Spatial Inequality, Civil Conflict and Cells: A Dynamic Spatial Probit Approach

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Abstract

This study examines the link between spatial income inequality and civil conflict in Africa. To that end we extend traditional empirical models of conflict to account for both endogenous and exogenous spatial interaction effects in the process of conflict by means of modern spatial econometric techniques. Using a geographically disaggregated annual high-resolution cell data for a sample of African countries during the period 1998 to 2013, we quantify the effect of spatial inequality on the probability of conflict incidence. Estimates show the existence of a positive and statistically significant relationship between spatial income inequality and conflict in African regions. This is partly due to the role played by spatial spillovers induced by spatial inequality in neighboring regions. The observed link is robust to the inclusion in the analysis of different explanatory variables that may affect both conflict and spatial inequality such as the level of economic development, the endowment of natural resources, infrastructures, geographical conditions, population density, fractionalization, polarization, social exclusion, or the share of urban population. The observed positive effect does not depend on the the level of data disaggregation, the type of conflict, the spatial inequality metric used in the analysis and the econometric specification employed to capture the nature of spatial spillovers.

Keywords: Conflict, Spatial Inequality, Africa, Dynamic Spatial Panel, Spatial Probit.

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1 Introduction

This paper investigates the the link between spatial inequality and civil conflict in the African continent paying special attention to the role played by spatial spillovers. Africa is the region of the world that has been most affected by conflicts after the Second World War. Still today, the problem of social conflict is a major issue in Africa. As a point of fact, in early January of 2016, twenty-eight countries and 201 militias-guerrillas, separatist and anarchic groups were involved in conflicts across the continent. Therefore, increasing our understanding on the determinants of civil conflict in Africa is of major importance, from both the humanitarian and the economic point of view.

To date, most of the existing literature has investigated civil conflict at the country level. This strand of literature usually finds that (i) the level income (Alesina *et al.*, 1996), (ii) the lack of state control (Fearon, 2003), (iii) the endowment of particular natural resources such as oil and diamonds (Ross, 2012), (iv) the level of polarization and fragmentation in ethnic divisions (Esteban and Ray, 2011, Montalvo and Reynal-Querol, 2005), (v) the degree of political and fiscal decentralization (Ezcurra, 2015) are among the key drivers of civil conflict. However, the study of the relationship between spatial inequality and civil conflict has received hardly any attention. Indeed, to the best of our knowledge, only Ezcurra (2018) has examined this issue employing Theil and Gini indexes to investigate conflict at the country scale in a global sample of countries finding a positive relationship.[1] The lack of analysis on the spatial inequality-conflict connection in the African setting is especially remarkable given that, as we will see below, there are several reasons to assume that spatial inequality should affect the incidence of conflict.

Civil conflict never engulfs entire countries, but instead, takes place in confined regions that differ notably from the rest of the nation (Buhaug et al. 2011). If country level factors do not change in a given country, and some specific areas experience conflicts while others do not, lower-scale local factors should be the drivers of the observed within country variation of conflict events. This being the case, the high cross-sectional variability of civil conflict outcomes among regions within African countries, suggests the need to investigate in depth the causes of conflict taking into account specific local factors.

[1] Buhaug et al. 2011 also consider the role played by spatial variation in income using less refined metrics: positive and negative cell income deviations with respect to the country mean, measured by means of the Gross Cell Product estimate of Nordhaus (2006).

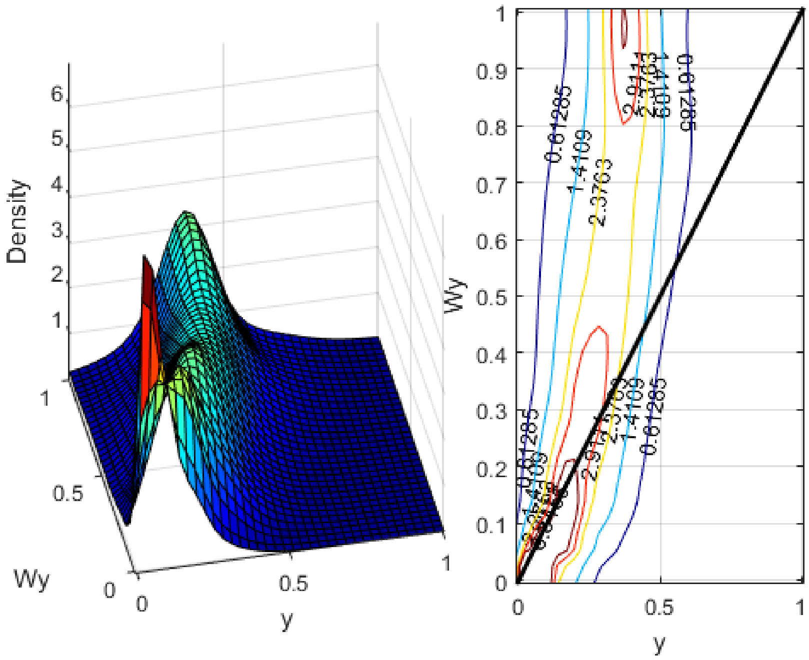
Another relevant point that has been overlooked by most research on civil conflict is that civil conflicts are correlated in space and time. Internal conflicts and wars are likely to be contagious given that refugee flows, disease, lawlessness, and the illicit trades in drugs, weapons, and minerals may generate spillover effects into the neighboring regions of conflict zones. As Beck and Gledistch (2004) point out, although diffusion processes may well underlie many of the phenomena studied by political scientists, most political economy research still relies on statistical models that assume that the individual observations are independent of one another.

The arguments suggesting the relevance of space and geography when modeling the phenomenon of civil conflict in Africa can be corroborated when looking at Figure (**??**), which highlights the role played by the spatial location in explaining civil conflict outcomes. Figure (**??**) reports the estimates of a stochastic kernel following the methodology outlined by Magrini (2009).[2] Stochastic kernel estimation allows capturing the transitions between the original distribution of fractions of years and the neighbour's-relative conflict distribution for our sample units. To read this diagram note that a value of 1 on the horizontal axes indicates the African average fraction of years with conflict incidence, a value of 2 indicates twice the African average, and so on. On the other hand, contour lines give the probability that any region will experience that specific relative rate of conflict. Estimated spatially conditioned stochastic kernel results reveal that the probability mass tends to be located parallel to the axis corresponding to the original distribution. Accordingly, spatial effects appear as a relevant factor explaining the observed variability in the fraction of years of civil-conflict. These findings regarding the role of space suggest that it is necessary to accommodate such interdependence in the modelling process and that an explicit accounting for spatial effects is required by means of spatial econometric models.

Importantly, major problems in the validity of conventional econometric inference may arise if the spatial characteristics of the data are ignored. The consequences of omitting these interactions from the model specification are potentially important from an econometric perspective, and may cause estimates to become biased, inconsistent and/or inefficient (Anselin, 2006; Elhorst, 2014). In this regard, only a handful of studies have paid attention to the spatial dimension of civil conflict focusing on climate, agricultural and price-shocks by employing spatial econometrics techniques (e.g. Fdjelde, 2015, Berman *et al*, 2017; Harari and La Ferrara, 2018). However, these

[2]The estimation of the stochastic kernel relies in Gaussian kernel smoothing functions and it is performed by employing the L-stage Direct Plug-In estimator with an adaptive bandwidth scaling pilot estimates of the joint distribution by $\alpha = 0.5$.

Figure 1: Spatial Effects in African Civil Conflict



studies fail to apply and perform state of the art spatial econometric analysis as (i) they usually rely on point estimates, which are no valid to perform inference in the context of spatial econometric models (LeSage, 2014) and (ii) they do not properly take into account the fact that the estimation of spatial models when the dependent variable takes the form of a binary response variable requires a set of specific modeling techniques different to those where the dependent variable is continuous.[3]

To extend our understanding on the patterns and causes of civil conflict, in this paper, we attempt to take a step further in understanding the relationship between spatial inequality and conflict by (i) taking the analysis to a different scale and (ii) by employing modern dynamic spatial modeling techniques.

First, we conduct a disaggregated analysis taking as units of observation 110×110 km subnational "cells", and we estimate the incidence of conflict as a function of spatial inequality and a number of other covariates at the cell level. This grid results in a sample of 2,742 cell observations. For each cell, high resolution data on income, price shocks, infrastructures, measures of spatial ethnic distribution, exclusion from political

[3]Recently Harari and La Ferrara (2018) estimate a Dynamic Spatial Durbin model by means of the dynamic spatial panel data estimator developed by Lee and Yu (2010) which is only suitable for continuous variables and report point estimates.

power and other characteristics are derived by intersecting different databases with geo-localized information. As explained by Berman et al. (2017), relying on spatially disaggregated units of analysis has advantages with respect country-data analysis. Focusing on small spatial units, allows us to match information on the geographic localization of the distribution of agricultural crops, oil and gas, mineral distribution and climate variables with information on local ethnic identities and their national political status. Second, working with cells ensures that our definition of a location is not endogenous to conflict events and it mitigates concerns of potential measurement error in the geo-location of events.

Another relevant distinct feature of this analysis is that we pay special attention to the underlying geographical dimension of the processes of civil conflict. In particular, the present analysis takes explicitly into account the possibility that civil conflict of any given region in Africa is influenced by the existence of conflict in neighboring regions. Accordingly, the sample cells are not treated as isolated units that evolve independently of each other, and spatial effects are incorporated formally into the analysis by means of Dynamic Spatial Probit Models, which are estimated by means of the Approximate Likelihood Estimator algorithm (ALE) developed by Martinetti and Geniaux (2016) which is more accurate and faster than existing Bayesian or Likelihood based procedures to process spatially dependent binary data. This approach allows us to investigate the role played by spatial spillovers in explaining the impact of spatial inequality on civil conflict in Africa by properly drawing from the structural form of the model.

The paper is organized as follows. In Section 2 we review the theoretical framework linking spatial inequality to civil conflict events. In Section 3, we first discuss the empirical methodology and our key control variables providing a justification for their inclusion in the study their effects on conflict.

In section 3 describe the dataset employed in the study, focusing on the key dependent vaiable and our key control variables and providing a justification for their inclusion in the study their effects on conflict.

2 Why Should Local Spatial Inequality matter for Conflict?

Recent literature has emphasized the importance of geographic differences in income and wealth as drivers of civil conflict (Alesina and Zhurasvskaya, 2011; Buhaug et al., 2011; Ezcurra and Palacios, 2016; Ezcurra, 2018).

