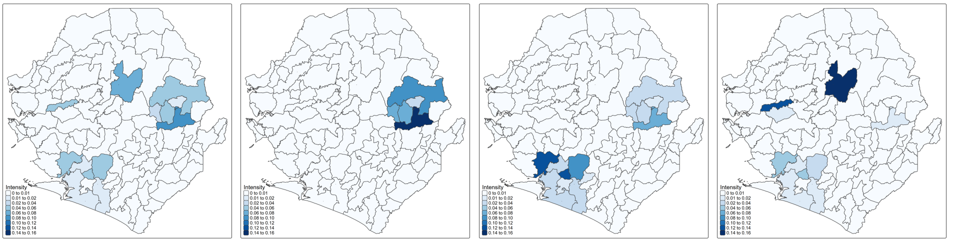
sizeable intertemporal variation in the different minerals' relative importance: Diamonds were the most important mineral up to 2004, bauxite from 2005–2011, and iron thereafter. Gold and rutile play only a minor role throughout the sample period.[22]

We use these data to build a measure of local resource rents $r_l$. Due to backward and forward linkages, most industrial mines have an economic impact beyond the mining area. For example, Aragón and Rud (2013) document economic spillovers from an industrial gold mining that extend up to 100 km. We thus assume that resource rents do not only materialize right at the mines but are spread out in space.[23] More specifically, we assume that the local resource rents $r_l$ increase in the size and the proximity of mining areas and the revenues from the corresponding mineral in a given year. We proceed in two steps. First, we distribute the annual revenues (as measured by net exports) across mining areas. For each mineral, we distribute the mineral-specific annual revenues across all mining areas that primarily extract the respective mineral, and we do so in proportion to the size of these mining areas. Second, we compute each ward's annual resource rents $r_l$ based on the mining area-specific annual revenues. For each mining area, we assume that the rents that accrue in different wards are proportional to the inverse geodesic distance between the centroids of the mining area and these wards.[24] The use of the inverse distance represents a specific spatial decay function. We will test for the robustness of our results using alternative distance decays and measures without any spatial smoothing below.

[22] Online Appendix Figure C.2 presents each mineral's net exports in USD and relative to GDP. This figure highlights that the overall importance of the mining sector has been greatest during the civil war (given the imploding GDP) and in later years (due to the iron boom and despite robust growth).

[23] Consistently, Berman et al. (2017) document that positive mineral price shocks increase conflicts in neighboring $0.5 \times 0.5$ degree grid cells too, but less so than in the grid cells where the mines are located. In addition, nearby localities may lay claims on royalties (resource rents) because they may host crucial infrastructure or suffer from pollution associated with resource extraction (e.g., Aragón and Rud, 2016; Bruederle and Hodler, 2019).

[24] We assign a distance of one kilometer to mines (and later conflicts) within a ward.



(A) Sample period (B) Diamond period (C) Bauxite period (D) Iron period

FIGURE 4. Local resource rents averaged across different time periods. All panels plot time-averaged values of the relative local resource rents $r_l/r$. Panel A is based on the entire sample period (1997–2018), panel B on the period dominated by diamond exports (1997–2004), panel C on the period dominated by bauxite exports (2005–2011), and panel D on the period dominated by iron exports (2012–2018).

We focus on relative local resource rents $r_l/r$, as they matter for local conflict exposure according to our theoretical model.[25] Panel A of Figure 4 shows the distribution of $r_l/r$, averaged over the entire sample period, across wards. By construction, these shares are highest close to large mining areas and much smaller further away. Panels B–D show the corresponding distributions when averaging $r_l/r$ over various shorter periods. There are remarkable changes in the spatial patterns over time because different minerals are extracted in different parts of the country (seen in panel A of Figure 3) and are important in different years (seen in panel B of Figure 3). For example, there is a large iron mine, but no other mines north of the center. Therefore, this area had low relative local resource rents until the beginning of the iron boom in 2012.

*3.2.3. Conflict.* We base our measures of actual conflict on the Armed Conflict Location and Event Data (ACLED, Raleigh et al., 2023). ACLED contains information on the date and type of conflict events, the involved actors (e.g., the government, rebel groups, or civilians), and the geolocation. Following Eberle et al. (2025), we include events classified as battles, riots, or violence

[25] The use of relative, rather than absolute, local resource rents has the added advantage that the results would remain unchanged if a fraction of the mining revenues were captured by actors outside of the model, e.g., international mining companies, as long as this fraction was identical across locations.

against civilians. Our results are robust to including all events (i.e., to adding protests and strategic deployments) as in Berman et al. (2017) and McGuirk and Nunn (2025) as well as to excluding individual event types (e.g., violence against civilians).

We assume that observed local conflict exposure increases in the proximity to conflict events, not least because people know there is some randomness in the exact location of such events. Therefore, to construct our ward-level measure of observed local conflict exposure, we first weigh each event by the inverse distance between the conflict location and the ward's centroid and then calculate the sum of these inverse distance-weighted events. The resulting measure of observed local conflict exposure is strictly positive (albeit potentially very close to zero), given that there is at least one conflict event in each year of our sample period. This, in turn, will allow us to estimate elasticities using log-log specifications. We will test for the robustness of our results using alternative distance decays and conflict measures without any spatial smoothing below.

We use two measures for the country's aggregate propensity for conflict in a given year: the count of conflict events and the share of wards with at least one conflict event.

## 4. Empirical validation

In this section, we use the data from Sierra Leone to provide empirical support for our theoretically derived measures of the local and the aggregate propensity for conflict: the predicted local conflict exposure and the national peace deficit.

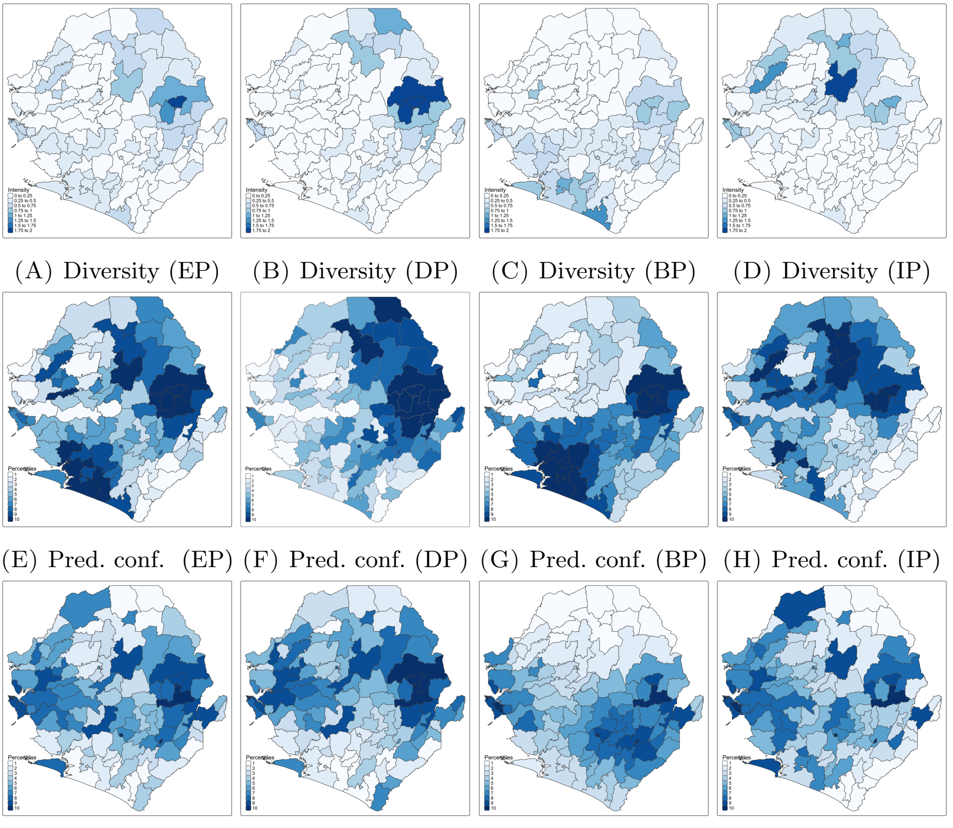
### 4.1. Local conflict exposure

We first compute the predicted local conflict exposure for every ward and year. Given that our theoretical model is static, we first compare the predicted and the observed local conflict exposure across wards. We later employ standard two-way fixed effects regressions and two-stage least squares regressions to minimize the chance that our validation is driven by unobserved factors across wards.

