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My neighbour's war:
Spatial dependence of conflict incidence in West Africa

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My neighbour's war
Spatial dependence of conflict incidence in West Africa

Mario A. Maggioni and Sara Balestri[1]

Abstract

Although recent empirical literature acknowledges that organized violence tends to cluster geographically, the limited use of disaggregated data and of accurate spatial estimation techniques fail in explaining the spatial structure of conflict events. In this paper we analyse conflict incidence in West Africa through the provision of an illustrative case (the Mano River Region) by: (i) performing the analysis with the smallest possible sub-national disaggregated areas; (ii) taking into account the location of valuable resources (lootable diamonds and gold); and (iii) applying the most suitable spatial econometric specifications. Our results show the existence of relevant cross-border spillover effects of conflict events; and confirm that natural valuable resources are strong predictors of organized violence location. Moreover, we demonstrate that events concerning incompatibilities on government and/or territory are more strongly related to diamonds location, whereas events between no-state armed groups are indifferently connected to the location of both valuable resources.

KEYWORDS: Civil war, Africa, Natural Resources, Diamonds, Gold, Spatial Analysis

JEL classification numbers: Q34, D74, C21, N47, N57

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War is like a fire.
One man may start it, but it will spread all over.
T.H. White, *The Once and Future* King, 1958

1. Introduction

From the seminal study of Anselin and O'Loughlin (1992), the fact that internal armed conflicts are likely to spread across borders, making neighbouring areas prone to violence, is an established result in the literature. On the same perspective, recent studies provide empirical evidence that organized violence events cluster in space and diffuse across neighbouring countries (Gleditsch, 2002; Murdoch and Sandler, 2002; Saleyhan and Gleditsch, 2006; Buhaug and Gleditsch, 2008; Gleditsch et al., 2008; Schutte and Weidmann, 2011; Phillips, 2015).

In this paper we argue that, despite this vast literature, the spatial structure of conflict events occurrence has not yet been properly assessed because of the underuse of appropriate spatial estimation techniques.

At the same time, the quantitative literature on civil conflicts has progressively become attentive to the importance of exploring sub-national patterns of violence, in order to properly understand conflict dynamics. Countries, indeed, are rarely – if ever – characterized by constant features across their borders; rather, they often encompass very different physical, social and political local-environments which may well explain a large share of existing intra-country variations in conflict incidence. In addition, conflicts usually originate in specific sub-areas of a state, due to local conditions; and, even when they spread and affect large portions of the territory, they very rarely cover more than a quarter of a country's land (Raleigh et al. 2010).

This work builds on these strands of applied research and examines sub-national variations in civil conflicts correlates, through the use of fine-grained spatial disaggregated data, to highlight the need of dealing with spatial dependency and neighbouring effects in order to get unbiased and consistent estimates on the causes and facilitators of civil wars. We provide a paradigmatic case – the Mano River Region – to corroborate our arguments.

Our results suggest that conflict events cluster in space following specific paths of contagion influenced by local determinants, such as the presence of lootable natural resources (diamonds and gold), negative deviations in normal rainfall levels, and population density. We found also evidence that the persistence of conflict events in a given territory is largely explained by the specific characteristics of such events, namely the types of involved actors (in particular, whether governmental parties versus no-state fighting parties are involved).

This paper is organized as follows: we firstly discuss the theoretical basis of our empirical strategy. We subsequently present the econometric analysis – based on a specific case study, the Mano River Region – in which the hypothesis of spatial dependence in conflict events occurrence is tested by using a spatially disaggregated research design. A final section discusses the implications of our findings and suggests extensions for future research.

2. Modelling spatial dependency in civil conflict analysis

Conflict occurrence is characterized by spatial non-randomness, and it is correlated with local variations of social, economic and geographical features (such as, among others: orographic conditions, resource locations, human settlements, and institutional power). Diffusion of violence is likely to follow specific spatial paths and to be fuelled by geographical drivers (rough terrain and forested areas affect the way fighting parties may deploy their forces); however, non-geographic factors may also play a relevant role (for example: human settlements may either act as obstacle or, on the contrary, as a valuable attractor for the spreading of conflicts). In other words, conflict occurrence typically exhibits a spatially concentrated (and often auto-correlated) pattern; thus, conflict events cannot be treated as independent events when performing econometric analyses. Despite this evidence, a large part of the literature on civil conflicts still neglects the impact of spatial dependency in conflict occurrence, and avoids detecting spill-over and neighbouring effects at the proper scale of investigation.

Our approach is grounded on the following considerations: i) conflicts typically occur, in a given moment in time, within a restricted number of areas sharing similar geographical, political and socio-economic factors; thus, a sub-national perspective of civil conflicts should be applied; ii) conflicts often occur and/or diffuse across borders; thus, in order to deal with transnational space, it is better to use exogenously defined territorial units; iii) the recent availability of disaggregated data at high spatial resolution allows the use of properly specified spatial autocorrelation estimation models; iv) the accessibility of data on events of organized violence allows the detection of, otherwise hidden, significant spatial, categorical, and temporal variations in the dynamics of conflicts.

Firstly, we adopt a sub-national approach to overcome the main shortcomings of a country-level analysis, since neighbouring and regional relationships set the trajectory (peaceful or warring) for individual states (Gleditsch, 2002), and conflict-prone neighbours considerably increase the risk for individuals countries to be involved in conflicts (Anselin and O'Loughlin, 1992). More recently, empirical evidence confirmed that effects of civil war tend to spill over into neighbouring countries (Buhaug and Gleditsch, 2008), particularly in Sub-Saharan Africa, where events of large-scale violence are often located in border areas (Gersovitz and Kriger, 2013). Furthermore, fighting parties may benefit from a transnational space: reciprocal interaction across neighbouring countries is indeed a common feature in several conflicts (Banegas and Marshall-Fratani, 2007), contributing to sustain mutually reinforcing mechanisms among overlapping patterns of organized violence (Salehyan, 2009).