As explained by Ezcurra (2018) the theoretical link between inequality and social conflict is based on the relative deprivation theory proposed by Gurr (1970). This theory suggests the existence of a causal relationship between income distribution outcomes and radical actions (or even violence) when there is a significant difference between what the individuals receive and what they expect. However, while earlier studies found higher levels of political violence in more unequal countries (Muller and Seligson, 1987), recent empirical evidence analyzing the role of vertical inequalities has failed to identify a significant relationship (Fearon and Laitin, 2003; Collier and Hoeffler 2004, Boix; 2008). These studies consider measures of vertical income inequality across individuals, usually by means of Gini indexes or using income shares by quantiles.

Within economics, the identification-alienation framework developed by Esteban and Ray (2011) offers a formal explanation linking stratification along income lines with conflict intensity. They provide a theory linking the inequality *within* groups with the intensity of conflicts. Their model suggests for a group to fight, it requires two inputs: resources provided by the rich and labor provided by the poor. A high-intensity conflict has at least two opportunity costs: both the contributing resources and the one's labor to fight. In this framework, inequality decreases both opportunity costs. For the rich, the opportunity costs of resources to fund fighters will be lower because the poor will require smaller compensation to fight. On the other hand, high levels of economic inequality within an ethnic group could breed resentment which weakens cohesiveness and the group's ability to take collective action. Steward (2000) argues that different social classes within a group may connect more closely with their equivalents in other ethnic groups rather than identifying with the population of their own ethnic group but corresponding from a different social class. Empirical analysis supports both interpretations. Whereas Kuhn and Weidman, 2015; and Huge and Mayoral, 2017 find a positive relationship between the economic inequality within ethnic groups and, respectively, the onset and incidence of conflict, Sambanis and Milanovic (2011) argue that intra-regional inequality weakens mobilization actions because of income gains from victory must be distributed among the population.

By contrast, other authors point to the relevance of horizontal inequalities across geographical areas or across groups. Horizontal inequality refers to inequality between groups that coincide with identity-based cleavages (Stewart, 2002, 2008). In this regard, Østby, Nordås and Rød (2009) study group-level economic inequalities using geocoded conflict and surveys data from Sub-Saharan Africa. The conclusion shows the relevance of both economic and social group-level differences as drivers of conflict. Nevertheless, Huge and Mayoral (2017) find no relationship between horizontal inequality between groups and the onset of conflict. In addition to ethnicity, religion or gender identifiers (Gurr, 1994; Alesina et al., 2016, Caprioli, 2005) horizontal inequality can be based on a variety of geographical identifiers such as urban-rural groups (Gurr, 1994) or subnational regions between the countries (Ezcurra and Palacios, 2016; Ezcurra, 2018). In this regard, income disparities are likely to generate contention over local versus central control and redistribution. Therefore, inequalities between sub-national areas measured by geographical income variation are likely to give rise to willingness and opportunities for rebel mobilization. As pointed out by Buhaugh et al (2011), previous research has focused on the effects of regional inequality on ethnic mobilization, but geographic inequalities can fuel conflict even in the absence of ethic cleavages, which in developing countries are often ambiguous. [4]. In the developing world regional inequalities are often large (Kanbur and Venables, 2005; Williamson, 1965) and the state often displays a strong tendency toward urban bias and neglect peripherical areas.

Using high-resolution geographically disaggregated data Buhaugh et al (2011) shows that local conditions matter for conflict mobilization arguing that this might be due to the fact that concentrated regional inequalities and lack of state involvement are more likely to give rise to rebel mobilization than diffuse social inequalities.[5]. However, although grievances are often thought to be local in nature, they are rarely measured and investigated in that way and only few studies have focused on the effects of local spatial inequality focusing on different aspects.[6]

[4] Looking only at ethnic groups as in Cederman et al. (2011) will, by construction, make it very difficult to consider how spatial inequality could shape conflict without ethnic referents (i.e, like Marxist inspired insurgencies and/or nationalist secessionism)

[5] In addition, since ethnic group settlement areas can be large, a single group average can mask considerable internal geographical variation

[6] Gulati and Ray (2016) analyze access and exclusion from markets and public services such as health care or schooling. They find that initially, some inequality may help to the provision of some basic services demanded by rich neighbors but that with increasing inequality the poor may have not access to the market. Aruajo et al. (2008) argue that social investments in Ecuador are less frequent in unequal neighborhoods as they are usually blocked by local elites who do not benefit from them. Similarly, the literature on crime also suggests that the frame of reference is local as crime is more frequent on unequal cities or metros (Glaeser et al., 2009).

Taken together, the arguments outlined above suggest the final impact of spatial income inequality on civil conflict should be positive, but whether o not increasing spatial inequality at the local level increases the likelihood of conflicts is an empirical issue that has not been investigated yet, and therefore, further empirical research is needed to shed light on the relationship between these variables. For this reason, the rest of the paper is devoted to studying empirically this issue using data for Africa.

3 Measuring Conflict and Spatial Inequality

Our baseline unit of analysis are cells of size 1×1 grades latitude and longitude in a grid of Africa (in the equator this amounts to approximately 110×110 km). This is the result of intersecting grid cells provided by the PRIO-GRID structure, with a map of the entire Africa and their national political borders provided by The Global Administrative Unit Layers (2010), a project from UN Food and Agricultural Organization (FAO).

3.1 Conflict

Our key dependent variable is a metric of civil conflict for a sample of 2,742 cell observations during the period 1998-2013. The dependent variable of our study is a binary variable that takes the value of 1 if there is a conflict in the period 1998-2013 and 0 if there is no conflict. By social conflict, we refer to within-country unrest, ranging from peaceful demonstrations, processions, and strikes to violent riots, violence against civilians and civil war (Esteban and Ray, 2016). We rely on the ACLED Dataset which registers "a range of violent and non-violent actions by political agents, including governments, rebels, militias, communal groups, political parties, rioters, protesters and civilians". Following Berman *et al.* (2015, 2017), McGuirk and Burke (2017), and Manotas-Hidalgo *et al.* (2018), for each year and cell, we code the overall incidence ACLED data with a value of 1 if cell i experienced a conflict during the year, and zero otherwise. This dummy represents our conflict incidence variable. We focus on conflict incidence for two reasons. First, as Harari and La Ferrara (2018) point out, regressions where the dependent variable consists on onset and termination would imply the loss of a large number of observations resulting in a small and unrepresentative sample. Second, modeling spatial spillovers and diffusion effects over time is more naturally assessed with incidence.

Figure 2: The Geographical Distribution of Conflict Events in Africa

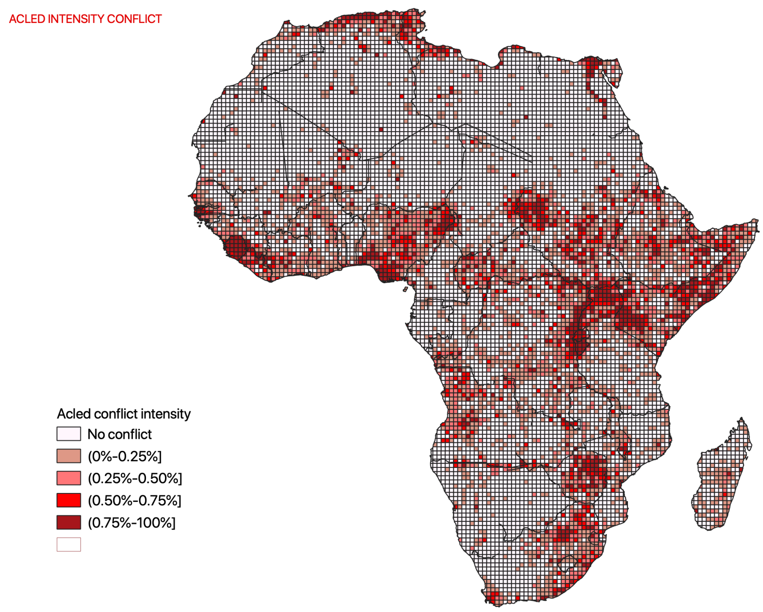


Figure (??), which shows the geographical distribution of the fraction of years with conflict during the period 1997-2014. As observed, there is a clear pattern of spatial dependence. Conflicts are more likely to occur in some geographical locations than in others. In western Africa, we find a hotspot of conflict events in the south of Senegal, Sierra Leone, and the frontier of Nigeria and Cameroon, whereas in the northern part Africa, most of the conflict events are located in the north of Algeria, in Tunicia and in Egypt. As refers to the area that comprises Central Africa: Congo, the border of the Democratic Republic of Congo with Rwanda and Burundi, together with the west of Angola, also present a high spatial concentration of conflicts. In the south, we find a lower number of conflicts, usually confined in Lesotho and the east of South Africa while in the horn of Africa, we find conflicts to be located mostly in Somalia and Ethiopia.