*4.1.1. Computation and graphical evidence.* The predicted local conflict exposure $e_l$ depends on the relative local resource rents $r_l/r$ and the ethnic diversity among discordant groups $D_{l,G^*}$ (see equation (5)). We start the computation of the predicted local conflict exposure by determining the set of discordant groups $G^*$ in any given year (see Online Appendix Figure C.3, panel A). To provide some intuition on how this set depends on the country's ethnic and mining geographies, let us focus on the four main ethnic groups. The Kono are over-represented in the diamond-mining area. According to our theoretical model, they were deprived of some local resource rents and part of the set of discordant groups in most years (except in some late years when diamonds played a minor role). The Mende, who are over-represented in the bauxite-mining area, were a discordant group exclusively during the bauxite boom, and the Limba, who are over-represented in the iron-mining area, were a discordant group exclusively during the iron boom. The Temne, too, were a discordant group in some years during the iron boom.

In a second step, we use the set of discordant groups $G^*$ and their local over-representation $s_l/s$ to compute the ethnic diversity among discordant groups $D_{l,G^*}$ for any ward and year. Figure 5 maps these local diversity indices averaged over the entire sample period in panel A and averaged over the diamond-, bauxite- or iron-dominated periods in panels B–D. We see large changes in the ethnic diversity among discordant groups over time, resulting from the changes in the relative local resource rents and the associated changes in the set of discordant groups.

In a third step, the relative local resource rents $r_l/r$ and the ethnic diversity among discordant groups jointly determine the predicted local conflict exposure $e_l$ across wards. Figure 5 maps the predicted local conflict exposure (in percentiles) averaged over the entire sample period in panel E and averaged over the different sub-periods in panels F–H.



(A) Diversity (EP) (B) Diversity (DP) (C) Diversity (BP) (D) Diversity (IP)

(E) Pred. conf. (EP) (F) Pred. conf. (DP) (G) Pred. conf. (BP) (H) Pred. conf. (IP)

(I) Obs. conf. (EP) (J) Obs. conf. (DP) (K) Obs. conf. (BP) (L) Obs. conf. (IP)

FIGURE 5. Visual evidence. Panels A–D plot the time-averaged ethnic diversity among discordant groups $D_{l',G*}$; panels E–H the time-averaged predicted local conflict exposure $e_l$ (in percentiles); and panels I–L the time-averaged observed local conflict exposure (in percentiles). Panels A, E, and I are based on the entire sample period (EP, 1997–2018); panels B, F, and J on the period dominated by diamond exports (DP, 1997–2004); panels C, G, and K on the period dominated by bauxite exports (BP, 2005–2011); and panels D, H and L on the period dominated by iron exports (IP, 2012–2018).

Finally, we can compare the predicted and the observed local conflict exposure. Figure 5 maps the observed local conflict exposure (in percentiles) averaged over the entire sample period in panel I and averaged over the different sub-periods in panels J–L. Comparing panels E and I suggests a positive correlation between predicted and observed local conflict exposures during our entire sample period. The raw correlation between the log-transformed predicted and observed local conflict exposures is 0.23. It is reassuring to see that the predicted and the observed local conflict exposure remain somewhat synchronized over time, with the raw correlation ranging from 0.22 (in the diamond-dominated period, DP) to 0.29 (in the iron-dominated period, IP).

*4.1.2. Cross-sectional evidence.* We now evaluate the predictive power of our theoretical model using the following cross-sectional OLS regression in our sample of 107 wards:

$$\ln(\text{Observed conflict exposure}_l) = \beta \ln(\text{Predicted conflict exposure}_l) + \Gamma \mathbf{X}_l + \varepsilon_l, \tag{6}$$

where $\mathbf{X}_l$ is a vector of control variables that includes the log of the ward population based on the 2004 census, the log of the ward area, and fixed effects for the four provinces. Coefficient $\beta$ corresponds to the elasticity of observed local conflict exposure with respect to predicted local conflict exposure. When interpreting this elasticity, it is important to keep in mind that the theoretically predicted local conflict exposure $e_l$ only captures the systemic effect of a country's ethnic and mining geographies on the probability of local conflict and, thereby, ignores mechanical determinants such as population size and political economy determinants like ethno-regional favoritism. While our theoretical model is silent about the magnitude of this elasticity, we expect it to be positive and statistically significant.

Table 1 presents our main cross-sectional estimates with spatially clustered Conley standard errors.[26] Panel A shows the results when all variables are time-averaged over the entire sample period. The different columns differ in the set of control variables and fixed effects. The estimated elasticity is positive in all columns and statistically significant at the 5% level unless we add province-fixed effects. The estimated elasticity is 14% in the absence of any control variables in column (1) and drops to 5% in the most demanding specification in column (4). The $R^2$ is 0.062 in column (1) and increases when adding further controls. To assess the explanatory power of predicted conflict exposure, we compare it

[26]Standard errors are estimated using the acreg package by Colella et al. (2023). We enforce a linear decay in the spatial dependence of the error terms with a distance cutoff of 100km. We later show that the results do not depend on this specific distance cutoff.

TABLE 1. Cross-sectional relation between predicted and observed conflict exposure

| | *Dependent variable: Log observed conflict exposure* | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| *Panel A: Full period* | | | | |
| Log predicted conflict exposure | 0.138*** | 0.117*** | 0.052** | 0.051* |
| | (0.045) | (0.042) | (0.024) | (0.028) |
| R2 | 0.0617 | 0.242 | 0.771 | 0.834 |
| *Panel B: Diamond period* | | | | |
| Log predicted conflict exposure | 0.087*** | 0.075*** | 0.057* | 0.083** |
| | (0.023) | (0.016) | (0.031) | (0.035) |
| R2 | 0.0755 | 0.219 | 0.533 | 0.688 |
| *Panel C: Bauxite period* | | | | |
| Log predicted conflict exposure | 0.105** | 0.117*** | 0.065** | -0.021 |
| | (0.048) | (0.044) | (0.027) | (0.032) |
| R2 | 0.0649 | 0.245 | 0.736 | 0.794 |
| *Panel D: Iron period* | | | | |
| Log predicted conflict exposure | 0.174* | 0.127* | 0.091*** | 0.071** |
| | (0.096) | (0.074) | (0.031) | (0.028) |
| R2 | 0.0695 | 0.218 | 0.762 | 0.832 |
| Population control | – | ✓ | ✓ | ✓ |
| Area control | – | – | ✓ | ✓ |
| Province-fixed effects | – | – | – | ✓ |
| Observations | 107 | 107 | 107 | 107 |

Notes: The table reports the result of regressing the log of observed conflict exposure on the log of predicted conflict exposure (see eq. 6), with different control variables and fixed effects across columns (1)–(4). Population control is the log of the ward population based on the 2004 census. Area control is the log of the ward area. Panel A provides cross-sectional evidence after time-averaging all variables across the entire sample period (1997-2018). Panel B averages all variables across the period dominated by diamond exports (1997–2004), panel C across the period dominated by bauxite exports (2005–2011), and panel D across the period dominated by iron ore exports (2012–2018). Standard errors are spatially clustered with a distance cutoff of 100km. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

to the explanatory power of local population size, which is a rather mechanical predictor of local conflict, and local resource rents, which are a well-established predictor of local conflict.[27] We find that predicted conflict exposure explains around one-third of the variation in conflict explained by population size, but four times more than local resource rents.

[27]The $R^2$ is 0.198 (0.016) when regressing log observed conflict exposure on log population (log local resource rents) only.