Secondly, we use geo-referenced data on events of organized violence – referring to broader internal and 'internationalized internal' armed conflicts as defined by UCDP-PRIO (Uppsala Conflict Data Program/Peace Research Institute, Oslo) Armed Conflict Dataset – to explore patterns of diffusion and spatial dependency in their locations. To avoid the possibility to include in our dependent variable spurious effects of spatial dependency due to operational choices in the coding of conflicts' occurrence and spatial extension, we decided to focus on individual events of organized violence and to construct a variable of organized violence incidence. Furthering the insights provided in a previous work, we argue that the adoption of events of organized violence as the dependent variable in our analysis is an effective solution to get rid of possible spatial effects deriving from its codification.

Thus, we explore conflict dynamics in West Africa by providing an illustrative regional case (the Mano River Region) and performing the analysis with the smallest possible sub-national disaggregated areas. Following promising results obtained by several scholars (among others, Buhaug and Rød, 2006; Theisen et al., 2012; Weidmann, 2015), we decide to employ an exogenous grid structure to model that regional space, using regular cells as (exogenous) sub-national unit of analysis. In this way, we are able to properly model the analysis of civil conflict occurrence by taking into account the existence of spatial autocorrelation phenomena, regardless of any definition of political borders and avoiding over-aggregation of data at the country level.

In this paper we devote particular attention to the effects of the location of lootable natural resources, since they have been found to be significant predictors in different dimensions of conflict, namely the outbreak and duration of conflict[2], and third-party interventions (Findley and Marineau, 2015). As widely accepted in the literature on civil conflict, *lootable resources* refer to lucrative, easy-to-transport resources produced in a market with very low barriers to entry (Le Billon, 2001; Ross, 2004; Humphreys, 2005; Snyder, 2006; Snyder and Bhavnani, 2005). As a matter of fact, lootable natural resources played a prominent role in the Mano River Region by fuelling military actions of domestic and third-party actors during the whole progression of conflict events.

In particular, the illegal exploitation of diamonds in Sierra Leone led to forging the well-known "blood diamonds" label, referring to diamonds mined in conflict areas and sold to finance insurgencies and warlords' private interests. The violent events occurring in the area were also the background for other regional dynamics, such as the turmoil in Cote d'Ivoire after the 1999 coup, when the country became one of the privileged routes for conflict-diamonds exports from Liberia and war-torn Sierra Leone. Although this evidence is well established by several illustrative studies, the way diamonds location matters on the occurrence and diffusion of organized violence has not been properly explored yet. Complementarily, the role of gold on regional conflict dynamics – less prominent with respect to diamonds, but still relevant in the "warlord logic" along the line of the "greed theory" of civil wars (Collier and Hoeffler, 2004) – has been largely ignored by quantitative studies (Balestri, 2012; Balestri, Maggioni, 2014). For these reasons, in this paper we test whether both valuable natural resources (alluvial diamonds and gold deposits) may explain spatial paths of diffusion of conflict events within the Mano River Region.

3. Cross-border conflicts across West Africa: the Mano River Region

We decided to address the conflicts in the Mano River Region since this specific area displays in a limited size territory (751,429 Sq. Km, thus only 3.6% of Sub-Saharan Africa) a number of relevant and common characteristics of other African countries. Firstly, borders are porous: this implies that, once conflict events have actually broken out, neighbouring areas are likely to be overflown by illicit movements of arms, resources and militias. Secondly, borders are highly contested since they are the result of stratified historical contingencies, including legacy of European colonialism, and often cut across pre-existing

[2] Inception studies on this issue are Collier (2000); Collier and Hoeffler (2004); Fearon (2004). For a recent literature review, see Blattman (2010).

cultural and political regions (Silberfein and Conteh, 2006). Within this framework, social and political instability easily spreads across borders, and belligerents may attempt to use neighbouring countries' territories as military base, safe heavens, source of supplies and recruitment district for potential fighters.

The Mano River Region hosted a clear example of regional warfare with global connections (Hoffman, 2004), where cross-border movement of natural resources, weapons and fighters has been a major characteristic of the organized violence which spread through the whole region for years.

The period of observation (1989-2014) allows capturing post-Cold War events of organized violence, including the most update data on conflict events.

In a context of latent instability, armed violence finally broke up in Liberia culminating in the first Liberian civil war (1989-1997). Pervasive destabilizing effects overflowed into the whole region until violence seeped through Sierra Leone in 1991, feeding a long-lasting civil conflict (1991-2002), and later spreading to Guinea (2000-2001). In Cote d'Ivoire, the coup of 1999 started a spiral of instability throughout the country, considerably complicated by flows of displaced people, and renegade soldiers and militias from neighbouring countries; and culminated in 2002, when heavy fighting broke out in Bouake, the second largest city, resulting in the outbreak of the first Ivorian civil war. Meanwhile, violence returned to Liberia when in 1999 national dissidents, organized in the rebel group Liberians United for Reconciliation and Democracy (LURD) and backed by the government of Guinea, emerged in the north of the country. In 2003 a second rebel group, the Ivoirian-backed Movement for Democracy in Liberia (MODEL), emerged in the south. The internal division between north (Muslim) and south (Christian) regions and the civil unrest in Cote d'Ivoire deeply affected the ability to recover from the first civil war, and left a pervasive legacy in the socio-political setting. After months of sporadic violence, in 2011 the use of armed force escalated into a full-military conflict, giving start to the second Ivorian civil war (2010-2011).