3.2 Spatial Inequality Measurements

On the other hand, our base-line metric of spatial inequality for each cell i of size 110×110 kilometers is a spatial Gini Index of income per capita based on estimates of income per capita at the 11×11 kilometers scale. Given that the measurement of

GDP per capita at high-resolution is a daunting task, we follow the recent practice of using the level of satellite night lights density as a proxy of local income (Henderson et al., 2012; Michalopoulos and Papaiannou, 2013; Alesina et al., 2016). Following this strand of research, we use average nighttime light emission from the DMSP-OLS Nighttime Lights Time Series Version 4 (Average Visible, Stable Lights, Cloud Free Coverages), calibrated to account for inter-satellite differences and inter-annual sensor decay, using calibration values from Elvidge et.al. (2014) [7] and population data from the World pop geospatial open dataset, Version 2.0. The World pop database estimates of the total number of people per grid square for five timepoints between 2000 and 2020 at five year interval. We interpolate the data from 2000 to 2015 for adjusted to our database. Using 11×11 kilometers resolution data enables us to derive income distributions and aggregate for cells of size 110×110 kilometers. Then, spatial income distributions and selected summary measures can be derived. These data are uniquely qualified to the purposes of the paper. In particular, we calculate the spatial Gini coefficient as our income inequality measure. We use this index as the baseline measure of inequality, mainly because it is the ubiquitous standard in the inequality literature. This index is defined as:

$$G(y) = 1 - 2\int_0^1 L(p;y)\,dp \tag{1}$$

where the Lorenz curve of spatial income, $L(p;y)$, at such p-values of ranked relative cumulated cells (so that, $p \in (0,1)$) can be defined mathematically by the expression:

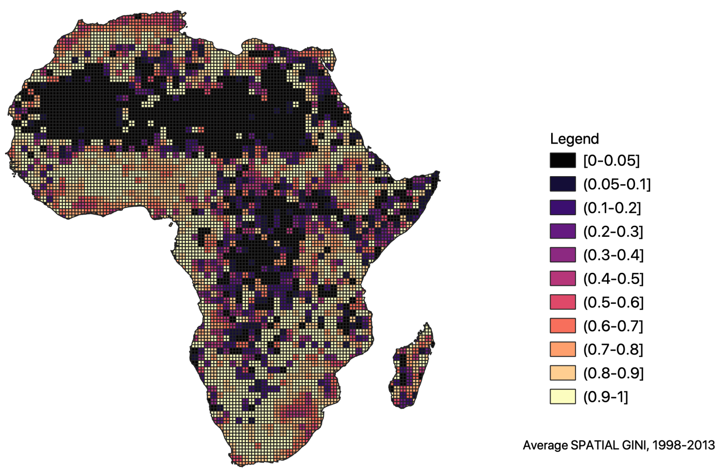
$$p = F(q) \Rightarrow L(p;y) = \int_0^q y f(y)\,\frac{dy}{d\mu_y} \tag{2}$$

where p is a percentile function, $F(q)$ is the distribution function measuring the proportion of the cells having a standard of living below or equal to q and μ_y denotes the average income per capita in the cell. Note that $G(y)$ takes values between 0 (perfect equality) and 1 (complete inequality).

Figure (**??**) shows the geographical distribution of the average of our Spatial Gini Index during the period 1998-2013. The spatial inequality appears to be also clustered in space, although we can observe that the distribution of our variable is very polarized

[7] Firstly, we apply the formula and the coefficients of calibration from the paper of Elvidge et al. (2014), table 6.2 for each satellite on our nightlights data. Secondly, for the years in which we have data from two satellites, we calculate the average data for each year. As Elvidge et al. point out, the intercalibration makes possible to detect changes in the brightness of lights across time series.

Figure 3: Spatial Inequality in Africa: Average 1998-2013



between the values of 0, in deserts, jungles and some interior areas of the continent, and near 1 in the west, around the equator, south of Africa, including some important cities as in Nairobi and Lagos. Nevertheless, the index displays more local variation in the northern coast of Morocco, Algeria, and Tunisia, north of Egypt, and some urbanization areas, as in Dakar, Accra, Johannesburg, and Petroria, for example.

4 Empirical Strategy

4.1 Econometric Model

When considering the choice of an econometric specification to investigate the connection between spatial inequality and civil conflict, it is important to note that Figure **??** suggests that conflict events in Africa are not randomly distributed across space. On the contrary, there seems to be spatial clusters of cells with a high incidence of conflicts, and the incidence of conflict in the neighborhood of any cell seems to be positively related to own conflict occurrence. On the other hand, there are a number of studies that highlight the persistence of conflict (see, Fjelde, 2015; Harari and La Ferrara, 2018). The implications of these issues are potentially important from an econometric perspective as the omission of relevant space-time terms may affect the validity of the findings. For this reason, we consider the following Dynamic Spatial Durbin Probit Model (DSDPM):

$$Y_t = \mu + \iota_N \alpha_t + \tau Y_{t-1} + \rho W Y_t + \eta W Y_{t-1} + X_t \beta + W X_t \theta + \epsilon_t \tag{3}$$

where Y_t is a $N \times 1$ vector consisting of observations for the conflict binary variable for every cell $i = 1, \ldots, N$ at a particular point in time $t = 1, \ldots, T$, X_t, is an $N \times K$ matrix of exogenous aggregate socioeconomic and economic covariates with associated response parameters β contained in a $K \times 1$ vector that are assumed to influence conflict. τ, the response parameter of the lagged dependent variable Y_{t-1} is assumed to be restricted to the interval $(-1, 1)$ and $\epsilon_t = (\epsilon_{1t}, \ldots, \epsilon_{Nt})^{'}$ is a $N \times 1$ vector that represents the corresponding disturbance term which is assumed to be i.i.d with zero mean and finite variance σ^2. The variables WY_t and WY_{t-1} denote contemporaneous and lagged endogenous interaction effects among the dependent variable. In turn, ρ is called the spatial auto-regressive coefficient. W is a $N \times N$ matrix of known constants describing the spatial arrangement of the cells in the sample. Its diagonal elements are equal to zero by assumption, since no cell can be viewed as its own neighbour. $\mu = (\mu_1, \ldots, \mu_c)^{'}$ is a vector of country fixed effects, $\alpha_t = (\alpha_1, ..., \alpha_T)^{'}$ denote time specific effects and ι_N is a $N \times 1$ vector of ones. Country fixed effects control for all country-specific time invariant variables whose omission could bias the estimates, while time-period fixed effects control for all time-specific, space invariant variables whose omission could bias the estimates in a typical time series (Baltagi, 2001; Elhorst, 2010).

A large amount of literature has investigated the efficient and consistent of spatial probit models (for a review, see Calabrese and Elkink, 2014). These authors analyze the performance of different algorithms to estimate spatial probits. The expectation-maximization algorithm (EM) of McMillen (1992), the Bayesian Gibbs sampler by LeSage (2000), the recursive importance sampling (RIS) by Beron and Vijverberg (2004), the generalized method of moments (GMM) by Pikse and Slade (1998), and the Geweke-Hajivassiliou-Keene (GHK) of Pace and LeSage (2011). From this review, only the RIS and the Gibbs sampler perform well in terms of accuracy but they become unfeasible for large samples with $n > 1,000$. This issue is of paramount relevance in our context as our sample greatly exceeds that size. R-package SpatialProbitfit developed by Martinetti and Geniaux (2016) allows to perform these calculations in our context, where the sample of observations $NT = 43,872$ clearly above the $1,000$ limit of other estimators. Recently, Martinetti and Geniaux (2017) propose an approximated maximum likelihood (AML) estimator which is not only efficient and consistent but also much faster than existing alternatives in the literature to obtain estimates of $\hat{\delta} = [\hat{\mu}, \hat{\beta}, \hat{\tau}, \hat{\rho}, \hat{\eta}, \hat{\theta}, \hat{\sigma}^2]$

As explained by Martinetti and Geniaux (2017) consistent and efficient estimates of the $\hat{\delta}$ parameters for the case of the DSDPM can be obtained by maximizing the following likelihood function:

$$L(\delta) = \Phi_{NT}(x \in A|\Sigma) = \frac{1}{(2\pi)^{NT/2}|\Sigma|^{1/2}} \int_{A_1}\int_{A_2}\cdots\int_{A_{NT}} e^{-\left(\frac{1}{2}x'\Sigma^{-1}x\right)}\textbf{??} \tag{4}$$

where $A = \{A_i\}_{i\in 1,\ldots,NT} = (a_i, b_i)_{i\in 1,\ldots,NT}$ and

$$a_i = \begin{cases} \left[(I-\rho W)^{-1}(\mu + \iota_N\alpha_t + \tau Y_{t-1} + \eta W Y_{t-1} + X_t\beta + \theta W X_t)\right]_i & if \quad Y_{it} = 0 \\ -\infty \quad if \quad Y_{it} = 1 \end{cases}$$

$$b_i = \begin{cases} \infty \quad if \quad y_{it} = 0 \\ \left[(I-\rho W)^{-1}(\mu + \iota_N\alpha_t + \tau Y_{t-1} + \eta W Y_{t-1} + X_t\beta + \theta W X_t)\right]_i & if \quad Y_{it} = 1 \end{cases}$$

Multivariate normal distribution (MVN) probabilities expressed as a multiple integral cannot be computed exactly and since there exists no closed formula in Equation (**??**) as long as $\Sigma \neq I_n$ numerical integration methods, simulation methods or analytical approximations have to be employed. The AML algorithm proposed by Martinetti and Geniaux (2017): (i) rewrites the MVN probabilities as the product of univariate conditional probabilities and (ii) approximates these univariate conditional probabilities (recalculating iteratively for each i the integral limits a_i and b_i) with the average value of a random variable that follows a truncated univariate distribution.

The specification in Equation (**??**) is particularly useful in this context, because the DSDPM allows one to estimate consistently the effect of spatial inequality on conflict when endogeneity is induced by the omission of a (spatially autoregressive) variable. Indeed, LeSage and Pace (2009) show that if an unobserved or unknown but relevant variable following a first-order autoregressive process is omitted from the model, the DSDPM produces unbiased coefficient estimates. Additionally, this model does not impose prior restrictions on the magnitude of potential spillovers effects. Furthermore, the DSDPM is an attractive starting point for spatial econometric modelling because it includes as special cases two alternative specifications widely used in the literature: the *Dynamic Spatial Lag Probit Model* (DSLPM) and the *Dynamic Spatial Error Probit Model* (DSEPM). As can be checked, the DSDPM can be simplified to the DSLPM when $\theta = 0$:

$$Y_t = \mu + \alpha_t + \tau Y_{t-1} + \rho W Y_t + \eta W Y_{t-1} + X_t\beta + \epsilon_t \tag{5}$$

and to the DSEPM if $\theta + \rho\beta = 0$:

$$\begin{aligned} Y_t = \mu + \iota_N \alpha_t + \tau Y_{t-1} + \eta W Y_{t-1} + X_t\beta + W X_t \theta + \upsilon_t \\ \upsilon_t = \lambda W \upsilon_t + \epsilon_t \end{aligned} \tag{6}$$

where $\epsilon_t \sim i.i.d.$. In fact, the DSDPM produces unbiased coefficient estimates even when the true data-generation process is a spatial lag or a spatial error model.