In panels B–D, we document a positive and statistically significant elasticity of observed local conflict exposure with respect to predicted local conflict exposure in the three periods dominated by different minerals and, thus, different mining regions (except in column (4) of panel C). In addition, the $R^2$ is typically of similar size as in panel A. We conclude that the results reported in panel A are not driven by a single period.

*4.1.3. Panel and IV evidence.* The cross-sectional evidence confirms the predictive power of our theoretical model, but does not lend itself to a causal interpretation due to a myriad of potentially omitted variables. To allow for causal interpretation, we use the panel of 107 wards over 22 years and run standard OLS two-way fixed effects regressions and two-stage least squares (2SLS) regressions with a generated instrument inspired by a commonly used instrumental variables (IV) approach.

The OLS two-way fixed effects specification is:

$$\ln(\text{Observed conflict exposure}_{lt}) = \delta \ln(\text{Predicted conflict exposure}_{lt}) + FE_l + FE_t + \varepsilon_{lt}, \quad (7)$$

where $FE_l$ and $FE_t$ are ward- and year-fixed effects, respectively. Our coefficient of interest is $\delta$, which captures the intertemporal elasticity of observed local conflict exposure with respect to predicted local conflict exposure.

OLS estimates are potentially biased, with the direction of the bias being a priori uncertain. A downward bias is plausible because conflict events may reduce mining activities and, thereby, local resource rents and the predicted local conflict exposure. However, an upward bias is possible too if governments or militia groups use local mineral rents to finance conflict (Berman et al., 2017). Such endogeneity concerns are common in studies on the effect of resource rents on conflict. Many researchers rely on plausibly exogenous variation in global commodity/mineral prices to mitigate these concerns (e.g., Bazzi and Blattman, 2014; Berman and Couttenier, 2015; Berman et al., 2017; Dube and Vargas, 2013). We build on this identification strategy and construct a generated instrument for the predicted conflict exposure based on the observed group-level population shares and predicted relative local resource rents. These predicted relative local resource rents are derived using shift-share instruments that interact plausibly exogenous global mineral price shocks with cross-sectional exposure shares based on the wards' proximity to different mining areas. Using a generated instrument is necessary to obtain a meaningful reduced-form relationship that captures the essence of our theoretical model.

Following Berman et al. (2017), we measure the price shocks by the log of the global mineral prices. The mineral-specific exposure shares of a given ward are computed in a similar fashion to the local resources rents $r_l$. That is, we take the inverse distance to each mineral location, where each location is weighted by the time-invariant size of the corresponding mining area, and then normalize the resulting ward-level proximity values to shares. We use mineral-specific proximity-price interaction terms in the zero (or instrument-generating) stage to predict the relative local resource rents:

$$r_{lt}/r_t = \sum_{j \in \{B,D,I\}} \gamma_j [\ln(\text{proximity}_l^j) \times \ln(\text{price}_t^j)] + FE_l + FE_t + \zeta_{lt}, \tag{8}$$

where $B$, $D$, and $I$ stand for the three main minerals: bauxite, diamonds, and iron.[28] These interaction terms allow for identification via exogenous shifts (Borusyak et al., 2022), where each yearly price change is a plausibly exogenous shift we can exploit for identification (see Borusyak et al., 2025). Our identification strategy relies on the assumption that conflict events in Sierra Leone do not impact global mineral prices. This assumption seems

[28] Metalary (2025) provides global prices for bauxite, gold, iron ore, and titanium metals (which include rutile), while Rapaport (2025) provides global prices for diamonds. Net exports of bauxite, diamonds, and iron are much larger than net exports of gold and rutile (see Figure 3). We abstract from gold, as it is currently only mined in artisanal mines, and from rutile, as we only observe exports and prices for titanium metals, but not for rutile specifically. Results are similar when adding titanium proximity-price interactions in the zero stage. (Results available upon request.) Figure C.4 shows the cross-sectional and temporal distributions of the different components of our shift-share instruments used in the zero stage. The variables entering the interaction terms are all absorbed by the ward- and year-fixed effects.

plausible given that Sierra Leone's exports are unimportant in these minerals' international trade, with global export shares never exceeding 2% for bauxite, diamonds, and iron (see Online Appendix Table B.2).[29] We also find no evidence that conflict in Sierra Leone (either in $t$ or $t-1$) affects either global bauxite or iron prices (see Online Appendix Figure C.6). Diamond prices, in contrast, are somewhat affected by conflict in Sierra Leone. We present robustness tests with an alternative instrument in Section 4.1.5.

We compute our generated instrument, which we call generated conflict exposure, using equations (3) and (5), the observed group-level population shares $s_l^g$ and the instrumented (predicted) relative local resource rents $\widehat{r_l/r}$.[30] We use this generated instrument in the first stage of our main 2SLS specification:

$$\ln(\text{Predicted conflict exposure}_{lt}) = \psi \ln(\text{Generated conflict exposure}_{lt}) + FE_l + FE_t + \nu_{lt}. \tag{9}$$

Wooldridge (2010) highlights that generated instruments behave like regular instruments in models which are linear in parameters (such as 2SLS).[31] The second stage of our main 2SLS specification is identical to equation (7) except that we replace the explanatory variable with its predicted value.

Table 2 presents our panel data estimates. Panel A reports the OLS two-way fixed effects estimates. Column (1) presents the results of equation (7). We find an estimated intertemporal elasticity of observed local conflict exposure with respect to predicted local conflict exposure of around 6%. Columns (2)–(4) add linear time trends for ever smaller subnational administrative units

[29] One concern in our setting is that there is some serial correlation in the global mineral prices (the shifts) for which we account below.

[30] Panel B of Online Appendix Figure C.3 shows the set of discordant groups based on the instrumented relative local resource rents.

[31] Further adjustment of the standard errors is thus not required (see Wooldridge, 2010, chapter 6).

Table 2. Within-ward relation between predicted and observed conflict exposure

| | *Dependent variable: Log observed conflict exposure* | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| *Panel A: OLS* | | | | |
| Log predicted conflict exposure | 0.060*** | 0.044** | 0.038** | 0.039** |
| | (0.020) | (0.017) | (0.018) | (0.020) |
| *Panel B: 2SLS, second stage* | | | | |
| Log predicted conflict exposure | 0.157*** | 0.157*** | 0.167*** | 0.183*** |
| | (0.050) | (0.050) | (0.055) | (0.065) |
| *Panel C: 2SLS, first stage – Dependent variable: Log predicted conflict exposure* | | | | |
| Log generated conflict exposure | 0.939*** | 0.887*** | 0.838*** | 0.840*** |
| | (0.066) | (0.090) | (0.096) | (0.114) |
| First-stage F-stat | 180.6 | 84.57 | 66.55 | 43.30 |
| *Panel D: Zero stage – Dependent variable: Relative local resource rents* | | | | |
| Bauxite proximity-price interaction | 0.420*** | | | |
| | (0.050) | | | |
| Diamond proximity-price interaction | -0.853*** | | | |
| | (0.054) | | | |
| Iron proximity-price interaction | 0.109*** | | | |
| | (0.015) | | | |
| Ward-fixed effects | ✓ | ✓ | ✓ | ✓ |
| Year-fixed effects | ✓ | ✓ | ✓ | ✓ |
| Province trends | – | ✓ | – | – |
| District trends | – | – | ✓ | – |
| Ward trends | – | – | – | ✓ |
| Observations | 2354 | 2354 | 2354 | 2354 |

Notes: The table reports the results of regressing the log of observed conflict exposure on the log of predicted conflict exposure as well as ward- and year-fixed effects (see eq. 7), with different time trends across columns (1)–(4). Panel A reports OLS fixed effects regressions, panel B second-stage 2SLS regressions, and panel C the corresponding first-stage regressions (see eq. 9). The reported first-stage F-stat is the Kleibergen-Paap rk Wald F statistic. Panel D presents the zero- or instrument-generating-stage regressions (see eq. 8) and is estimated with a fractional response model to guarantee strictly positive instrumented (predicted) relative resource rents for each ward and year. The set of discordant groups for each year is shown in Online Appendix Figure C.3. Standard errors are spatially clustered with a distance cutoff of 100km. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

(based on Global Administrative Areas, 2022). The coefficient estimates remain statistically significant but become somewhat smaller.[32]

[32] A potential issue is that the two-way fixed effect estimator introduces a correlation between the regression weights and treatment intensity, thus biasing our estimates (De Chaisemartin and d'Haultfoeuille, 2020). However, testing for the correlation between weights and treatment intensity suggests that our estimator does not suffer from the issue in columns (1) and (2), but that including more restrictive time trends leads to a correlation.