In the Mano River Region experience, illicit natural resources flows played a prominent role in financing military actions and encouraging self-interested desires of wealth accumulation. Recent evidence (UN, 2013) casts light on the critical issue represented by the misuse of wealth derived from natural resources exploitation to augment potential fighting forces and to support equipment necessities for all armed actors involved. Despite the enforcement of multiple sanctions and embargos to stop such illicit flows across borders, limited results have been obtained, making room for rent-seeking behaviours and perpetuating conditions of instability and latent violence.

4. Research design and models specification

This work aims at providing evidence of spatial neighbouring effects in the occurrence of conflict events, through the use of a paradigmatic case study. In particular, we examine the existence of spatial dependency and diffusion effects in the occurrence of civil conflict events in the Mano River Region and empirically evaluate how they are influenced by local characteristics such as the presence of lootable natural resources.

Our empirical approach contributes to the debate on conflict dynamics and overcome some of the shortcomings in the existing literature on civil conflicts, deriving from the

underestimation of spatial dependency in the occurrence of events of organized violence. This paper differs from previous empirical studies since it encompasses the spatial econometric approach to civil conflicts with an empirical framework which stresses the role that local determinants play in diffusing conflict events in neighbouring areas.
Throughout the paper we argue that country-level analysis does not entirely capture the complexity of organized violence occurrence, and leaves out causal interconnections at the local scale. To substantiate our hypothesis, we adopt a spatially disaggregated approach based on an exogenous geography, drawn from the PRIO-GRID v.2.0 dataset, built as a 0.5x0.5 degree resolution regular grid, which determines a sample of 265 equally sized cells that are constant across time and space, corresponding to the territories of Liberia, Sierra Leone, Guinea and Cote d'Ivoire territories. These 265 cell units are therefore our units of analysis.
We use this exogenous geography to compute a contiguity-based spatial weight matrix: a neighbour is defined as a cell sharing any boundary point of any given cell (first order "queen" matrix). On the whole sample, 68% of cells hold 8 neighbours, whereas the others are characterized by a lower number of neighbouring cells. To create proportional weights, given the unequal number of neighbours of the unit of observation, we row standardized the matrix.
The empirical analysis assesses the existence of spatial dependency paths at local scale, by applying a time-invariant definition of conflict incidence as the average measure of conflict events occurrence in any given cell throughout the whole period of observation.
In particular, we test our hypothesis by estimating the base model:

$$\text{EV\_INC}_{c,i,t} = \alpha + \beta X_c + \gamma X_{c,t-1} + \mu_i + \varepsilon_{c,i,t}$$

where c denotes the cell, i the country and t the period of observation; X is a vector of controls, either time-invariant or measured at time $t-1$; and μ are country fixed effects. A preliminary estimation through OLS of the base model allowed us to test residuals for spatial dependency. We found that the Moran's I error (4.601) is significant at 1% level, and the Lagrange multiplier test indicates that dependency is not due to spatial correlation in the error terms, and suggests the adoption of a Spatial Autoregressive Model (SAR). That is our measure of incidence of organized violence is clearly characterized by spatial auto-correlation, deserving a proper model specification to account for such dependency. Thus, we model it by a maximum likelihood estimation of a SAR model, which assumes that conflict events incidence may produce spill-over effects on neighbouring areas, fuelling geographical clusters of violence. The base model is enriched by the introduction of the spatial-lag of the dependent variable:

$$\text{EV\_INC}_{c,i,t} = \alpha + \beta X_c + \gamma X_{c,t-1} + \rho W^* \text{EV\_INC} + \mu_i + \varepsilon_{c,i,t} \qquad [1]$$

where ρ is the spatial autoregressive parameters and W^* *EV_INC* stands for the product of the row-standardized connectivity matrix (W) and the observed values of the dependent variable. The simultaneity–endogeneity issue implied by the inclusion of the spatial lag does not constitute a concern in our analysis, given the use of a measure of violence incidence in any given cell (Franzese and Hays, 2007). We perform several specifications of the same model, whose results are shown from Model 1 to Model 1.3 (Table 2 and Table 4).

We further expect the spatial correlation to be present not only in the dependent variable, but also in the covariates. The introduction of a spatial autocorrelation matrix for controls is less problematic, since it does not imply a simultaneity problem. In the final specification, the expected spatial correlation in conflict events location is thus attributed to both direct contagion effects of the conflict variable, and to the fact that local determinants are also spatially correlated. To assess this possibility, we adopt a maximum likelihood estimation of a Spatial Durbin Model (SDM) in which a spatial autoregressive term for each independent variable is included:

$$\mathrm{EV\_INC}_{c,i,t} = \alpha + \beta X_c + \gamma X_{c,t-1} + \rho W^* \, \mathrm{EV\_INC} + \varphi W^* X + \mu_i + \varepsilon_{c,i,t} \qquad [2]$$

where ρ and φ denote the spatial autoregressive parameters, W denotes the spatial weight "queen" contiguity matrix, and all the other terms are defined as above. As before, different specifications are computed whose results are shown by Model 2 and Model 2.1 (Table 4).