4.2 Inference

An important issue in spatial econometric analysis is that the presence of spatial lags of the dependent and explanatory variables complicates the interpretation of the parameters in Equation (**??**) (Anselin and Le Gallo, 2006). For example, if the coefficients β_k and θ_k in the DSDPM happen to be significant, this does not automatically mean that the indirect effect of the kth explanatory variable on conflict is also significant. Conversely, if one or two of these coefficients are insignificant, the indirect effect may still be significant. As shown by LeSage and Pace (2009), in a model with an endogenous spatial interaction term, a change in a particular explanatory variable in cell i has a *direct effect* on that cell, but also an *indirect effect* on the remaining cells. In this context, the direct effect captures the average change in the conflict of a particular cell caused by a one unit change in that cell's explanatory variable. In turn, the indirect effect can be interpreted as the aggregate impact on conflict of a specific cell of the change in an explanatory variable in all other cells, or alternatively as the impact of changing an explanatory variable in a particular cell on the conflict of the remaining cells. LeSage and Pace (2009) show that the numerical magnitudes of these two calculations of the indirect effect are identical due to symmetries in computation. Finally, the *total effect* is the sum of the direct and indirect impacts.

A further complication is that in probit models, the parameter magnitudes associated with the estimated coefficients do not have the same marginal effects interpretation as in standard regression models. This arises due to non-linearity in the normal probability distribution. The magnitude of impact on the expected probability of the event Y occurring varies with the level of say the *k-th* explanatory variable, X_k. Because the magnitude of impact on changes in expected probability varies with the level of X_k, model estimates are often interpreted using mean values of a regressor such as $\bar{X}_k$. The marginal effects are then interpreted as the change in the event probability associated with a change in the average or typical sample observation for variable X_k.

Hence, to carry out inference with the DSPDM we resort to the matrix of partial derivatives of Y_t with respect the *k-th* explanatory variable of X_t in cell 1 up to cell n at a particular point in time t is given by:

$$\frac{\partial Y_t}{\partial X_t^k} = \phi\left([I - \rho W]^{-1} I_n \left[\bar{X}_k \beta_k + W \bar{X}_k \theta_k\right]\right) \odot [I - \rho W]^{-1} I_n \left[\beta_k + W\theta_k\right] \tag{7}$$

where $\bar{X}_k$ denotes the mean value of the $k - th$ variable and the expression $\phi(.)$ is the standard normal density. *Direct effects* correspond to diagonal terms in Equations (**??**) whereas the *indirect effect* are captured by off-diagonal terms. In order to draw inferences regarding the statistical significance of the direct and indirect effects, LeSage and Pace (2009, p. 39) suggest simulating the distribution of the direct and indirect effects using the variance-covariance matrix implied by the maximum likelihood estimates. The analytical form of the variance-covariance matrix of the parameter estimates used in this context is taken from Anselin 1988, pp. 64-65) but without heteroskedasticity. A problem with the R-package of Martinetti and Geniaux (2016) is that it does not provide any information on the statistical significance of the direct and indirect effects of the regressors. For that reason, we develop R routines that complement the R-software package of Martinetti and Geniaux (2016), using both the trace method proposed by LeSage and Pace (2009) and the standard variance-covariance draw approach implemented by Elhorst (2012) in MATLAB.

4.3 Control variables

Our choice of control variables is mainly guided by the need to account for factors which may affect both conflict and the spatial inequality and, consequently, whose omission might bias the estimated effect of spatial inequality on civil conflict. On the basis of a review of the literature on civil conflict, our DSPDM incorporates various controls related to the economic, geographical and socio-demographic characteristics of the cell. We now describe these controls and provide a brief conceptual justification for their inclusion in the analysis.[8]

4.3.1 Economic factors

To control for economic differences across cells we consider (i) the level of economic development, (ii) the existence of natural resources and (iii) the role of unexpected commodity price shocks.

As pointed out by Esteban and Ray (2016), one the most important findings of the literature on conflict is the negative relationship between civil war and **per capita income**. In this regard, Fearon and Laitin (2003a), Collier and Hoeffler (1998, 2004), or Hegre and Sambanis (2006) find a negative and robust relationship. There are diverse theoretical reasons for this observed relationship. First, in economies where the GDP per capita is low, the state financial, administrative, police and military capabilities are limited which implies that rebel groups can expect a greater likelihood of success in low-income region (Fearon and Laitin, 2003). Second, as pointed by Miguel *et al.* (2004) conflict events might be originated by negative income shocks. In this context, the opportunity cost of enlisting as a rebel and engaging in a civil conflict is lower (Coller and Hoeffler, 2004) which may exacerbate and scale conflict. Nevertheless, recent studies cast doubt on the validity of previous findings given that once historical and institutional factors are controlled for, the link becomes insignificant (Djankow and Reynal-Querol, 2010). To proxy income per capita we use the night light per capita variable"night light calibration mean" from the PRIO-GRID 2.0 which measures nighttime light emission and the "pop hyd sum" which measures the sum of number of persons within each cell.

In addition, the endowment of some **natural resources** in a given cell is also likely to affect the probability of conflict (Collier and Hoeffler, 2004; Ross, 2012; 2015). According to Berman *et al.* (2017), the most likely explanation in this regard is the "greed" as natural resources deliver rents that increase the prize of rebellion against the state. Other explanations point to the fact that controlling natural resources may allow rebels looting resources and relax financial constraints making the rebellion more sustainable in time. Recently, some papers have employed disaggregated data by administrative regions analyzing the link between natural resources and conflict

[8] Table **??** presents the detailed definitions and sources of all the control variables used in the paper. Several descriptive statistics are included in Table **??**.

finding a positive relationship (Dube and Vargas, 2013; Basedau and Pierskalla, 2014). To proxy differentials in the endowment of natural resources, we construct a dummy variable that takes a value of 1 if the cell has oil, gas and/or diamonds mines and 0 if it lacks of any of these resources. To construct this index we merge information of Natural Resources from PRIO-GRID v.1.2 and v.2.0 datasets with the USGS dataset of mines.

Commodity price shocks are also expected to have an effect on the probability of conflict. There are several theories of the effect of income shocks on conflicts. Specifically, models of rebellion find that civilians incentives to rebel rises as economic opportunities and household income decline (Grossman 1991). In general equilibrium, household rents are disproportionally affected by the shocks relative to government incomes. The opportunity cost theory predicts a stronger inverse relationship between the prices of labor-intensive commodities (as annual agricultural crops) and conflict. (Dal Bó and Dal Bó, 2011). Predictions of the "state-is-aprize" theory therefore, suggest that rising prices should increase the risk of insurrection as a mechanism to capture rents, especially in the case of mineral and oil and gas. However, according to the state capacity theory, rising rents provide the state with a stronger capacity to to prevent social conflict as resources allow the state to counter insurgents and strengthen control (Rosss, 2012), thus lowering the probability of conflict. Hence, the a priori-effect of price shocks is ambiguous. We include the geometric weighted average of three max-min normalized indexes based on unexpected shocks to prices in oil, gas, agriculture and minerals. This composite index is calculated for each cell i and each period of time t as: $S_{it} = \left(S^A_{it} \times S^E_{it} \times SM_{it}\right)^{1/3}$ where S^A, S^E and S^M represent the agricultural, extractive and mineral shocks, respectively. Following Manotas-Hidalgo *et al.* (2018), for each commodity component K of the price shock index for each cell i, the size and sign of the shock is obtained as the residual $\hat{\epsilon}_{i,t}$ from the following dynamic-panel regression:[9]

$$lnP^K_{i,t} = \alpha_{i,0} + \alpha_{i,1}t + \sum_{l=1}^{L} \theta_{i,p} lnP^K_{i,t-l} + \epsilon_{i,t} \tag{8}$$

where the maximum lag length is set to $L = 3$. The regression from which the unexpected shocks are derived consists of time-series observations from 1990 to 2014.

4.3.2 Geographical and Climatic factors

To control for the role played by geographical and climatic characteristics of the cell we include (i) an index of infrastructure accessibility, (ii) a metric of drought intensity, (iii) distance to the border of the country and (iv) the degree of terrain ruggedness.

An important factor to explain the existence of conflicts or peace in a specific region is whether or not it is located in the periphery or in the center of the country given that conflicts are more prone to start in **border locations**, where state capacity is low and where rebels can operate easily. As Buhaug and Rod (2006) point out, an advantage for rebels is that they chose the area of operation. Therefore, rebellions are likely to explode in remote and inaccessible areas, where the power of government forces is lower. In addition, populated villages with relatively lower level of connection or without roads that connect them to the main cities, or to the capital, are more likely to be isolated both economically and politically, leading to a disadvantage respect other places. This, in turn, could foster the emergence of comparative grievance and increase the likelihood of a conflict. To control for differences in the **degree of state capacity and accessibility** we develop an arithmetic averaged index that takes as components the distance to the nearest road, the distance to the nearest port , the

[9]Agricultural prices are calculated as $P^A_{it} = \sum_{c=1}^{C} w_{ic} P^A_{ct}$ where w_{ic} is the time-invariant crop share of each agricultural commodity c taken from the M3-Crops dataset and P^A_{ct} is the international crop price for the $c = 1, \ldots, C$ agricultural commodities (banana, barley, cocoa, coffee, cotton, groundnuts, maize, oranges, olive oil, rice, soybeans, sugar cane, sunflower, tea and wheat). On the other hand, the price index for oil and gas is calculated as $P^E_{it} = \sum_{c=1}^{3} e_{ic} P^E_{ct}$ where e_{ic} is a categorical variable coded as 1 if there is an oil field, 2 if there is gas and 3 if there is oil and gas and P^E_{ct} is the annual price series of the resource under consideration (if $c = 3$ we use the average price of the two) taken from the IMF. Finally, the mineral commodity price index is calculated as $P^M_{it} = \sum_{j=1}^{n} m_{ij} P^M_{jt}$ where m_{ij} is a dummy variable of mineral-j mine presence in cell i, and P^M_{jt} is the annual price for minerals produced in mine j (if we have more than one mine in a cell, $m_{ij} = 1/j$. we merge the information from two databases: the Mineral Resources Data System provided by the United States Geological Survey, and the information on gems, diamonds and gold contained in the PRIO-GRID v.2.0 database. The set of minerals considered are bauxite, coal, copper, diammonioum, phospate, gold, iron, ore, lead, nickel, manganese, phospate, potash, silver, tin, uranium and zinc.

distance to the nearest airport and the distance to the capital such that the higher the distances, the lower the accesibility score. [10]

Climate conditions never prompt conflicts by themselves, but severe climatic conditions can lead to a change on the likelihood and intensity of conflicts. For instance, **droughts** can reduce crop productivity by amplifying existing stress on water resources (Niang et al. 2014). In turn, crop productivity reduction affects income and, hence, can exert an impact of a wide variety of social events, such as violence between farming groups and other interpersonal conflict. Previous literature has focused on different dimensions of climate variability (temperature, precipitations or droughts) and their links with the onset and intensity of violence but results are mixed. Burke *et al.* (2009) find that higher temperatures increases the probability of civil wars in Sub-Saharan Africa. Nel and Righarts (2008) finds that climate disasters (storms, floods, droughts and extreme temperature) impact positively on the onset of violence. Using subnational data Theisen *et al.* (2011) study the impact of droughts conditioned to some other social variables, such as the political exclusion of ethnic groups, population, infant mortality or regime type. They conclude that extreme climatic events such as droughts do not matter for conflict. On the contrary, Uexkull (2014) find that areas depending on rainfed agriculture, or those exposed to sustained droughts are more vulnerable to civil conflict. More recently, Harari and La Ferrara (2018) explore in both within-year variation in crop growing season and weather, and spatial variation in crop cover and their impact on conflicts finding that shocks taking place during the growing season of local crops positively affects conflict incidence. To control for climatic variability across cells, we include the coefficient of variation of temperatures during the period 1998-2013.