The remaining panels of Table 2 present our 2SLS estimates. The second-stage results in panel B show that the estimated intertemporal elasticity of observed local conflict exposure with respect to predicted local conflict exposure is 16%–18%, which is substantially higher than our OLS two-way fixed effects estimates. This difference suggests that mining activities may indeed fall in response to conflict events. Panel C reports the first-stage results. The first-stage F-stats of the instruments far exceed common thresholds for instruments' power, as is common for generated instruments. Finally, panel D shows that our price proximity interactions have predictive power for the relative local resource rents.[33]

*4.1.4. Zooming in on the role of discordant groups.* We have established a close connection between the predicted and the observed local conflict exposure. As the theoretical model emphasizes the role of discordant groups, we provide three pieces of evidence suggesting that discordant groups drive this close connection.

First, we run additional specifications controlling for the logs of the relative local resource rents $r_l/r$ and the instrumented relative local resource rents $\widehat{r_l/r}$. Those specifications account for the possibility that the effect of the predicted local conflict exposure could simply reflect the effect of local resource rents, as the latter are a key ingredient in the computation of the former (see equation (5)) and known to be a key determinant of conflict (e.g., Berman et al., 2017; Morelli and Rohner, 2015). The results reported in Online Appendix Table C.4 show that the effect of the predicted local conflict exposure on the observed local conflict exposure remains statistically significant in most specifications. In

Given the similarity in the estimates across columns, we view this as a minor issue in our setting.

[33]Panel D shows that increases in bauxite and, to a lesser extent, iron prices have strong positive effects on the instrumented relative local resource rents in wards close to bauxite and iron mines. We also see that increases in diamond prices reduce predicted local resource rents in wards close to diamond mines. The main reason for this (maybe surprising) result is that the rise in diamond prices coincided with the decreasing importance of the diamond sector in Sierra Leone after the civil war.

contrast, the effects of the (non-instrumented) local resource rents are typically negative (see panels A and B), while the instrumented local resource rents have a positive but statistically insignificant effect (see panel C).

Second, we run additional tests to ascertain whether the effect of the predicted local conflict exposure is driven by the interaction of relative local resource rents and the local diversity among discordant groups $D_{l,G^*}$ or whether it is just about diversity more generally. To test this, we run placebo tests for which we construct a placebo predicted local conflict exposure by interacting the relative local resource rents with the local diversity among *non*-discordant groups, i.e., $D_{l,G'}$ computed for the set of groups $G' = G \backslash G^*$. Online Appendix Table C.5 shows that this placebo measure of predicted local conflict exposure does not predict observed local conflict exposure, neither in the panel OLS nor the 2SLS estimations. This non-result suggests that it is indeed discordant groups that play an essential role in local conflicts.

Third, we provide evidence for the mechanism proposed by our theoretical model. Our model predicts that discordant groups initiate local conflicts and are more likely to do so in more resource-rich locations. Following other recent studies (Couttenier et al., 2024; Eberle et al., 2025; Gehring and Schaudt, 2026), we use the ACLED's information on the actors involved in conflict events and match these actors to the ethnic groups in our dataset whenever possible.[34] We then estimate the following three-way fixed effects specification via pseudo-Poisson maximum likelihood (PPML):

$$\begin{aligned} Conflict\ events_{glt} = {} & \beta_1\, Discordant_{gt} \times Resource\ rents_{lt} + \beta_2\, Discordant_{gt} + \\ & \beta_3\, Resource\ rents_{lt} + FE_g + FE_l + FE_t + \varepsilon_{glt} \end{aligned} \tag{10}$$

where $Conflict\ events_{glt}$ is the number of conflict events involving actors matched to group $g$ in ward $l$ and year $t$, $Discordant_{gt}$ a dummy variable indicating whether group $g$ is in the set of discordant groups in year $t$, and

[34] We can match at least one actor to an ethnic group in 71% of the conflict events in our sample. Online Appendix Table C.3 provides details on the matching.

$Resource\,rents_{lt}$ are the relative local resource rents $r_{lt}/r_t$ in year $t$. We expect coefficient $\beta_1$ to be positive, suggesting that discordant groups in resource-rich wards are more likely to be involved in conflicts than discordant groups in resource-poor wards or non-discordant groups in resource-rich wards.

Column (1) of Table 3 presents the results for this specification. The coefficient on the interaction term is positive and significant, confirming that discordant groups in resource-rich wards are particularly likely to be involved in conflicts. Columns (2) and (3) add ward-by-year and ethnicity-by-year fixed effects, respectively. It is reassuring that the coefficient on the interaction term remains similar in column (3), where the ethnicity-by-year fixed effects absorb all time-varying group-level confounders like a group's proximity to mines or its access to the central government.[35]

*4.1.5. Sensitivity analysis.* We conduct various robustness tests. First, we focus on the coding of our dependent variable: the observed local conflict exposure. We start by including all ACLED events to construct our dependent variable (as in, e.g., Berman et al., 2017; McGuirk and Nunn, 2025), after which we drop single event categories and actor types in turn. The coefficient estimates remain similar throughout most of these perturbations (see Online Appendix Figure C.7). The main exception is that the coefficient estimates (especially in the 2SLS regressions) become considerably smaller if we exclude conflict events involving rebels and militias. This finding is reassuring as it is precisely those actors that we expect to engage in local conflicts according to our theoretical argument.

Second, we focus on the construction of our independent variable, the predicted conflict exposure. We could mismeasure our predicted conflict exposure due to unstable ethnic group shares within wards over time, affecting the groups' local over-representation, or the mismeasurement of the local resource rents. Given that the ethnic population shares are quite stable

[35] Online Appendix Table C.6 shows that we obtain similar results when including all conflict events in ACLED that we can match to ethnic groups, i.e., not only battles, riots, and violence against civilians, but also protests and strategic deployments.

TABLE 3. Group-ward level evidence: Resource rents and discordant groups

| | *Dependent variable: Conflict events* | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| Resource rents × Discordant | 14.636** | 17.758*** | 11.638* |
| | (6.819) | (5.955) | (6.979) |
| Discordant | -1.773*** | -1.841*** | |
| | (0.274) | (0.465) | |
| Resource rents | -2.453 | | -2.596 |
| | (5.789) | | (5.791) |
| Ethnicity-fixed effects | ✓ | ✓ | – |
| Ward-fixed effects | ✓ | – | ✓ |
| Year-fixed effects | ✓ | – | – |
| Ethnicity-by-year-fixed effects | – | – | ✓ |
| Ward-by-year-fixed effects | – | ✓ | – |
| Observations | 28,248 | 28,248 | 28,248 |

Notes: This table presents results at the group-ward-year level (rather than the ward-year level as Table 2). The results are based on regressing the number of conflict events (of the types battles, riots, and violence against civilians) per ethnic group and ward on the local relative local resource rents $r_{lt}/r_t$, a dummy variable indicating whether an ethnic group is discordant in year $t$, and their interaction (see eq. 10). The conflict actors and their ethnic matching are presented in Online Appendix Table C.3. The set of discordant groups in each year is shown in panel A of Online Appendix Figure C.3. The specifications are estimated using pseudo-poison maximum likelihood. Standard errors are clustered at the ward and ethnicity-by-year levels. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