5. Data description

Dependent Variable – The dependent variable (EV_INC) for the cross-sectional analysis is a measure of incidence of organized violence in any given cell, calculated as the fraction of years over the sample period (1989-2014) with at least one conflict event. We rely on data from the UCDP Geo-referenced Event Dataset v.3.0 (UCDP GED) (Sundberg and Melander, 2013) to calculate it. We include all types of violent events recorded in the UCDP-GED dataset – namely "state-based", "no-state based" and "one-sided" events – in order to account for all major expressions of organized violence. The original dataset records all events that result in at least one fatality, referring to all conflicts which meet the minimum threshold of 25 annual battle-related deaths, as defined by the UCDP Conflict Dataset. Each event is geo-referenced by the provision of latitude/longitude coordinates and date of occurrence.

We over impose, through GIS techniques, the above mentioned grid structure on the geo-referenced conflict events data, and check whether a given cell has been involved in a conflict event in a given year within the period (1989-2014). Finally, we collapse the cell-year observations to create a time-invariant measure of conflict incidence in any given cell for the entire period of observation. Such measure captures the persistence of violence at local level, thus avoiding the limit of using political border definition.

Totally, we plot the 2,362 conflict events which occurred throughout the whole period of observation in an area corresponding to 41% of the region under scrutiny (more specifically, they occurred in 109 cells out of the 265 cells of the sample), suggesting a territorially recurrence of organized violence.

[Figure 1 about here]

Sierra Leone is the country where the majority of violent events (1,473 events that means 62% of total events) took place, as clearly showed in Figure 1.

To verify whether conflict events incidence displays a clustered pattern or is randomly spread throughout the space, we perform a local Moran's I statistical test which returns a coefficient of 0.664 (p-value: 0.000), confirming a high spatial dependence path across events. Among the 265 cells which structure the gridded space, 44 cell units show up as spatial clusters, thus roughly corresponding to 16% of the sample. This preliminary result strongly supports the need for a spatial econometric approach.

Regressors – In order to verify whether local conditions foster a/o hinder the outburst and development of conflict events and, in the meantime, to control for possible spatial autocorrelation effects, we analyse the sub-national variations of civil war correlates, recorded (whenever possible) at the "cell" level of the above mentioned grid structure.

In the analysis we include five determinants of civil conflicts which describes specific conditions of opportunity for violence outbreak at local scale: the presence of lootable natural resources (in particular: diamonds and gold); some orographic characteristics (including the percentage of mountainous terrain or forest area) and climatic variables (with particular attention to rain/drought conditions); a number of socio-economic dimensions (such as: population density and ethnic exclusion, geographical distance from a political power centre, proximity to a border). We also indirectly control for other usual explanatory variables (such as GDP and political regime type) by including country fixed effects.

As far as the role played by lootable resources, we used georeferenced data on location and characteristics of diamonds deposits from DIADATA (Gilmore et al., 2005) and of gold deposits from GOLDATA (Balestri, 2015). Through the use of GIS techniques, we plot their geographical locations and we code for each resource a dummy variable which takes the value of 1 if a deposit existing within a given cell was known at the beginning of the period; 0 otherwise. We included alluvial and superficial deposits in order to consider only the more easily exploitable sites in wartime. In our sample, 34 cells record the presence of diamonds, 14 cells of gold, while only 3 cells shows the presence of both resources. Since all deposits were already known before the occurrence of conflict events, we do not have to worry for possible reverse causality. Empirical evidence points out that extractive resources with high economic value and limited traceability have either been largely exploited by fighting groups in order to sustain conflict costs and to accumulate private wealth; or have been the reason for conflicts events aimed at establishing control over a specific territory. Thus we expect a positive correlation of the presence of such resources with conflicts.

The second set of correlates of civil conflict refers to pure geographic characteristics, namely the percentage of mountainous and forested areas within each cell, measured as average pixel values based on high-resolution raster data provided by respectively the UNEP's Mountain Watch Report (2002) and Globcover 2009 dataset. Whereas the elevation and slope of terrain are on average very low (less than 10% of the area can be defined mountainous), forests show up as a major characteristic, covering, on average, 41% of the Mano River Region. It is more difficult to specify an expected sign of the coefficients for these variables: on the one hand, mountains and forest may act as an obstacle to fast movement of troops, thus we should expect a negative correlation with conflict events; on the other, the same environment may facilitate the activity of rebellious or insurgent groups practicing guerrilla warfare, thus causing the coefficients sign to be positive.

As to geo-political predictors of civil conflict, we proxied distance to state's political power centre by including the distance from the country's capital, measured in kilometres (as derived from the CShapes Dataset, Weidmann et al., 2010), and the proximity to a (internal) border as a dummy variable which takes the value 1 if the cell (even a tiny part of it) lies on a border, 0 otherwise. In general, civil conflict events are more likely to happen near the capital, when the aim of the war is a change of regime. Conversely, border regions, as described above, are an ideal base and hideaways for rebellious parties engaged in a civil conflict.

Both sets of predictors (geographic and geo-political variables) are time invariant, thus they do not change in any of the cross-sectional specifications.

We also control for population density, derived by original data taken from the Gridded Population of the World v.3, and for the number of excluded (discriminated or powerless) groups as defined in the GeoEPR/EPR 2014 v.2 dataset. Population size is expected to be positively associated to conflict events incidence: concentration of population in a specific location, as well as in neighbouring areas, might facilitate mobilization, reduce coordination costs and raise the value of controlling that territory. Population is therefore considered a location-specific factor in the analysis of civil conflicts, and its role is robustly assessed by several studies (among others, Raleigh and Hegre 2009).