Most authors generally introduce **mountainous and forested terrain** variables in their models for controlling the rebel opportunities for conflicts (Fearon and Laitin, 2003). They argue that insurgents are weak comparative to government. If the government knows how to fight them, it is easier to capture them. Basically, mountains and forested terrain give a protection to rebels to the possibility of being captured by the governmental forces, even though the capacity of the state is stronger. In addition, rugged terrain affects comes with lower state capacity, higher difficulties to farming, and because of the harder transportation costs to higher trade costs and remoteness. We introduce in our model the variable terrain ruggedness to control these aspects.

[10]The log of capital distance metric is taken from PRIO-GRID whereas the other distance metrics are calculated using the cShapes dataset v.0.4-2. All distances are spherical distances in km from the cell centroid. For each distance metric m we calculate the following index of accesibility for each cell: $I_c^m = 1 - \left(\frac{d-min(d)}{max(d)-min(d)}\right)$

4.3.3 Socio-demographic factors

To control for differences in socio-demographic characteristics of the cell we include (i) an index of population density, (ii) a metric of spatial ethnolinquistic fracctionalization, (iii) a metric of spatial polarization, (iv) an index of social exclusion and (v) the share of urban population.

Political scientists have emphasize the potential importance of ethnic diversity in the incidence of conflict at the national level as it may lead to grievances and to violence (Baseadu and Pierskalla, 2014; Cederman *et al.*, 2009, 2011; Wimmer *et al.* 2009). Consequently, the index of ethnic fractionalization as a measure of diversity has been used in several empirical studies of conflict with the idea that ethnically diverse societies have a higher probability of ethnic conflict. Nevertheless, results from many of these empirical studies are inconclusive which motivated Esteban and Ray (1994) to develop a measure of ethnic polarization. Whereas **spatial ethnic fractionalization** measures the probability that individuals from a given cell do not belong to the same ethnic group, the **spatial polarization index** assesses how far the distribution of the ethnic groups in the cell is from a bipolar distribution. Following Montalvo and Reynal-Querol (2017) we compute the spatial ethno-fractionalization index as:

$$EF_c = 1 - \sum_{i=1}^{N} \pi_i^2 \tag{9}$$

where π is the proportion of area that belongs to the ethnic group i. Thus, this index measures how spatially fractionalized is the population of different ethnic-linguistic groups in the cell. On the other hand, the spatial ethno-linguistic polarization index for each cell is calculated as:

$$EP_c = 4 \sum_{i=1}^{N} \pi_i^2 (1 - \pi_i) \tag{10}$$

Notice that as fractionalization increases monotonically if ethnic groups are divided into smaller groups, polarization is maximized when there are precisely just to equally large groups. While we do not expect a concrete effect for ethnic fractionalization we expect that increasing polarization has a positive effect on conflict.

Regarding **excluded political relevant ethnic groups**, Cederman et al. (2009) develop a new geodatabase (Geo-EPR-ETH v.2.0)[11] with all political relevant ethnic

[11] https://icr.ethz.ch/data/epr/geoepr/

groups and their access to the state power from the Ethnic Power Relations Dataset (ERP).[12] These results emphasize both the political inclusion and exclusion dimension of ethnic groups as important determinants contributing to violence at the national level. (Cederman *et al.*, 2009). Excluded groups from the central power are defined as relevant ethnic communities that are excluded from government relevant processes. Although to date only a few papers have used this variable in empirical analysis with disaggregated data at the cell level (see, Basedau and Pierskalla, 2014) we expect exclusion to be a relevant driver increasing the likelihood of conflict.

Population is a factor deeply studied in the literature of conflict. Collier and Hoeffler, (2004); Fearon and Laitin (2003); or Hegre and Sambanis, (2006) among others find that large countries have more civil wars than smaller countries. Following Raleigh and Hegre (2009), the simplest explanation of this relationship is the assumption of a homogenous and constant "per-capita conflict propensity", based on the thesis of Collier and Hoeffler, (2002). "[...] If there is a given probability that a randomly picked individual starts or joins a rebellion, then the risk of rebellion increases with population" (Raleigh and Hegre, 2009; pg. 225). At the cell level, Raleigh and Hegre (2009), Buhaug *et al.*(2011); and Fjelde (2015) find a positive relationship between population size and conflict events. Thus we expect a positive effect of population on conflict outcomes.

Urbanization Recently, the accelerated and acute urban development in the African countries have increased the attention in studies concerning the conflict. In fact, this is often the case in Sub-Saharan countries, where many people live in urban areas that have a high level of inequality. Thus, urbanization may easily lead to both a decrease in opportunities cost and an increase in grievance motives for leading to social unrest.

Quantitative previous studies bring contradictories results. For example, Auvinen (1997) find that urbanization is directly linked with political unrest but decrease the probability of irregular executive transfer. On the other hand, Collier and Hoeffler, (2004) argue that low urbanization could hinder government capability, whereas Urdal (2008) find no evidence between urbanization growth and civil war. Others find that food riots are more prone in urban areas, where authorities could respond to provoking government policy changes (McGuirk and Burke, 2017; Manotas et al. 2018).

Urban concentration supplies anti-regime mobilization, yet cities are not the most suitable for the organization of large-scale insurrection. Controlling by the variation

[12] https://icr.ethz.ch/data/epr/geoepr/

in time of urban areas and how urbanization is distributed in a country may help to understand this issue. To that end, using time-series cross-sectional data, Nedal et al. (2015) and Schulz, (2016) find that urban concentration in the largest cities increases the motivation for the feasibility of rebellion. In our paper, we use a time-variant urban area variable in each cell to understand how is the geographic distribution of urbanization and its relationship with conflict.

4.4 Spatial Weights Matrix Selection

The estimation of the various spatial models described above requires to define previously a spatial weights matrix. Given that this is a critical issue in spatial econometric modelling (Corrado and Fingleton, 2012), a broad range of alternative specifications of W are considered. The first spatial weights matrix is based on the concept of first order contiguity, according to which $w_{ij} = 1$ if regions i and j are physically adjacent and 0 otherwise. Given the nature of our dataset this implies that contiguity corresponds to the 8-nearest neighbors. Secondly, we consider several matrices based on the k-nearest neighbors ($k = 25, 49, 81$) computed from the great circle distance between the centroids of the various cells (Le Gallo and Ertur, 2003). Note that this set of nearest neighbor matrices correspond to the second order, third-order and fourth order neighbors. For each set of k-nearest neighbors we consider unweighted matrices[13]. As an alternative, we base our k-nearest neighbor matrices on inverse power and negative exponential decay distance weights. In particular, we consider inverse distance and exponential distance decay matrices are considered, whose off-diagonal elements are defined by $w_{ij} = \frac{1}{d_{ij}^{\alpha}}$ for $\alpha = 2$ and $w_{ij} = exp(-\theta d_{ij})$ for $\theta = 0.025$ and 0.05 respectively. As can be observed, the different matrices described above are based in all cases on the geographical distance between the sample cells, which in itself is strictly exogenous. This is consistent with the recommendation of Anselin and Bera (1998) and allows the researcher to avoid the identification problems raised by Manski (1993). Furthermore, as is common practice in applied research, all the matrices are row-standardized, so that it is relative, and not absolute, distance which matters.

In the literature there are different criteria to determine the spatial weights ma-

[13]

$$W = \begin{cases} w_{ij}(k) = 0 \quad if \quad i = j \\ w_{ij}(k) = 0 \quad if \quad i \neq j, j \notin nbd(i)_k \\ w_{ij}(k) = \frac{1}{k} \quad if \quad i \neq j, j \in nbd(i)_k \end{cases}$$

where w_{ij} terms denote the spatial weights connecting i and j, $nbd(i)_k$ denotes the neighbourhood of i given k

Table 1: Definitions, sources and descriptive statistics of the variables

Variable	Definition	Source	Mean	Std. Dev	Expected Effect
Dependent variable					
Conflict	Dummy variable that takes a value of 1 if conflict events existed in the cell	ACLED			
Economic factors					
Spatial Index Inequality	Spatial Gini coefficient	NOAA, WORLDPOP	0.49	0.44	+
Nights Lights per capita	Nighttime light emission divided population	NOAA, PRIO-GRID 2.0	0.17	0.11	-
Price Shocks	Composite index based on the geometrically weighted average of indexes of price shocks in agricultural, oil and gas and minerals	IMF, GEM, MRDS M3-crops, PRIO-GRID 2.0	0.4927	0.0149	?
Natural Resources	Dummy variable that takes a value of 1 if there are natural resources and 0 otherwise	MRDS, PRIO-GRID 2.0	0.1371	0.3440	?
Geography and Climate					
Accessibility	Composite index based on the arithmetic mean of the sub-indexes of distances to the capital, distance to the nearest road, distance to the nearest port and distance to the nearest airpot	Own calculations cShapes dataset v.0.4-2	0.5963	0.8783	+
Droughts	The proportion of months out of 12 months that are part of the longest streak of consecutive months ending in the given year with SPEI-1 values below -1.5.	NOAA/NWS	0.047	0.066	+
Terrain Ruggedness Index	Measures of topographic heterogeneity in wildlife habitats	Nunn and Puga (2012)	0.581	0.796	+
Social and Demographic					
Population	Log of total cell population	HYDE Datase	334681.5	865404.8	+
Excluded	Number of excluded groups (discriminated or powerless) settled in the grid cell	GeoEPR/EPR 2014	0 .455	0.645	+
Polarization	Spatial ethnic polarization computed to each cell	GREG	0.287	0.361	?
Spatial Ethnic Fractionalization	Standard Herfindahl index of spatial ethnic diversity/fractionalization	GREG	0.226	0 .251	?
Urban	The percentage area of the cell covered by urban area	ISAM-HYDE	0.113	0.601	?