(see Online Appendix Table C.7), we test the sensitivity of our results for perturbations of the measurement of local resource rents in two ways. One approach includes artisanal and small-scale mining fields, distributing mineral-specific export revenues across both industrial and artisanal mines (see Online Appendix B.3 for details). The other approach distributes industrial resource revenues based on nighttime light emissions (Li et al., 2020) within mining areas, instead of using the physical size of these areas. Our results remain similar throughout these perturbations (see Online Appendix Figure C.8).[36]

Third, we test whether our results are driven by the spatial decay function, $distance^{-1}$, that we use to compute the local resource rents and the observed

[36] Our results remain similar also when recomputing the ethnic diversity among discordant groups based on the population distribution among the four largest groups, which are the only groups that were politically relevant throughout the sample period (according to the Ethnic Power Relations data by Vogt et al., 2015).

local conflict exposure.[37] However, we find similar results for a range of distance decays from $distance^{-0.5}$ to $distance^{-2}$ (see Online Appendix Figure C.9).[38] Importantly, results are similar when varying the distance decay only for the measurement of either local resource rents or observed local conflict exposure to break any potential spatial correlation introduced by a common decay function. When using dependent variables exclusively based on the presence of conflicts in the wards under consideration, we also obtain consistent results, although the panel results are less precisely estimated (see Online Appendix Table C.8). When further dropping the spatial smoothing of resource rents and assigning equal rents to all wards within 50 km of an industrial mine, the general pattern remains again consistent while precision is more varied (see Online Appendix Table C.9). This remains also the case when incorporating the intensive margin of conflict and using the sum of conflict events within wards as the dependent variable (see Online Appendix Table C.10). Relatedly, the precision of our estimates does not depend on the specific distance cutoff we use to calculate the Conley standard errors (see Online Appendix Figure C.10).

Fourth, motivated by the literature on ethno-regional favoritism and our theoretical model, which allows for ward-specific priority weights (see equation (1)), we control for two proxies measuring how politically well-connected the population of a ward is. The first is the share of the population in a ward that identifies with the same ethnic group as the current president of Sierra Leone. The second is the share identifying with a politically included ethnic group (according to the Ethnic Power Relations data by Vogt et al., 2015). We find similar elasticity estimates (see Online Appendix Figure C.11), suggesting that ethno-regional favoritism does not substantially alter the systemic conflict pressure captured by our variable of interest.

[37]The natural resource literature and the conflict literature, unlike the trade literature, lack well-established distance decay functions.

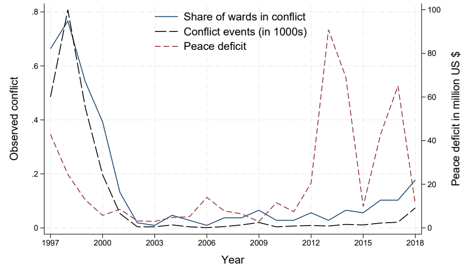
[38]The point coefficients generally become larger for steeper decays for conflict, but the confidence intervals prohibit any qualitative statements with respect to differing effect sizes.

Fifth, we conduct additional tests recommended by Borusyak et al. (2025) to gauge the validity of our shift-share instruments based on exogenous shifts. Online Appendix Table C.11 summarizes the results of these tests. To account for serial correlation in the global mineral prices, we control for the lagged instruments (i.e., the lagged price-proximity interactions), add linear and quadratic ward-level time trends, and even interact the different exposure shares with year dummies (essentially purging our estimates of all time-varying factors that correlate with the proximity to mines of a given mineral). Moreover, we cluster standard errors at the level of the shifts (i.e., the annual level) as suggested by Borusyak et al. (2025). Throughout all columns, results remain stable, suggesting that identification via exogenous shifts is feasible in our setting.

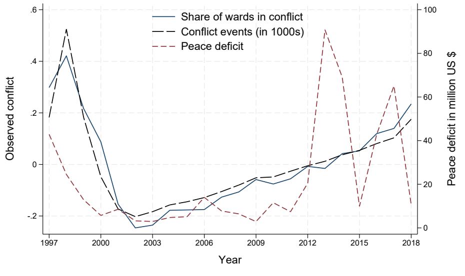
Finally, we investigate the role of one specific shift-share instrument: the diamond proximity-price interaction. Possible concerns are related to the negative sign of its coefficient in the zero stage (see Table 2) and the possibility that unobservable factors related to the diamond trade could have influenced conflict dynamics during the civil war. We leverage the close collaboration between Botswana, a diamond-rich country, and De Beers, the world's largest diamond company, which introduced quotas on the sale of diamonds from Botswana to influence global prices (e.g., IMF, 1999). We replace the diamond proximity-price interaction with an interaction between the proximity to diamond mines and Botswana's diamond exports in the zero stage (see Online Appendix Table C.12). Further, we run specifications that exclude the diamond proximity-price interaction from the zero stage or the diamond period (1997–2004) from our sample (see Online Appendix Table C.13). Our results remain similar in all these robustness tests.

### 4.2. Changes in country-wide conflict over time

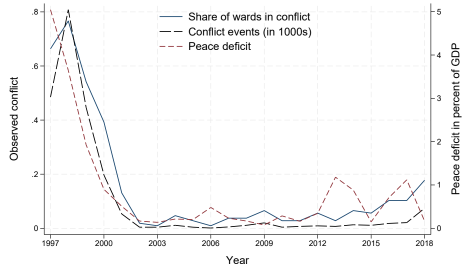
We now analyze whether our theoretical model can also predict intertemporal changes in a country's aggregate propensity for conflict. We have argued earlier that the national peace deficit $\Delta$, which quantifies the extra transfers necessary



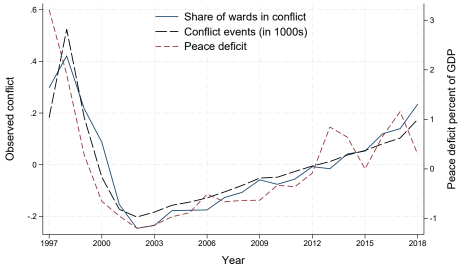

(A) No adjustment




(B) Detrended time series




(C) Peace deficit normalized by GDP




(D) Both adjustments

FIGURE 6. Changes in country-wide propensity for conflict over time. Panel A plots the share of wards with at least one conflict event (blue line), the number of conflict events in thousands (black dashed line), and the peace deficit in million US dollars (dashed red line) over time. Panel B replicates panel A after detrending all three time series. Panel C replicates panel A after dividing the peace deficit by GDP. Panel D replicates panel A after dividing the peace deficit by GDP and then detrending all three time series.

to guarantee peace in every location, is a good theoretical proxy for this propensity. In practice, however, the fiscal capacity for peacekeeping comes from borrowing or taxing other sectors of the economy, and such capacity is arguably proportional to the size of the economy. This capacity was low in the years of the civil war, but grew with the growing economy. To account for this, we propose detrending the relevant time series or expressing the peace deficit as a percentage of GDP (according to World Bank, 2022).

Figure 6 plots the national peace deficit over time, as well as two proxies for the actual aggregate propensity for conflict: the share of wards that experience at least one conflict event in a given year and the number of conflict events in a given year. The time series are detrended in panels B and D, and the peace deficit is normalized by GDP in panels C and D. We see that these three variables co-move quite strongly as soon as we use at least one of the two proposed approaches to account for the large changes in the size of the economy and the state's fiscal capacity over time. The raw correlation between the peace deficit and the share of wards in conflict (number of conflict events) is 0.076 (0.054) in panel A but increases to 0.369 (0.353), 0.881 (0.858), and 0.840 (0.809) in panels B, C, and D, respectively. We conclude that our theoretical model has considerable predictive power for explaining intertemporal changes in Sierra Leone's aggregate propensity for conflict.