We also include in the analysis a second socio-political dimension, namely the number of excluded groups: exclusion from the political system, and consequent inability to pursue interests and to address social tensions and grievances in a peaceful way, might be a trigger for violence (Cederman et al., 2010; Asal et al.,2015).

We finally considered two variables for climate variability: rain – an indicator of the yearly total amount of precipitations, in millimetres, in any given cell, based on monthly meteorological statistics from the GPCP v.2.2 Combined Precipitation Data Set (Huffman et al., 2012); and a proxy for drought as the deviation from normal long-term rainfall levels in the last month of the rainy season, based on the Standardized Precipitation Index derived from CAMS_OPI precipitation dataset[3]. This set of climatic variables are evidently time-variant, therefore we compute average values of yearly observations.

Although the empirical literature (as reviewed in Gleditsch, 2012) has not yet provided convincing evidence about the link between climate change and conflict, several scholar such as Hendrix and Salehyan (2012) suggest that scarcity of renewable resources, such as water, may explain violence outbreak; Fjelde and von Uexkull (2013) prove that large negative deviations in rainfall from the historical norm are associated with a higher risk of communal conflict; and Devlin and Hendrix (2014) show that lower mean levels of precipitation (and higher variability of precipitation in dyads) make conflict more likely. Climate variability seems indeed connected to local outburst of violence. As regards the Mano River Region, given the fact that population heavily relies on rain-fed agriculture, the reduction of income and loss of livelihoods deriving from negative rainfall anomalies may facilitate local mobilization for violence outbreak.

[3] In particular, positive SPI values indicate greater than median precipitation level, and negative values indicate less than median precipitation level.

[Tab 1. around here]

6. Results

The main finding of this study is the provision of empirical evidence about spatial dependency in the occurrence of events of organized violence: across different specifications, the autoregressive term is always steadily significant at 1% level and positive (Table 2). In other words, local conditions determine the existence of conflict events in a given locations; however, conflict events display also relevant spillover effects.

[Table 2 around here]

In particular, in Model 1 the autoregressive term ρ is highly significant and positive in sign, suggesting that the level of conflict incidence experienced by any given cell depends on the level achieved in neighbouring cells. Therefore, violence contagion is a common feature in our sample. As expected, the presence of lootable resources is confirmed as positively and significantly associated to organized violence: both diamonds and gold, indeed, are significant at 5% level and predict a rise in conflict incidence when present in a cell. Among the other covariates, it deserves to be noted that increased levels of conflict incidence are associated to higher population density and to being a border cell too. Rainfall deviation proxy is negative in sign, suggesting that drought periods are associated with a higher level of violence outbreak, as expected.

Since the different nature of conflict events, especially in terms of involved actors, may imply different spatial patterns, we test this hypothesis by focussing on three events typologies: state-based events, no-state based events and one-sided events. The variable *state-based event* first refers to a conflict situation where one of the sides aims at replacing the central government (or changing its composition) and/or where the status/independence of a specified territory is contested. *No-state based events* refers to the occurrence of conflicts events characterized by the use of armed force between two organised armed groups, neither of which is the government or a state. The variable *one-sided event* refers to the use of armed force by the government of a state or by a formally organized group against civilians. In our sample, one-sided events are strongly related to state-based events ($r^2 = 0.689$), thus signalling a relevant geographical overlap of these two events. For this reason, we decided to control in our specification variables for state-based and no-state based by introducing two dummy variables, which take the value of 1 if at least one event of the mentioned categories occurred in any given cell[4].

As shown in Model 1.1, the controls for events' typology are highly significant in explaining the persistence of violence in a given cell, thus reducing the coefficient of the spatial lag of the dependent variable. However, the actual reduction of the magnitude effect of the diamond variable and the non-significance of gold variable raises some doubts about the consistency of such an outcome. While there are no *a priori* reasons why either gold or diamond should

[4] In the sample, 74 cells have hosted state-based events (almost 28% of the territory), whereas 35 cells hosted no-state based events (13% of the territory); in 27 cells both state-based and no-state based events took place.

be more related to a specific type of event of organized violence – given the fact that their deposits can be exploited by small-scale and low-technology methods, and that there are well developed illegal markets for both resources – it is reasonable to argue that, if this is the case, the combined effect of the two predictors modelled in a multiplicative way (events' typology times natural resource) may better capture the persistence of organized violence in space.

Since there are no strong theoretical reasons to drive our decision on which interactive combination of such predictors should be used in the analysis, we followed a pragmatic data-driven approach and tried to keep as low as possible the correlation between covariates (Tab.3). This process led us to include in SAR specification the following interactive variables: *state-based event*diamond* and *no-state based event*gold*.

[Tab. 3 around here]

Results obtained in Model 1.2 support our hypothesis. Here, the strength of spatial interdependence, captured by the value of the ρ coefficient, bounces back to 0.427 (significant at 1%). Interactive dummy variables are highly significant (at the 1% level) and positive in sign: whether at least one state event occurs in a cell characterized by the presence of lootable diamonds, the effect on conflict events incidence is larger. The same happens whether at least one no-state event occurs in a cell characterized by gold deposits. We verified also the consistency of results with a different combination of interactive variables, namely *no-state event*diamond* and *state-event*gold*: the first covariate does not reach statistical significance, whereas the latter (coefficient: 0.0670) is significant at 1% level and positive in sign[5]. In other words, gold seems to indifferently interact with both events types, whereas diamonds seem to play a role in state-based events only.