Notes: ACLED denotes the Armed Conflict Location and Event Dataset (ACLED Dataset) (Raleigh *et al.*, 2017), GEM Global Economic Monitor IMF International Monetary Fund, MRDS Mineral Resources Data System, M3-crops (Monfreda *et al.*, 2008), GREG Geo-referencing of Ethnic Groups, NOAA National Oceanic and Atmospheric Administration (US), NWS National Weather Service, HSWD Harmonized World Soil Database v 1.2, GeoEPR/EPR. ISAM-HYDE historical land use dataset

Table 2: Spatial Weights Matrix Selection.

k-nearest neighbors W matrix	Log Likelihood	Var Resid σ_u^2	Posterior Model Probabilities (PMPs)	R^2 response	R^2 bin pred
$(k=8)$ & $1/d^{\alpha}$, $\alpha=2.00$	12863.16	3.41	0.00	0.44	0.781
$(k=8)$ & $exp-(\theta d)$, $\theta=0.025$	12804.88	3.40	0.00	0.44	0.780
$(k=8)$ & $exp-(\theta d)$, $\theta=0.05$	12803.90	3.41	0.00	0.44	0.780
$(k=8)$ unweighted	12813.31	3.36	0.00	0.44	0.780
$(k=25)$ & $1/d^{\alpha}$, $\alpha=2.00$	12816.02	3.40	0.00	0.44	0.781
$(k=25)$ & $exp-(\theta d)$, $\theta=0.025$	12862.69	3.25	0.00	0.43	0.783
$(k=25)$ & $exp-(\theta d)$, $\theta=0.05$	12839.89	3.24	0.00	0.43	0.782
$(k=25)$ unweighted	12813.31	3.36	0.00	0.44	0.780
$(k=49)$ & $1/d^{\alpha}$, $\alpha=2.00$	12839.54	3.29	0.01	0.44	0.781
$(k=49)$ & $exp-(\theta d)$, $\theta=0.025$	13101.21	2.93	0.01	0.41	0.783
$(k=49)$ & $exp-(\theta d)$, $\theta=0.05$	13046.37	2.95	0.01	0.41	0.783
$(k=49)$ unweighted	13183.70	2.86	0.01	0.41	0.781
$(k=81)$ & $1/d^{\alpha}$, $\alpha=2.00$	12833.48	3.22	0.14	0.43	0.781
$(k=81)$ & $exp-(\theta d)$, $\theta=0.025$	13261.39	2.83	0.18	0.40	0.785
$(k=81)$ & $exp-(\theta d)$, $\theta=0.05$	13173.04	2.86	0.19	0.41	0.784
$(k=81)$ unweighted	13283.92	2.81	0.45	0.40	0.786

Notes: Bayesian Markov Monte Carlo (MCMC) routines for spatial probit panels required to compute Bayesian posterior model probabilities do not exist yet. As an alternative, all cross-sectional arguments of James LeSage routines are replaced by their spatial panel counterparts, for example a block-diagonal $NT \times NT$ matrix, $diag(W,...,W)$ as argument for W. All W's are row-normalized. In the Bayesian estimation exercise, non-informative diffuse priors for the model parameters (β, θ, σ) are used following the recommendation of LeSage (2014). In particular, a normal-gamma conjugate prior is used for β, θ and σ while a beta prior for ρ is used. To that end, parameter c is set to zero and T to a very large number $(1e+12)$ which results in a diffuse prior for β, θ. Diffuse priors for σ are obtained setting $d=0$ and $v=0$. Finally, the parameterization of the prior for ρ is done by setting $a_0 = 1.01$. As noted by LeSage and Pace (2009), pp. 142, the $Beta\,(a_0, a_0)$ prior for ρ with $a_0 = 1.01$ is highly non-informative and diffuse as it takes the form of a relatively uniform distribution centered on a mean value of zero for the parameter ρ

trix that best describe the data. The most widely used approach is to compare the log-likelihood function values. Nevertheless, this approach has been criticized because it only finds a local maximum among competing models and it may be the case that the correctly specified W is not included (Vega and Elhorst, 2015). As an alternative criterion, LeSage (2014), Rios et al. (2017) and Da Silva et al. (2017) propose the employment of the Bayesian posterior model probability, while Elhorst *et al.* (2013) suggests selecting the model with the lowest parameter estimate of the residual variance. In addition to these metrics, we also consider the R^2 of the model. The results of employing the different criteria are shown in Table (**??**). As observed, the best spatial weight matrix in this context is the unweighted 81-nearest neighbour's matrix given that for all the goodness of fit metrics considered it provides a superior fit when compared to the alternative specifications. For this reason, our results are derived based on this connectivity matrix.

5 Results

5.1 Main Results

The first column of Table (**??**) presents the results obtained when the country-fixed and time-period effects model is estimated by means of Maximum Likelihood assuming that the disturbances are independent and identically distributed. As can be observed, the coefficient of the spatial Gini coefficient is positive and statistically significant at the 1% level. This seems to indicate the existence of a positive relationship between spatial inequality and conflict in the African continent. Furthermore, the results show that the coefficients reported in column 1 suggest a negative effect of price shocks, distance to the border of the country and spatial ethnic fractionalization. On the other hand, positive effects are observed in night-lights per capita, resources, urbanization levels, population levels, accessibility, terrain ruggedness and spatial ethnic polarization. Nevertheless, these findings should be taken with caution. In particular it is important to recall that, as mentioned above, there are important reasons to believe that spatial effects play an important role in explaining conflict patterns in the African setting, which may cause estimates of the non-spatial probit model to become biased, inconsistent and/or inefficient.

Column 3 of Table (**??**) presents the results from the DSPDM, whereas the - DSPLM and the DSPEM are presented respectively in columns 2 and 4 when they are estimated by the Approximate Maximum Likelihood algorithm of Martinetti and Geniaux (2016). As can be observed, the coefficients estimates of the dependent variable lagged in time Y_{t-1} in space WY_t and the coefficient of the dependent variable lagged in space and time WY_{t-1} are positive and significant. This result confirms that the dynamic spatial panel data modeling framework used in this analysis is suitable for studying the evolution of civil conflict. Importantly, these results suggest the existence of simultaneous and lagged positive spillovers. Thus, civil conflict in a cell is likely to propagate to neighboring cells. However, before continuing it is important to evaluate which is the best spatial specification in this context. To that end, likelihood-ratio tests (LR- DSPDM -DSPLM and LR- DSPDM -DSPEM) are calculated to find out if the SDM can be simplified respectively to the SLM ($H_0 : \theta = 0$) or the SEM ($H_0 : \theta + \rho\beta = 0$). The null hypotheses of both tests are rejected LR-SDM-SLM, (p=0.00) and . LR-SDM-SEM (p=0.00). This implies that the DSPDM is the appropriate specification in this context. In fact, this conclusion is consistent with the information provided by the various measures of goodness-of-fit included in Table (**??**).

Table 3: Estimation Results: Spatial Inequality and Civil Conflict.

Model	Non-spatial	Spatial Lag	Spatial Durbin	Spatial error
Conflict (t-1)	0.998***	0.986***	0.955***	0.998***
	[0.02]	[0.04]	[0.02]	[0.03]
Neighbour's Conflict (t-1)	1.808***	1.786***	0.372***	1.808***
	[0.07]	[0.08]	[0.05]	[0.07]
Spatial Income Inequality	0.327***	0.332***	0.293***	0.327***
	[0.02]	[0.03]	[0.03]	[0.04]
Night Lights per capita	2.258***	2.266***	2.461***	2.258***
	[0.10]	[0.11]	[0.15]	[0.10]
Resources	0.171***	0.168***	0.154***	0.171***
	[0.02]	[0.02]	[0.02]	[0.03]
Price shocks	-1.134**	-1.123**	-1.190***	-1.134**
	[0.38]	[0.45]	[0.43]	[0.45]
Urbanization	0.106***	0.102***	0.110***	0.106***
	[0.02]	[0.01]	[0.02]	[0.02]
Population density	0.001***	0.001***	0.001***	0.001***
	[0.00]	[0.00]	[0.00]	[0.00]
Accesibility	0.009***	0.033***	0.038***	0.009***
	[0.00]	[0.00]	[0.00]	[0.00]
Terrain ruggedness	0.073***	0.084***	0.088***	0.073***
	[0.01]	[0.02]	[0.01]	[0.01]
Droughts	0.018	0.018	-0.266	0.018
	[0.17]	[0.23]	[0.22]	[0.22]
Distance to the border	-0.055***	-0.048***	-0.066***	-0.055***
	[0.01]	[0.02]	[0.01]	[0.01]
Spatial Ethnic-frac	-0.520***	-0.528***	-0.646***	-0.520***
	[0.10]	[0.17]	[0.11]	[0.17]
Excluded groups	0.023	0.024	-0.035	0.023
	[0.02]	[0.04]	[0.02]	[0.03]
Spatial Ethnic-polariz	0.463***	0.458***	0.509***	0.463***
	[0.07]	[0.11]	[0.07]	[0.11]
Neighbour's Spatial Income Inequality			-0.061	
			[0.07]	
Neighbour's Night Lights per capita			-1.578***	
			[0.17]	
Neighbour's Resources			0.006	
			[0.08]	
Neighbour's Price shocks			1.015	
			[0.63]	
Neighbour's Urbanization			0.109	
			[0.09]	
Neighbour's Population density			0.000	
			[0.00]	
Neighbour's Accesibility			-0.046***	
			[0.00]	
Neighbour's Terrain ruggedness			0.019	
			[0.03]	
Neighbour's Droughts			0.293	
			[0.25]	
Neighbour's Distance to the border			0.033	
			[0.03]	
Neighbour's Spatial Ethnic-fractionalization			0.767***	
			[0.25]	
Neighbour's Excluded groups			0.175***	
			[0.05]	
Neighbour's Ethnic-polarization			-0.793***	
			[0.18]	
W Y(t) / WU(t)		0.541***	0.553***	0.560***
		[0.01]	[0.01]	[0.01]
Log Likelihood	11,963.16	12,302.15	13,342.56	12,297.18
R-squared	0.29	0.33	0.78	0.32
Country and time effects	Yes	Yes	Yes	Yes

Notes: The dependent variable is in all cases the binary variable of civil conflict incidence of the various cells at each year. standard errors in brackets. * Significant at 10% level, ** significant at 5% level, *** significant at 1% level.