## 5. External validity: Sub-Saharan Africa

In this section, we look into the external validity of the empirical findings discussed in the previous section. For this purpose, we prepare a second panel dataset that includes all 28 ethnically diverse sub-Saharan African countries with mines reported in the Raw Material Data (RMD, S&P Global Market Intelligence, 2025) and, again, the years from 1997–2018. Following the literature (e.g., Berman et al., 2017), we use $0.5 \times 0.5$ decimal degree grid cells as subnational units. To overcome the lack of high-quality data on the spatial distribution of ethnic groups, we follow Desmet et al. (2020) and employ an iterative proportional fitting algorithm to predict the country-level population share of each group in each cell, which allows us to compute each group's over-representation in each cell. Further, we again combine the information about the location and size of mines from RMD and Maus et al. (2020) with the net export data from United Nations Statistics Division (2025) to compute the cell-level resource rents (as described in Section 3.2.2); and rely on ACLED (Raleigh et al., 2023) to compute observed conflict exposure (as described in Section 3.2.3).[39]

[39] Online Appendix D provides more information about this second panel dataset. Note that Comtrade has missing net export data for some minerals in some countries and years (see Online Appendix Table D.4). As long as we have net export data for at least some minerals in a given country-year, we compute the local resource rents using these data.

TABLE 4. External validity: Aggregate conflict propensity and peace deficit

| | *Dependent variable:* | | | |
|---|---|---|---|---|
| | *Log conflict events* | *Log conflict events (all)* | *Conflict events* | *Conflict events (all)* |
| | (1) | (2) | (3) | (4) |
| Log peace deficit | 0.134* | 0.145** | 0.157 | 0.201* |
| | (0.073) | (0.070) | (0.110) | (0.104) |
| Specification | OLS | OLS | PPML | PPML |
| Country-fixed effects | ✓ | ✓ | ✓ | ✓ |
| Year-fixed effects | ✓ | ✓ | ✓ | ✓ |
| Observations | 533 | 533 | 533 | 533 |

Notes: The table reports the results from OLS regressions of the log of the number of conflict events plus one on the log of the peace deficit in columns (1) and (2); and Poisson pseudo maximum likelihood (PPML) estimations of the number of conflict events on the log of the peace deficit in columns (3) and (4). The dependent variable is based on battles, riots, and violence against civilians in columns (1) and (3), but on all reported events (including protests and strategic deployments) in columns (2) and (4). The units of analysis are country-years. See Online Appendix D for more information about the data. Standard errors are clustered at the country level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Because it includes many countries, this second dataset allows us to test more rigorously whether the peace deficit has predictive power for a country's aggregate propensity for conflict. In column (1) of Table 4, we regress the log number of conflict events on the log peace deficit, accounting for country- and year-fixed effects. In the remaining columns, we use a broader definition of conflict events (including protests and strategic deployments) or employ Poisson pseudo maximum likelihood rather than OLS. We find that the estimated intertemporal elasticity of the number of conflict events with respect to the peace deficit is 13%–20%, with varying levels of statistical significance. Hence, higher peace deficits tend to go hand in hand with more conflict events, implying that the peace deficit has predictive power for a country's aggregate propensity for conflict.

We also use this second panel dataset to check the external validity of our empirical tests of the predictive power of our theoretically derived measure for

The panel, however, is unbalanced because we lack export data for all minerals in some country-years.

the *local* propensity for conflict. First, we again find a positive cross-sectional relation between predicted and observed conflict exposure (see Online Appendix Table D.1). Second, we confirm a positive relation in two-way fixed effects regressions (see Online Appendix Table D.2, panel A). Finally, we also employ the 2SLS approach discussed in Section 4.1.3. Thereby, we run the zero-stage regressions, used to predict the relative grid cell-level resource rents, separately for each country before calculating the generated conflict exposure used in the first stage. We find substantial positive effects of predicted conflict exposure on observed conflict exposure in the second stage (see Online Appendix Table D.2, panel B), even when excluding the Democratic Republic of the Congo and South Africa, which may have market power for some minerals. While the estimated coefficients are generally smaller in this larger sample than in our Sierra Leone-based analysis, they remain positive and statistically significant in most specifications. We conclude that our theoretically derived measure of local conflict exposure has predictive power beyond Sierra Leone.

## 6. Counterfactual analyses

We now employ our two theoretical concepts – the peace deficit and local conflict exposure – to predict how the hypothetical development of known mineral deposits in Sierra Leone would shape conflict in the country. We do so for all discovered mineral deposits reported in the RMD as of 2019 (listed in Online Appendix Table B.1). Figure 7 shows that these deposits differ with respect to their locations and main minerals (using differently colored symbols for the different minerals). For some of these deposits, we know the holder of the prospecting license, but we lack information on the current development plans. For others, the government has already awarded mining licenses. Examples include the Baomahun project, whose license holder is FG Gold, and the Nimini–Komahun project, whose license holder is Nimini Holdings Limited.

In our framework, opening new mines corresponds to changing the spatial distribution of local resource rents. We base our counterfactual analyses on the

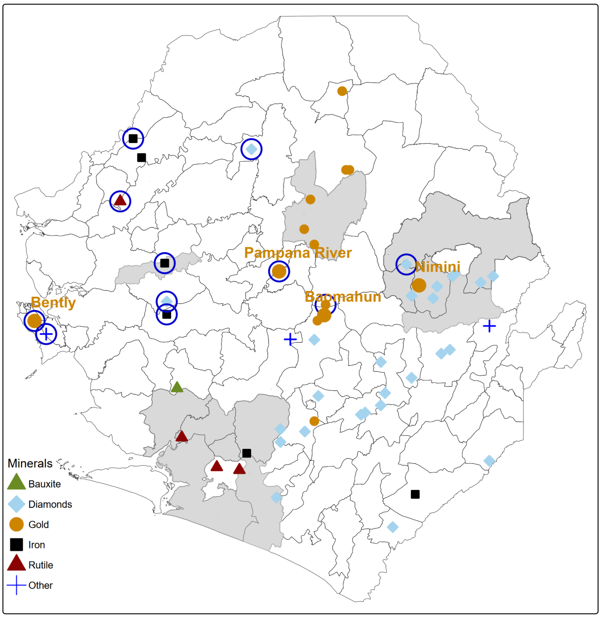



FIGURE 7. Known mineral deposits in Sierra Leone. This map shows the locations of known mineral deposits (as of 2019 based on the RMD, excluding deposits directly located in the national or a provincial capital city). Different symbols and colors indicate the primary metals of the deposits (with Other referring to nickel and ilmenite). The locations and names of the four potential new gold mines discussed in this section are highlighted with larger dots. The wards highlighted in grey depict the wards with currently active mines (as of 2018). Blue circles indicate deposits that decrease the peace deficit based on the analysis reported in Figure 8 in Section 6.1

following scenario: First, the revenues generated by the six existing industrial mines are the same as in the last year of our sample period. Second, new mines generate 10% of the aggregated revenues from the six existing industrial mines combined.[40]

### 6.1. New mines and the aggregate propensity for conflict

We use the peace deficit to predict the effects of new mines and the corresponding change in the spatial distribution of local resource rents on the

[40]The capacities of new mining projects are unknown. It is straightforward to run the counterfactual analyses with different assumptions about the revenues generated by new and existing mines.

aggregate propensity for conflict. The peace deficit quantifies the extra transfers necessary to guarantee peace at the national level and in every ward. Recall that the peace deficit can be written as $\Delta(\mathbf{r}, \mathbf{s}, G^*) = \sum_{g \in G^*} \left( \sum_{l \in L} r_l s_l^g - r s^g \right)$. Hence, it depends on the distributions of resource rents and discordant groups across wards. Any change in the peace deficit caused by the development of a new mine can thus be decomposed into a direct and an indirect effect.