As far as other covariates are concerned, drought periods are confirmed to be positively associated to the occurrence of conflict events in any given cell, suggesting an inverse relation between deviation from normal precipitation levels and violence persistence in space. This result supports the findings of other studies such as Fjelde and von Uexkull (2012), signalling that rainfall shortages affect spatial occurrence of conflict events, even in case of non-communal conflicts, as it is in our case. To further explore the robustness of this causal correlation, we replace the measure of rainfall deviations with the average measure of the yearly proportion of months that are part of the longest streak of severely dry conditions[6]. The main results still hold, confirming the finding that rainfall anomalies affect the incidence of organized violence.

Finally, population density is confirmed as a stable predictor throughout the different model specifications applied. Contrary to what expected (and to the established results in the literature), we do not find any significant effects for the presence of excluded groups.

In order to check the robustness of the results we followed a twofold estimation strategy. In the first strategy, we tested whether the existence of spatial spillovers on the dependent variable – detected in Models 1 to 3 according to a SAR specification – was robust to the

[5] Results not shown and available upon request.

[6] It is an indicator of within-year deviations in precipitation based on monthly data (SPI-6), where severely dry conditions refer to (standardized) deviation from long-term normal rainfall of the longest streak of consecutive months ending in the given year with a value below -1.5.

inclusion of spatially lagged covariates according to a SDM (Spatial Durbin Model) specification (Model 2). In the second strategy, we tested whether the existence of spatial spillovers was robust to changes in the definition of "proximity", i.e. to changes in the spatial weigh matrix (Model 1.3 and Model 2.1). Thus, we computed a second order queen contiguity matrix, which implies that each cell may hold till 16 neighboring cells. In our sample, each cell has 13 neighboring cells on average, with a minimum value of 4. The Moran's I statistical test returns a coefficient of 0.527 (p-value: 0.000), still confirming a high spatial dependence path across events. Results are shown in Table 4.

[Table 4 around here]

Looking to the SDM specification, a more nuanced picture emerges, since different valuable natural resources seem to sustain different contagion paths. In particular, the location of an exploitable deposit of gold in a given cell raises the level of no-state conflict incidence; whereas the location of diamonds deposits in neighbouring cells produces a similar effect for state-based events. The location of diamond deposits seems therefore to produce larger spillover effects in determining the level of local conflict incidence. As before, we checked whether the inclusion of a different combination of interactive variables produces consistent results. Once we adopt the combination *no-state based event*diamond* and *state-based event*gold*, the coefficient of the autoregressive term is confirmed (0.2851, significant at 1% level). Thus the main result of our analysis is stable to different model specifications. As far as natural resources are concerned, diamond deposits (in interaction with no-state based events) are significant when located in neighbouring cells (0.1591, significant at 1%), whereas gold (in interaction with state based events) is confirmed as a significant predictor of conflict events incidence in a given cell (0.0745, significant at 1%)[7].

Going back to Model 2, geographical features, namely the presence of mountainous and forested areas, turn out to be significant and negative in sign, suggesting that in the Mano River Region they mainly act as natural obstacle for violence outbreak. More specifically, it is reasonable to argue that forested areas may represent a disincentive for conflicts outbreaks because of the higher costs implied by the organization and movement of fighting parties in such a difficult terrain. It is useful to note that *no-state based events* – that means events of organized violence occurred between two organised armed groups, neither of which is the government of a state – occurred in a minority of the total number of cells involved in conflict events (16.6%).

Rebels and other no-governmental fighting parties are more likely to take advantage of non-regular territories, for example characterized by forests, in order to deploy their guerrilla-style military strategy and find shelters. Interestingly enough, mountainous terrain in neighbouring cells is significant and positively associated with conflict incidence in a given cell; this confirms that, *ceteribus paribus*, organized violence is, to some extent, more likely to happen in flatter areas.

A similar but reverse pattern is found for the drought variable: negative deviations from normal precipitation levels in a given cell increase conflict events incidence in the same cell,

[7] Results are not shown here but they are available upon request.

while they reduce conflict incidence when the variable refers to neighbouring cells. In other words, worsened conditions in the surroundings – due to drought episodes – make the occurrence of conflict events in a given cell less likely, as neighbouring areas are a more suitable environment for violence to raise.
In synthesis, the first strategy for robustness check – adopting a SDM instead of a SAR model to describe spatial dependency of conflict events – confirms the robustness of our results: sign, significance and size of the relevant coefficients remain stable.
The second strategy for robustness check implies the possibility that the chosen dimension of the spatial weight matrix is critically driving the results. For this reason we tested whether the inclusion of a second level queen contiguity matrix corroborates or contradicts our previously findings. Results are summarized in Table 4 in which Model 1.3 provides estimates for the SAR model enriched by interactive variables of event typology and natural resources, and Model 2.1 shows estimates for the complete SDM model. In Model 1.3, interactive variables are found steadily significant at 1% level, as well as all covariates previously found as significant predictors. The autoregressive term still confirms spatial dependency in conflict events incidence. This result is particularly relevant when analysed in view of Model 2.1: here the autoregressive term is no more significant, whereas other covariates maintain their explanatory power in a consistent way. Therefore, once we test for a possible enlarged reach of spillovers, we get evidence that while conflict events are very local (effect are present only when direct contiguity is considered), the interactions of valuable resources with conflicts type extend their effects over a second level contiguity (both coefficients for *State event*Diamonds* and *No State event*Gold* variables are positive and significant).