As mentioned in the previous section, correct interpretation of the parameter estimates in the DSPDM requires to take into account the direct, indirect and total effects associated with changes in the regressors. Table (**??**) shows this information. Focusing on the main aim of the paper, results reveal that the relationship between spatial inequality and civil conflict is positive and statistically significant, thus confirming the empirical evidence provided by the previous analysis and by Ezcurra (2018). As shown in Table (**??**) the simultaneous total effect of an increase in the level of spatial inequality exerts a positive impact on the probability of conflict of about 9.5%. Therefore, the observed effect is in line with the theoretical arguments outlined in Section 2. Nevertheless, this total effect is the sum of the direct and indirect impact of spatial inequality on conflict. The direct effect, Table (**??**) indicates that an increase in the degree of spatial inequality registered by a specific cell exerts a positive and statistically significant impact on the incidence of conflict. In turn, the indirect effect reinforces the direct effect but its not significant.

A distinctive feature of the framework adopted here with respect other studies on conflict is the possibility of assessing the relevance of direct and indirect effects. The direct impact estimates displayed in Table (**??**) show some interesting features that are consistent with the empirical literature analyzing civil conflict. First, as regards economic factors, there is evidence that an increase in the night light intensity and natural resources in cell i increase the probability of conflict in i. On the other hand, the direct impact of price shocks is negative. Second, with respect to socio-demographic variables it is observed that higher population density, urbanization levels, and polarization increase the likelihood of conflict whereas spatial ethnic fractionalization exerts a negative impact and the exclusion of groups is not significant. The effect of geographical and climatic variables such as accesibility or terrain ruggedness appears to be positive whereas the impact of the distance to the border is negative. In addition, we find an insignificant effect of droughts. Short run indirect effects are significant at the 5% level for five variables while two variables appear to be significant at the 10% level. Indirect effects significantly amplify direct effects for some regressors cases whereas for some other variables the indirect effects have the opposite sign of the direct effects. As can be observed, the sign of the indirect effects goes in line with that of the direct effects in the time lag of conflict, spatial income inequality, resources, urbanization, population density and terrain ruggedness. The amplification phenomenon is particularly pronounced in past conflicts, urbanization, and terrain ruggedness as the indirect effect accounts for more than a half of the total effect. The interpretation of this result is that if all cells $j = 1, \ldots, N$ other than i experience a change in X^k, this will have a stronger effect in i that if only i experiments a change in X^k even if i generate spillover effects that go back to i. On the contrary, for some other variables such as the night lights per capita, the price shocks, the accessibility, the distance to the border, or the fractionalization and polarization the indirect effects have the opposite sign than that observed in the direct effects.

As regards the total effects, we find that a conflict in period t-1 has a probability of conflict incidence in t by 53.8%. This result goes in line with previous studies of conflict at the country level, confirming that conflicts are highly persistent in time (Ezcurra and Manotas, 2017). At the local level, similar findings are presented by Harari and La Ferrara, 2018. In their model, conflict in a cell in the previous year leads to 33% of increase of the probability of conflict in the same cell at time t, whereas contemporaneous conflict in the neighboring cells leads to higher probability of conflict by nearly 4% in the cell itself (or around 30% in the average cell whereas in our model the likelihood of conflict increases by 56%). Nevertheless, we are also allowing for the spillover effects at time t-1, although the total magnitude is similar in both cases.

Regarding the total effects of our proxy of economic development and natural resources on conflict, in both cases, we find them to be positive. This suggests that an increase in the level of development and the natural resources are positively linked with the likelihood of conflict. Nevertheless, these results are only motivated for the direct effect of these variables on conflict, suggesting spillover effects are not redundant in this case. This seems to indicate the increase in the level of development and the presence of natural resources in neighboring cells do not lead to a significative higher probability of conflict. However, in the nightlights per capita variable, this indirect channel leads to getting smaller the total effect. Specifically, an increase of 1 unit of the nightlights per capita leads to an increase of conflict by 36.1%, because of the diminishing effect implied by the indirect channel (8.2%).

Although the total effect is not consistent with previous literature at the country level, which argues that the higher level of poverty leads to a higher likelihood of conflict, other studies at the local level obtain a similar result. For instance, Fjelde (2015) and Buhaug et al. (2011) argue that in poor countries, some specific areas with higher income attract violence through a "Honey pot effect " or the "state is a prize" mechanism. In this case, it could be coherent to have only the direct effect of the looting mechanism, that is consistent with a specific localization. In addition, the total effect of natural resources is reinforced by the indirect channel, although this effect is not significant. In particular, an increase of natural resources in cell i increases the likelihood of conflict by 6,5%. This effect is consistent with previous literature that analyzes the role of mines and conflict (Bernan et al, 2017) and the

Table 4: Spatial Durbin model: Direct, Indirect and Total Marginal effects.

Variable	Direct effects	Indirect effects	Total effects
Conflict (t-1)	0.175***	0.363***	0.538***
	(0.004)	(0.031)	(0.031)
Spatial Income Inequality	0.053***	0.042	0.095**
	(0.004)	(0.040)	(0.040)
Night Lights per capita	0.443***	-0.082	0.361***
	(0.019)	(0.066)	(0.063)
Resources	0.028***	0.037	0.065*
	(0.004)	(0.034)	(0.034)
Price shocks	-0.213***	0.129	-0.084
	(0.066)	(0.262)	(0.248)
Urbanization	0.020***	0.069*	0.089**
	(0.003)	(0.039)	(0.039)
Population density	0.000***	0.000**	0.000***
	(0.000)	(0.000)	(0.000)
Accesibility	0.007***	-0.010***	-0.003***
	(0.000)	(0.001)	(0.001)
Terrain ruggedness	0.016***	0.028*	0.044***
	(0.002)	(0.015)	(0.015)
Droughts	-0.047	0.060	0.013
	(0.032)	(0.115)	(0.108)
Distance to the border	-0.012***	-0.001	-0.013
	(0.002)	(0.012)	(0.012)
Spatial Ethnic-fractionalization	-0.012***	0.166*	0.051
	(0.010)	(0.099)	(0.099)
Excluded groups	-0.006	0.063***	0.057***
	(0.004)	(0.022)	(0.021)
Spatial Ethnic-polarization	0.090***	-0.206***	-0.115
	(0.009)	(0.078)	(0.078)

Notes: t-statistics in parentheses. *Significant at 10% level, ** significant at 5% level, *** significant at 1% level. Inferences regarding the statistical significance of these effects are based on the variation of 500 simulated parameter combinations drawn from the variance-covariance matrix implied by the AML estimates.

presence of oil and gas in grid cells on armed conflict (Basedau and Pierskalla, 2014).

On the other hand, the total impact of price shocks on conflict is not significant. Given that our variable is constructed with three types of shocks, we can find that this result could be with the fact that different mechanisms cancel significative effects on violence. The negative direct effect of price shocks on violence is associated with both the opportunity cost and state capacity mechanisms. This result is line with the findings reported by previous literature that linking the agricultural price shocks on civil war at the local level (Fdjelde, 2015, Bernal et al. 2017, McGuirk et al. 2017 and Manotas et al. 2018). Nevertheless, these findings should be treated with caution because of mineral price shocks affect positively on the likelihood of violence (Bernan et al, 2017; Manotas et al. 2018).

Looking at the effect of socio-demographic factors we find that increasing urbanization affects positively to the likelihood of conflict by 9%. These results are also consistent with the findings by previous literature that relates to the higher level of urbanization with conflict. Depending on the type of conflict, we can study if it is given by food riots, or by mobilization the feasibility of rebellion (Nedal et al. ,2015; Schulz, 2016; McGuirk and Burke, 2017 and Manotas et al. 2018). Next, we find that the total effect of population density is also significant and positive supporting the findings given by previous literature both at the country and local level. Now, we turn to the presence of ethnic diversity variables, the total effects of spatial fractionalization and the spatial polarization do not seem to affect the likelihood of conflict. We could argue that indirect effects cancel the direct effects of these variables. On the other hand, the total effect of the presence of excluded groups from the political power on conflict is positive and significant. In particular, an increase in excluded groups leads to an increase in conflict incidence by 5.7%. This result is in line with Cederman et al. 2011; Basedau and Pierskalla, 2014; Kuhn and Weidmann, 2015; Huber and Mayoral, 2018 and Manotas-Hidalgo et al. (2018).

Concerning the total effects of geographical and climate factors, we find that an increase of one point of the degree of accessibility (as a proxy of state capacity) leads to a decrease the conflict incidence by around 0.3%. We argue that state capacity in neighboring areas is important in order to prevent conflict, although other mechanisms could arise directly on the local level favouring the feasibility of mobilization of troops as direct effects.

Finally, the total effect of droughts is not significative whereas by mountainous and forested terrain are positive and significative. These results are consistent with the obtained by Harari and La Ferrara, 2018. SPEI outside the growing season does not affect the likelihood of conflict. Regarding terrain ruggedness, these results confirm the importance of geographical characteristics on the likelihood of conflict. For instance, an increase in this variable leads to and increase of conflict by 4.4%.

5.2 Robustness Checks

The analysis carried out so far suggests the existence of a negative and statistically significant link between the level of spatial income inequality and civil conflict in Africa. In particular, estimates seem to indicate that the observed relationship is amplified due to the existence of spatial spillovers induced by spatial inequality in neighboring cells. In the rest of this section the robustness of these findings is investigated.

As a first robustness test, it is examined to what extent the results may be sensitive to the choice of the measure used to quantify the incidence of conflict in the sample cells. To that end, we disaggregate the definition of conflict events, based on the ACLED classification. We first consider the dummy BATTLE, which equals 1 when a cell/year has experienced a battle of any kind, regardless of whether control of the contested location changes. This variable is concerning all the organized groups. In a second step, we consider the dummy variable VIOLENCE, which also equals 1 when a cell/year has experienced any kind of violence that involving two categories of conflict given by the ACLED classification: "violence against civilians" and "riots and protests". These categories include unorganized violence which not necessarily involve fatalities. These incidents capture events of crop theft, farm raids, and food riots, jointly with looting and more general rioting .