The direct effect is the change in the peace deficit that the shift in the resource rent distribution $\mathbf{r}$ would cause if the set of discordant groups $G^*$ remained fixed. It captures the extent to which the new mine raises the propensity for conflict by shifting resource rents to wards where discordant groups are over-represented. The indirect effect is the change in the peace deficit resulting from changes in the set of discordant groups $G^*$ (if any) caused by the development of the new mine and the corresponding change in the distribution of local resource rents. The indirect effect is driven by groups becoming discordant (typically groups over-represented around new mines) and groups leaving the set of discordant groups (typically groups under-represented around new mines).[41]

Figure 8 reports the predicted changes in the peace deficit from each hypothetical mining project. The direct and indirect effects are shown using red and white bars, respectively. The development of many deposits, including the Baomahun and the Nimini-Komahun projects, is predicted to increase the peace deficit and, therefore, the aggregate propensity for conflict. However, a considerable share of potential mines, including two potential gold mines at the Bently and the Pampana River deposits, are predicted to reduce the peace deficit.[42] We indicate these mines with blue circles in the map in Figure 7. We

[41]To define the direct and the indirect effect more explicitly, let us write the set of discordant groups as $G^*(\mathbf{r}, \mathbf{s})$, and let $\mathbf{r}$ and $\tilde{\mathbf{r}}$ be the resource rent distributions before and after the mine opening. Then, the direct effect is $\Delta(\tilde{\mathbf{r}}, \mathbf{s}, G^*(\mathbf{r}, \mathbf{s})) - \Delta(\mathbf{r}, \mathbf{s}, G^*(\mathbf{r}, \mathbf{s}))$, and the indirect effect $\Delta(\tilde{\mathbf{r}}, \mathbf{s}, G^*(\tilde{\mathbf{r}}, \mathbf{s})) - \Delta(\tilde{\mathbf{r}}, \mathbf{s}, G^*(\mathbf{r}, \mathbf{s}))$.

[42]The Bently deposit was prospected by Njahili Resources Limited, and the Pampana River deposit is owned by Sunergy.

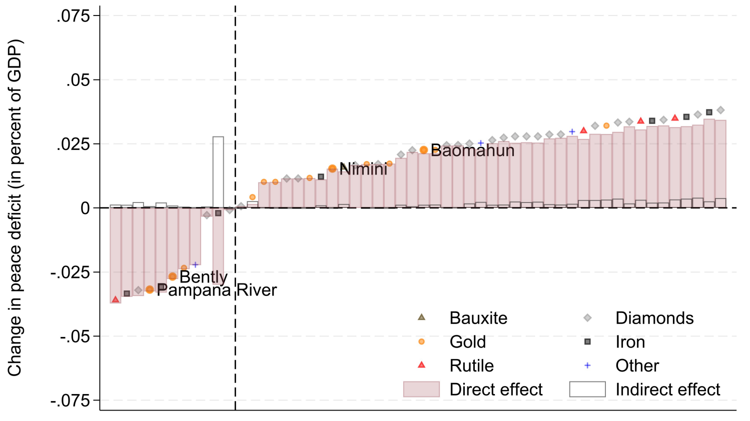



FIGURE 8. The predicted effects of new mines on aggregate propensity for conflict. This figure plots the simulated changes in the peace deficit (measured in percent of GDP) from mining any of the known deposits under the assumption that the revenues generated at this deposit are equal to 10% of the revenues of all existing mines combined. Different colors and shapes represent the total effect of different minerals. The red bars represent the direct effects (keeping the set of discordant groups fixed), and the white bars represent the indirect effects due to the change in the set of discordant groups.

conclude that *mining for peace* by developing new deposits seems feasible in Sierra Leone, especially in the country's northwest and far west.[43]

The variation in the predicted total effects on the peace deficit is mainly driven by the variation in the direct effects. Given that discordant groups are by definition over-represented in resource-rich locations, the direct effect tends to be positive for new mines located close to existing mines, such as the Nimini-Komahun project close to existing diamond mines, but negative for new mines that are far from existing mines, such as the Bentley deposit close to Freetown in the far west. However, the local ethnic geography matters as well. The Baomahun project and the Pampana River deposit are relatively close, but their (direct) effects on the peace deficit are very different. The reasons

[43]This insight is relevant to policymakers and international mining companies if peace-promoting mines are not systematically less attractive than peace-reducing mines from an economic viewpoint. Online Appendix Figure E.1 provides suggestive evidence that the peace deficit of mines is not systematically correlated with observable local risk factors (proxied by conflict incidents within 50km) or trade costs (proxied by the distance to the capital city, Freetown, which hosts the only container port within the country).

are that the Mende are locally over-represented around the Baomahun project (and most of the peace-reducing deposits in the southeast) while the Temne are locally over-represented around the Pampana River deposit (and some of the peace-promoting deposits in the country's northwest); and that the Mende are a discordant group while the Temne are not.

The indirect effects are either zero or positive but small. Positive indirect effects are typically driven by a single ethnic group joining or leaving the set of discordant groups. For example, the Kono (over-represented in the east) leave this set in case of new mines at the Bently or the Pampana River deposit, and the Limba (over-represented in the north) leave it in case of the Baomahun project.[44] Online Appendix Figures E.2 and E.3 illustrate that the indirect effects become larger if the new mines generate higher revenues.

Opening a mine also affects how subsequent mine openings at other deposits will affect the peace deficit. To illustrate this, Online Appendix Figure E.4 reports the predicted changes in the peace deficit from mine openings at each deposit, assuming that the Bamahuan or the Bentley gold deposit had already been developed. Comparing the two panels of Figure E.4 to Figure 8 reveals that developing the Baomahun deposit would shrink the set of other deposits where mining for peace is possible, while developing the Bently deposit would increase this set. Thus, mining the "right" deposits first can provide many opportunities to manage resource-related conflicts, while mining "wrong" deposits can dramatically limit these options. These results also suggest that if multiple mines were to be developed, a clever sequencing of the mine openings could reduce the aggregate propensity for conflict compared to a simultaneous opening of all those mines.

Mine closure can also affect the peace deficit and, hence, the country's aggregate propensity for conflict. Like mine openings, mine closures change the spatial distribution of resource rents and potentially the set of discordant

[44] There is one outlier with a large indirect effect in Figure 8. This is the Kukuna iron mine in the north-west of the country. This large indirect effect is because the Susu are heavily over-represented around this deposit and become a discordant group.

groups. In addition, they reduce the aggregate resource rents. Online Appendix Figure E.5 depicts the predicted effects on the peace deficit from closing each of the mines operating in Sierra Leone in 2018 separately. Once more, we find substantial differences across mines. Shutting down Sierra Rutile or SML would reduce the peace deficit, while closing any of the other mines would increase it.

Similarly, the peace deficit can be used to predict how changes in the world market prices of some minerals would affect the country's aggregate propensity for conflict. Online Appendix Figure E.6 shows that higher mineral prices tend to increase the peace deficit and that these effects differ across minerals.[45]

### 6.2. New mines and the local propensity for conflict

We now use the local conflict exposure $e_l$, defined in equation (5), to predict the effect of hypothetical new mines on the local propensity for conflict. This measure captures the systemic component of the local conflict pressure resulting from the interaction of the country's ethnic and mining geographies. Again, we can distinguish between a direct effect that results from the change in the relative local resource rents $r_l/r$ and, possibly, an indirect effect that results from changes in the set of discordant groups $G^*$ and, therefore, the local ethnic diversity among discordant groups $D_{l,G^*}$.[46]

The direct effect of a new mine on the local conflict exposure is typically positive for wards where the relative local resource rents increase, i.e., wards in close proximity to new mines, but negative for wards that experience a decrease in the relative local resource rents. The indirect effect is typically also positive (or at least non-negative) in wards close to a new mine, because previously non-discordant groups over-represented around this mine may become discordant.

[45] In case of bauxite, diamonds, and rutile the effects are quite large and mostly direct, because groups like the Mende and the Kono, which are over-represented in the corresponding mining areas, are discordant already. In contrast, the effect is smaller and mostly indirect for iron. The reason is that some groups that are over-represented close to iron mines, particularly the Temne, only become discordant when the iron price increases.