7. Conclusions

Applying a spatially disaggregated research design, and using the recently released georeferenced event data on armed conflicts, we explored whether such events show spatial pattern of dependency, and whether lootable natural resources statistically explain the location of clusters of violent events. Our analysis confirms that events of organized violence do not occur randomly; rather, they follow specific local conditions, which shape their spatial distribution. Thus, either omitting the role played by space dependence or improperly modelling its effects produces biased and inconsistent results, making policy implications potentially misleading.
Through an illustrative case, based on the Mano River Region, we provide evidence about the existence of relevant spillover effects of conflict events incidence. Using event data to minimize the existence of spurious effects in the magnitude of spatial dependency, and exploring local distribution of violence over time, we found suggestive evidence that lootable natural resources (diamonds and gold) are strong predictors of conflict location.
In other words, the availability of valuable resources – either as causes of conflict for the control of a given territory, or as instrumental means to finance conflicts – sustains violence episodes. This is particularly relevant when controlling for different typology of events: events of organized violence intended to capture a/o change institutional power (*state-based events*) seem to be more related to diamond location, whereas fighting events between no-state armed groups (*no state events*) are indifferently connected to both diamonds and gold deposits location.

A future extension of this work implies the explicit modelling of the time dimension, implicitly considered in the above analysis, in order to properly estimate the diffusion process of conflict events.

FIGURES and TABLES

Figure 1	Conflict events locations, 1989-2014
Table 1	Summary statistics
Table 2	Results for Spatial Auto-Regressive (SAR) models
Table 3	Correlations between interactive variables (events typology and natural resources)
Table 4	Robustness checks

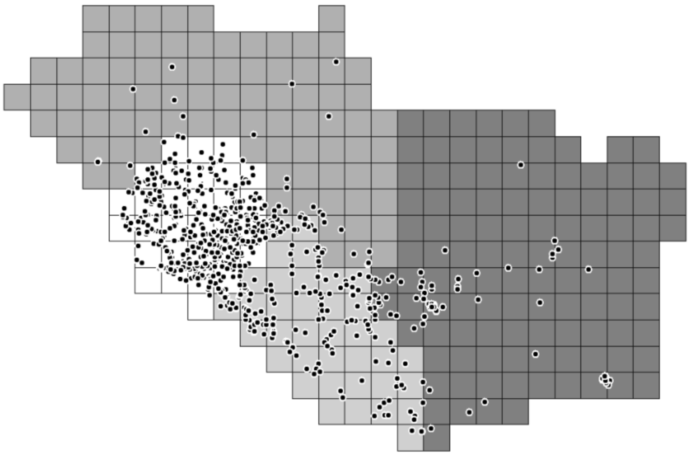

Figure 1 Conflict events locations, 1989-2014. Each shade of grey represents a different country. Proceeding clockwise: white cells correspond to Sierra Leone territory, slight dark grey cells to Guinea, dark grey cells to Ivory Coast, light grey cells to Liberia.

Table 1 *Summary Statistics*

Variable	Description	Obs	Mean	Std.Dev.	Min	Max	Source
EV_INC	Conflict Incidence by cell over the period 1989-2014	265	0.0656	0.1051	0	0.462	PRIO-GRID, 2015
Border cell	Dummy for cell crossed by a border	265	0.2415	0.4288	0	1	
Capital distance	Distance to capital city (km)	265	261,450	138,737	8	632	PRIO-GRID, 2015
Mountains	Mountainous terrain as share of cell area (percentage)	265	0,0991	0,1765	0	0,9417	UNEP 2002
Forests	Forested terrain as share of cell area (percentage)	265	41,3831	28,6434	0,029	98,185	Globcover, 2009
Precipitation_avg	Average precipitation per cell over the period 1989-2014 (mm)	265	1643,405	400,27	11247,22	2452,937	GPCP/NOAA, 2015
Drought_avg	Average deviation from long-term normal rainfall during last month of rainy season	265	-0.1975	0,0934	-0.3834	0,1004	CAMS_OPI
Diamonds	Dummy variable for the presence of lootable diamonds	265	0,1358	0,343276	0	1	DIADATA, 2005
Gold	Dummy variable for the presence of lootable gold deposits	265	0,0302	0,17142	0	1	GOLDATA, 2015
Exc_groups	Number of excluded groups per cell	265	1,5094	0,5938	0	2	GeoEPR-ETH, 2014
Population density	Population size for each cell (1990)	265	44,334	108,184	2,629	985,727	CIESIN, 2005
State event	dummy for at least one state-based event	265	0.2792	0.4494	0	1	PRIO-GRID, 2015
No state event	dummy for at least one no-state based event	265	0.1320	0.3392	0	1	PRIO-GRID, 2015
One-sided event	dummy for at least one one-sided event	265	0.3811	0.4865	0	1	PRIO-GRID, 2015

Note: *Precipitation_avg* and *Population density* variables are rescaled by 10^2 in econometric analysis for readability of results

Table 2 *Results for Spatial Auto-Regressive (SAR) models*

CONFLICT EVENTS INCIDENCE

Dependent variable: fraction of years over sample period with at least one conflict event