Tables (**??**) and (**??**) show the direct, indirect and total effects obtained when the DSPDM is estimated using these alternative definitions of civil conflict, As can be seen, the different effects of spatial inequality on conflict continue to be positive and statistically significant in all cases, confirming previous results.

As a second check, we investigate if our results depend on the metric of spatial inequality. To that end we calculate the coefficient of variation of night-light per capita and the hoover index using data at the 11×11 kilometers resolution to obtain a metric at the 110×110 scale. The results are shown in Tables (**??**) and (**??**). As observed, the positive link between spatial inequality and civil conflict seems to be

Table 5: Robustness Check (I): Alternative metric of Conflict (Battles)

Variable	Direct effects	Indirect effects	Total effects
Conflict (t-1)	0.179***	0.515***	0.695***
	(0.007)	(0.052)	(0.052)
Spatial Income Inequality	0.046***	0.055	0.100*
	(0.005)	(0.052)	(0.052)
Night Lights per capita	0.248***	-0.091	0.156*
	(0.023)	(0.088)	(0.085)
Resources	0.030***	0.153***	0.183***
	(0.005)	(0.048)	(0.048)
Price shocks	-0.107	-0.235	-0.342
	(0.087)	(0.382)	(0.367)
Urbanization	0.026***	0.027	0.053
	(0.004)	(0.051)	(0.052)
Population density	0.000**	0.001***	0.001***
	(0.000)	(0.000)	(0.000)
Accesibility	0.006***	-0.011***	-0.006***
	(0.000)	(0.001)	(0.001)
Terrain ruggedness	0.023***	0.039**	0.062***
	(0.003)	(0.018)	(0.018)
Droughts	0.000	-0.094	-0.094
	(0.042)	(0.154)	(0.142)
Distance to the border	-0.014***	-0.006	-0.021
	(0.003)	(0.015)	(0.015)
Spatial Ethnic-fractionalization	-0.121***	0.002	-0.120
	(0.014)	(0.131)	(0.133)
Excluded groups	0.002	0.097***	0.099***
	(0.005)	(0.029)	(0.029)
Spatial Ethnic-polarization	0.098***	-0.165*	-0.067
	(0.012)	(0.098)	(0.098)

Notes: standard errors in parentheses. *Significant at 10% level, ** significant at 5% level, *** significant at 1% level. Inferences regarding the statistical significance of these effects are based on the variation of 500 simulated parameter combinations drawn from the variance-covariance matrix implied by the AML estimates.

Table 6: Robustness Check (II): Alternative metric of Conflict (Violence)

Variable	Direct effects	Indirect effects	Total effects
Conflict (t-1)	0.204***	0.421***	0.625***
	0.006	0.040	0.040
Spatial Income Inequality	0.073***	0.063	0.135***
	0.005	0.045	0.045
Night Lights per capita	0.486***	0.027	0.513***
	0.024	0.079	0.076
Resources	0.033***	0.031	0.065
	0.005	0.041	0.041
Price shocks	-0.296***	0.182	-0.114
	0.088	0.328	0.311
Urbanization	0.025***	0.056	0.082*
	0.004	0.044	0.044
Population density	0.000***	0.000*	0.000***
	0.000	0.000	0.000
Accesibility	0.009***	-0.013***	-0.004***
	0.000	0.001	0.001
Terrain ruggedness	0.021***	0.033**	0.054***
	0.003	0.017	0.017
Droughts	-0.078*	0.099	0.021
	0.040	0.139	0.128
Distance to the border	-0.013***	-0.013	-0.026**
	0.003	0.014	0.013
Spatial Ethnic-fractionalization	-0.108***	0.096	-0.013
	0.013	0.111	0.112
Excluded groups	-0.010*	0.081***	0.071***
	0.005	0.026	0.026
Spatial Ethnic-polarization	0.093***	-0.107	-0.013
	0.012	0.085	0.086

Notes: standard errors in parentheses. *Significant at 10% level, ** significant at 5% level, *** significant at 1% level. Inferences regarding the statistical significance of these effects are based on the variation of 500 simulated parameter combinations drawn from the variance-covariance matrix implied by the AML estimates.

robust to the specific definition of spatial inequality.

Table 7: Robustness Check (III): Alternative Measure of Inequality (Coefficient of variation)

Variable	Direct effects	Indirect effects	Total effects
Conflict (t-1)	0.177***	0.353***	0.530***
	(0.004)	(0.031)	(0.031)
Spatial Income Inequality	0.004***	0.013**	0.017***
	(0.001	(0.006)	(0.006)
Night Lights per capita	0.431***	-0.068	0.362***
	(0.019	(0.062)	(0.061)
Resources	0.032***	0.051	0.084**
	(0.004)	(0.035)	(0.035)
Price shocks	-0.207***	0.147	-0.059
	(0.069)	(0.275)	(0.264)
Urbanization	0.021***	0.071*	0.092**
	(0.003	(0.037)	(0.037)
Population density	0.000***	0.000**	0.001***
	(0.000	(0.000)	(0.000)
Accesibility	0.008***	-0.011***	-0.003***
	(0.000)	(0.001)	(0.001)
Terrain ruggedness	0.017***	0.031**	0.047***
	(0.002)	(0.015)	(0.014)
Droughts	-0.056*	0.091	0.035
	(0.031)	(0.110)	0(0.102)
Distance to the border	-0.012***	-0.003	-0.015
	(0.002)	(0.012)	(0.011)
Spatial Ethnic-fractionalization	-0.115***	0.153	0.038
	(0.011)	(0.095)	(0.095)
Excluded groups	-0.008*	0.059***	0.051**
	(0.004)	(0.021)	(0.021)
Spatial Ethnic-polarization	0.091***	-0.192**	-0.101
	(0.010)	(0.076)	(0.077)

Notes: standard errors in parentheses. *Significant at 10% level, ** significant at 5% level, *** significant at 1% level. Inferences regarding the statistical significance of these effects are based on the variation of 500 simulated parameter combinations drawn from the variance-covariance matrix implied by the AML estimates.

Table 8: Robustness Check (IV): Alternative Measure of Inequality (Hoover Index)

Variable	Direct effects	Indirect effects	Total effects
Conflict (t-1)	0.176***	0.358***	0.534***
	(0.005)	(0.033)	(0.032)
Spatial Income Inequality	0.050***	0.034	0.083**
	(0.004)	(0.041)	(0.042)
Night Lights per capita	0.445***	-0.082	0.363***
	(0.018)	(0.067)	(0.064)
Resources	(0.029)***	(0.045	(0.074)**
	(0.004)	(0.037)	(0.037)
Price shocks	-0.206***	0.147	-0.059
	(0.070)	(0.270)	(0.257)
Urbanization	0.021***	0.069*	0.090**
	(0.003)	(0.040)	(0.040)
Population density	0.000***	0.000**	0.001***
	(0.000)	(0.000)	(0.000)
Accesibility	0.007***	-0.010***	-0.003***
	(0.000)	(0.001)	(0.001)
Terrain ruggedness	0.016***	0.028*	0.044***
	(0.002)	(0.016)	(0.015)
Droughts	-0.050*	0.062	0.012
	(0.030)	(0.108)	(0.102)
Distance to the border	-0.012***	-0.003	-0.015
	(0.002)	(0.012)	(0.012)
Spatial Ethnic-fractionalization	-0.115***	0.157*	0.042
	(0.010)	(0.095)	(0.095)
Excluded groups	-0.006	0.062***	0.056***
	(0.004)	(0.022)	(0.021)
Spatial Ethnic-polarization	0.090***	-0.198**	-0.107
	(0.009	(0.077)	(0.078)

Notes: standard errors in parentheses. *Significant at 10% level, ** significant at 5% level, *** significant at 1% level. Inferences regarding the statistical significance of these effects are based on the variation of 500 simulated parameter combinations drawn from the variance-covariance matrix implied by the AML estimates.

6 Conclusions

This preliminary version has studied how spatial inequality affect the likelihood of several definitions of conflicts. Previous literature relating inequality and conflict is devoted to the analysis at the country, regional or even ethnic groups level. Nevertheless, conflicts follow local patterns that seems to be correlated across time and scale. Following this idea, lower-scale factors should be the drivers of the within-country variation of conflicts, and understanding these drivers and their patterns are essential to task any government ´s policy.

To that end, information on the location of conflicts for the entire African continent has been used, employing a fine-grained panel data for the period 1998-2013 with a spatial resolution of 1 x 1 degree latitude and longitude. We have contributed to the existing literature in several ways. Firstly, we have created a spatial Gini at the cell level, taking both the night lights density, as a proxy of local income, and the population. In this first version, we have estimated the likelihood of conflict as a function of our spatial inequality Gini and a number of covariates. We conclude that spatial inequality affects positively to the likelihood of the incidence of conflict at the local level, and our results are robust to alternative metrics of conflicts and spatial inequality. Thus, spatial inequality is prone to breed conflict with the independence of its nature.

Secondly, unlike previous literature that analyzes the drivers of conflict at the cell level, we pay attention to the underlying geographical dimension of the process of conflict. In particular, we study the role played by the spatial spillovers in explaining the both the direct and indirect impact of spatial inequality on conflicts in Africa. We incorporate these effects formally by the means of Dynamic Spatial Probit Models, which are estimated employing the Approximate Likelihood Estimator algorithm (Martinetti and Geniaux, 2016). To the best of our knowledge, this is the first paper that studies properly the dynamic spatial process of conflict with a binary dependent variable, which improves the structural form of the model.

The framework that we have adopted can assess the relevance of the direct and indirect effects. Besides, the simultaneous total effects are the best indicator to evaluate the impact of changes the spatial inequality and our selection of control variables. Specifically, in addition to the role of spatial inequality, we find that variations in the level of income per capita, the presence of natural resources, population density, accessibility, the terrain ruggedness, and the presence of excluded groups of the central political power, are significative to explaining how changes the likelihood of conflict at the cell level.

These results suggest that policies designed to decrease the magnitude of income disparities at the local level should be targeted in space, taken into consideration that indirect effects on neighboring places also plays a role to the magnitude of these effects.

However, the results of this version should be taken with caution as important issues such as different definitions of conflicts, the omission of cell fixed effects, more robustness checks, and the estimation of our model following the Yu, Jong and Lee dynamic autoregressive Durbin model are aspects that may change, which in turn, may affect the validity of the reported results.

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