[46] Building on equation (5) and the notation introduced in footnote 41, the direct effect can be written as $[(\tilde{r}_l/\tilde{r}) - (r_l/r)]\, D_{l,G^*(\mathbf{r},\mathbf{s})}$, and the indirect effect as $(\tilde{r}_l/\tilde{r}) \left[D_{l,G^*(\tilde{\mathbf{r}},\mathbf{s})} - D_{l,G^*(\mathbf{r},\mathbf{s})}\right]$.

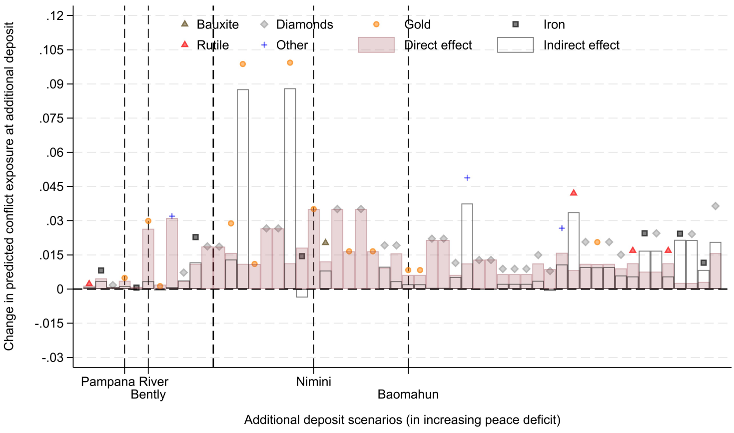



FIGURE 9. Predicted effects of new mines on the local propensity for conflict. This figure plots the simulated change that mining any of the known mineral deposits has on the local conflict exposure $e_l$ in the ward where this deposit is located, again under the assumption that the revenues generated at this deposit are equal to 10% of the revenues of all existing mines combined. Different colors and shapes represent the total effects for different minerals. The red bars represent the direct effects (keeping the set of discordant groups fixed), and the white bars represent the indirect effects due to the change in the set of discordant groups. The deposits are ordered by their effects on the peace deficit (as in Figure 8).

The indirect effects on the local conflict exposure in other wards are ambiguous and depend on the location of the new mines and the country's entire ethnic and mining geographies. However, the indirect effect can be positive even in faraway locations in which the newly discordant groups are prominently present. This possibility shows how conflicts can spread in our model.

Figure 9 illustrates how hypothetical new mines change the local conflict exposure in the wards hosting the corresponding deposits. The direct effects are always positive but differ in size due to differences in the local diversity among discordant groups. The indirect effects tend to be positive too. They are typically zero or small but can become large if a new mine in a resource-rich location makes a locally over-represented group discordant, such as in the case of two hypothetical new gold mines north of the center and close to the already active Tonkolili iron mine. It follows that the total effects on local conflict exposure in the wards hosting the new mines are always positive but vary greatly in size.

We have ordered the new mines by their effects on the peace deficit (as in Figure 8). This illustrates that there is no clear relation between a new mine's effects on the aggregate propensity for conflict and the propensity for conflict around the mine. This pattern also holds for the four hypothetical new gold mines on which we focused above. For example, while new mines at the Bently and the Pampana River deposits would reduce the aggregate propensity for conflict, the latter would cause a substantially smaller increase in the local propensity for conflict than the former. The reason is the lower local ethnic diversity among discordant groups in the ward hosting Pampana River deposit, where all discordant groups are under-represented, than in the ward hosting the Bently deposit, where two discordant groups (the Limba and the Sherbo) are heavily over-represented. Moreover, the Baomahun project considerably raises the aggregate propensity for conflict but has only a small effect on local conflict exposure.

We can also predict the effects of new mines on local conflict exposure in wards other than those hosting new mines. To illustrate this possibility, we predict the effects of each hypothetical new mine on the propensity for conflict in the wards hosting the six existing mines in Online Appendix Figure E.7. There is quite some variation in the effects across these mines, with the indirect effects often being stronger than the direct ones.

## 7. Conclusion: Mining policies for peace

Previous research suggests that natural resource rents are typically a curse for resource-extracting countries and regions. Given the increasing global demand for minerals from ethnically diverse and historically conflict-prone countries, we have reassessed the effects of mining on conflict. We have gone beyond purely local average effects and focused on the systemic component of the local conflict risk that results from a country's entire ethnic and mining geographies. We document that the development of different mineral deposits can have very different effects on a country's aggregate propensity for conflict and the spatial distribution of conflict risks. Governments, international mining companies, international organizations, and advocacy groups may benefit from considering these aggregate and local conflict externalities when deciding whether and under what terms to develop certain deposits.

Governments, which may be primarily concerned with a country's aggregate propensity for conflict, should focus on the effect of potential new mining projects on the peace deficit. The change in the peace deficit resulting from a new mine corresponds to the (positive or negative) monetary transfer to the planner necessary to ensure that this project leaves the country's aggregate propensity for conflict unchanged. Governments should make use of this information when designing policy. Ideally, they would include the change in the peace deficit in the price of the mining license. Alternatively, they could design the royalty and tax schemes in a manner that reflects the change in the peace deficit. If a government is unwilling or unable to implement such relatively subtle policies, it could consider the aggregate conflict externalities when deciding whether to allow a new mining project in a specific location. In addition, governments may also want to act upon information about local conflict externalities captured by our measure of local conflict exposure, e.g., if they are particularly concerned by higher conflict risks in some economically or politically important locations.

Our model offers important insights for revenue-sharing schemes too. Proposition 1 suggests a tight corset for such schemes when the avoidance of national conflict is prioritized. It prescribes that the aggregate resource revenues should be split proportionally to the ethnic groups' national population shares.[47] In reality, however, most resource-rich developing countries, including

[47] Alternatively, one could suggest revenue-sharing schemes designed based on the optimal transfers underlying Proposition 3. These transfers are derived in the proof of Proposition 3 in Online Appendix A and discussed in detail directly after the proof. However, we refrain from recommending the implementation of these transfers because they are based on the independence assumptions introduced in Section 2.4, which we consider appropriate for positive but not normative interpretations of the model (see footnote 12). Moreover, these transfers would discriminate between individuals with different ethnic markers within locations, which may be an undesirable property of revenue-sharing schemes.

Sierra Leone, have so-called derivation-based revenue-sharing schemes (Bauer et al., 2016). These schemes ensure that a fixed portion of the natural resource revenues is transferred back to the producing regions to address local claims over resource ownership or to compensate for pollution or other local externalities associated with resource extraction (Aragón and Rud, 2016; Bruederle and Hodler, 2019).[48] In the presence of ethnic segregation, such preferential treatment of producing regions violates the prescription of Proposition 1 and can thus lead to a higher (non-zero) risk of national conflict. Hence, revenue-sharing schemes must strike a balance between providing adequate compensation to mining regions and avoiding national conflict.

Many international mining companies (IMCs) care about conflict risks as well, e.g., because conflict can increase their production and transportation costs or undermine their social license to operate, i.e., "the ongoing approval and broad acceptance of society to conduct [their] activities" (Prno and Slocombe, 2012, p. 346). Hence, these IMCs would benefit from knowing the aggregate and local conflict externalities associated with their potential new mining projects. For example, if an IMC knew how its new project would shape the spatial distribution of local conflict risks, it would be better positioned to estimate the production costs at the mining site, the transportation costs from this site to the port, and the difficulty of obtaining the social license to operate.

Many IMCs follow the UN Guiding Principles on Business and Human Rights, which require companies to conduct human rights due diligence, among others, to avoid harming local communities. These principles are increasingly codified in national or supranational law. Thereby, it is often emphasized that conflict-affected areas warrant special attention (see, e.g., the European Union's Directive on Corporate Sustainability Due Diligence). To the best of our knowledge, we are the first to suggest a theoretical framework that can be

[48] Sierra Leone's Mines and Minerals Development Act from 2022 has several derivation-like features, e.g., revenues from land leases for constituency development funds and district councils.

brought to the data and help assess aggregate and local conflict externalities of new mining projects.

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