	(1)		(1.1)		(1.2)	
Rho (W*EV_INC)	0.4477	***	0.2998	***	0.4272	***
	(0.0789)		*(0.0748)*		*(0.0792)*	
Border cell	0.0190	**	0.0072		0.0114	
	(0.0092)		*(0.0077)*		*(0.0091)*	
Capital distance	0.0008		0.0004		0.0025	
	(0.0038)		*(0.0031)*		*(0.0036)*	
Mountains	-0.0009		-0.0049		-0.0059	
	(0.0238)		*(0.0197)*		*(0.0234)*	
Forests	-0.0001		-0.0000		-0.0001	
	(0.0001)		*(0.0001)*		*(0.0001)*	
Precipitation_avg	0.0012		-0.0015		0.0008	
	(0.0020)		*(0.0017)*		*(0.0020)*	
Drought_avg	-0.1381	**	-0.0831		-0.1382	**
	(0.0608)		*(0.0510)*		*(0.0593)*	
Diamonds	0.0244	**	0.0170	*		
	(0.0114)		*(0.0095)*			
Gold	0.0352	**	0.0165			
	(0.0166)		*(0.0138)*			
Marginalized ethnic groups	-0.0059		-0.0056		-0.0057	
	(0.0099)		*(0.0082)*		*(0.0097)*	
Population density	0.0124	***	0.0113	***	0.0114	***
	(0.0035)		*(0.0029)*		*(0.0035)*	
State event			0.0827	***		
			(0.0097)			
No State event			0.0564	***		
			(0.0105)			
State event*Diamonds					0.0428	***
					(0.0156)	
No State event*Gold					0.0872	***
					(0.0302)	
Constant	-0.0532		0.0075		-0.0431	
	(0.0397)		*(0.0336)*		*(0.0391)*	
Observations	***265***		***265***		***265***	
Country fixed effects	***X***		***X***		***X***	

*Significance levels: * p<0.1, ** p<0.05, ***p<0.01. Standard errors in parentheses*
W= first order queen contiguity matrix, row-standardized

Table 3 *Correlations between interactive variables (events typology and natural resources)*

Interactive Dummy Variables correlations
SAR Model

Variables	State event*Diamond	State event*Gold	No-state event*Diamond	No-state event*Gold
State event*Diamond	1.0000			
State event*Gold	0.2446	1.0000		
No-state event*Diamond	0.6181	0.2361	1.0000	
No-state event*Gold	0.1990	0.8134	0.3003	1.0000

Table 4 *Robustness checks*

CONFLICT EVENTS INCIDENCE

Dependent variable: fraction of years over sample period with at least one conflict event

	(2)		(1.3)		(2.1)	
Rho (W*EV_INC)	0.1849	*	0.2735	***	-0.1458	
	(0.0965)		*(0.0990)*		*(0.1156)*	
Border cell	0.0130		0.0085		0.0089	
	(0.0091)		*(0.0095)*		*(0.0091)*	
Capital distance	0.0029		0.0038		0.0071	
	(0.0112)		*(0.0038)*		*(0.0114)*	
Mountains	-0.0656	**	-0.0010		-0.0662	**
	(0.0309)		*(0.0245)*		*(0.0311)*	
Forests	-0.0004	*	-0.0002	*	-0.0004	*
	(0.0002)		*(0.0001)*		*(0.0002)*	
Precipitation_avg	-0.0028		0.0022		-0.0021	
	(0.0032)		*(0.0022)*		*(0.0032)*	
Drought_avg	-0.2844	***	-0.1364	**	-0.2776	***
	(0.0753)		*(0.0621)*		*(0.0755)*	
Marginalized ethnic groups	0.0056		-0.0071		0.0110	
	(0.0124)		*(0.0102)*		*(0.0126)*	
Population density	0.0139	***	0.0120	***	0.0146	***
	(0.0035)		*(0.0037)*		*(0.0034)*	
State event*Diamonds	0.0196		0.0614	***	0.0268	*
	(0.0151)		*(0.0158)*		*(0.0149)*	
No State event*Gold	0.0634	**	0.0891	***	0.0595	**
	(0.0296)		*(0.0317)*		*(0.0297)*	
W*Border cell	-0.0436	**			-0.0512	**
	(0.0222)				*(0.0228)*	
W*Capital distance	0.0021				0.0000	
	(0.0124)				*(0.0125)*	
W*Mountains	0.1075	**			0.1063	**
	(0.0491)				*(0.0494)*	
W*Forests	0.0003				0.0001	
	(0.0003)				*(0.0003)*	
W*Precipitation_avg	0.0056				0.0082	*
	(0.0043)				*(0.0045)*	
W*Drought_avg	0.2590	**			0.2180	*
	(0.1224)				*(0.1220)*	
W*Marginalized ethnic groups	-0.0091				-0.0184	
	(0.0192)				*(0.0193)*	
W*Population density	0.0036				0.0044	
	(0.0088)				*(0.0089)*	
W*State event*Diamonds	0.2144	***			0.2612	***
	(0.0352)				*(0.0347)*	
W*No State event*Gold	-0.0639				-0.0663	
	(0.0929)				*(0.0935)*	
Constant	-0.0684		-0.0655		-0.1233	
	(0.0507)		*(0.0413)*		*(0.0543)*	
Observations	***265***		***265***		***265***	
Country fixed effects	***X***		***X***		***X***	

*Significance levels: * $p<0.1$, ** $p<0.05$, ***$p<0.01$. Standard errors in parentheses*
In Model 2, W= first order queen contiguity matrix, row-standardized.
In Model 3 and Model 4, W=second order queen contiguity matrix, row-standardized

Conflict of Interest Statement

The authors certify that they have NO affiliations with or involvement in any organization or entity with any financial interest (such as honoraria; educational grants; participation in speakers' bureaus; membership, employment, consultancies, stock ownership, or other equity interest; and expert testimony or patent-licensing arrangements), or non-financial interest (such as personal or professional relationships, affiliations, knowledge or beliefs) in the subject matter or materials discussed in this manuscript.

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Notes