Conflict in Africa: Climate, Economic Shocks and Spill-Over Effects

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Abstract This study examines the relationship between weather shocks, economic conditions and conflict in Africa. Reverse causality in the economic growth-conflict relationship is addressed by using precipitation and temperature variables as instruments for economic growth. Furthermore, the role of extractive and non-extractive commodity price shocks is examined. While previous studies rely on country-level data sets, this study exploits a panel dataset of African first-order administrative units covering the time period 1992-2010. Sub-national gross domestic product (GDP) data for Africa is either unavailable or of poor quality. For this reason, night-time light data from satellites is utilized to estimate economic growth at the sub-national level. Spatial econometric methods are applied to account for conflict spill-overs via political, geographical and ethnic ties. Estimation results provide no evidence that economic growth has a significant causal impact on violence, but reveal strong spill-over effects.

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1 Introduction

Despite a vast number of empirical studies, there is still no consensus as to whether economic conditions have a causal impact on civil conflict. While some empirical studies find that income or price shocks affect conflict risk (Miguel et al., 2004; Brückner and Ciccone, 2010; Dube and Vargas, 2013), other studies cast doubt on this view (Djankov and Reynal-Querol, 2010; Bergholt and Lujala, 2012; Koubi et al., 2012). Hegre (2006) show that results in empirical conflict studies are highly sensitive to model specification. This study is an attempt to contribute to the debate by exploiting a new panel data set of African first-order administrative units[1].

Constrained by the lack of suitable sub-national data, empirical research usually focuses on countries as units of observations. The need for econometric analyses using more disaggregated data has been stressed by authors from many disciplines, including conflict research (e.g. Blattman and Miguel, 2010; Jensen et al., 2009). A recent study by Henderson et al. (2012) proposes a framework for predicting gross domestic product (GDP) using night-time light data from satellites for countries with missing or low quality national accounts data, as well as for sub-national areas (see also Nordhaus and Chen, 2012). This study builds upon Henderson et al. (2012) in order to estimate economic growth for African areas.

Based on the identification strategy proposed by Miguel et al. (2004), reverse causality in the economic growth-conflict relationship is addressed using rainfall and temperature as instruments for economic growth. The economic rationale for using rainfall is that African economies are highly dependent on agricultural production[2], but only a negligible share of agricultural land is irrigated (less than 4%; The World Bank, 2013). Barrios et al. (2010) show that rainfall is an important determinant of growth in Africa. Two recent empirical studies link annual temperature variations to economic output (Dell et al., 2008; Heal and Park, 2014), suggesting that measures of temperature may provide additional instruments for economic growth. Lanzafame (2014) find that temperature has a significant effect on economic growth in Africa, but rainfall seems to be less important. Both rainfall and temperature are widely used as instruments for economic growth or are directly related to political and socio-economic conditions (Kim, 2014; Burke and Leigh, 2010; Hsiang et al., 2013; Brückner and Ciccone, 2011). However, other authors express doubts over whether rainfall and/or temperature provide appropriate instruments arguing that the correlation is not sufficiently strong (Koubi et al., 2012). This study employs weak-identification-robust inference to account for the possibility that the causal impact of economic growth on conflict is only weakly identified by rainfall and temperature (Kleibergen, 2002, 2005; Magnusson, 2010; Finlay et al., 2013).

Commodity price changes provide another exogenous source of variation in economic conditions (Dube and Vargas, 2013; Bazzi and Blattman, 2013; Brückner and Ciccone, 2010), which is exploited in this study. Since commodity prices may affect conflict through channels other than income (e.g. via state revenues), commodity prices are not used as an instrument for economic growth, but are treated as exogenous regressors (Bazzi and Blattman, 2013). Commodity price data allows

[1] First-order administrative units correspond to states in the United States. In the following, the terms areas, sub-national areas or first-order administrative units are used interchangeably.

[2] The agricultural sector accounts for 65% of total labour force and 32% of GDP in Africa (The World Bank, 2013; Siebert et al., 2007).

for identifying the effect of prices on conflict for different commodity classes. Dal Bó and Dal Bó (2011) argue that conflict risk is decreasing in prices for labour-intensive goods, but increasing in prices for capital-intensive commodities; a view which is empirically supported by Dube and Vargas (2013).

Another focus of this study is on the spatial dimension of conflicts. Instead of treating sub-national areas as isolated units, the spatial econometric model employed allows conflict risk to depend on conflicts in spatially close areas. Note that, in this study, "space" does not only refer to geographic distance. Specifically, spatial weight matrices based on geographic, political and ethnic distance are considered, providing insights into mechanisms of conflict diffusion.

Estimation results suggest that climate variables have a significant impact on economic growth in African first-order administrative areas. There is, however, no evidence that economic growth estimated by night-time lights has a causal effect on conflict. There is limited evidence that commodity prices are a determinant of conflict. Spatial dynamics, on the other hand, are important in explaining conflict.

The structure of this study is as follows: The following section summarizes the theoretical literature on conflict and income. Section 3 gives an overview of previous empirical studies on the relationship between climate, economic conditions and conflict. Section 5 describes the data set. In Section 6, economic growth estimates using night-time light data are obtained. Section 7 presents estimation results. Concluding remarks are in Section 8.

2 Theoretical background

Rational choice theories predict two opposing effects of income on conflict. According to the *opportunity cost mechanism*, which has its roots in rational choice theories of crime (Becker, 1968), low income is associated with high conflict risk due to low opportunity cost on the individual level (Collier and Hoeffler, 1998, 2004; Collier et al., 2009). In contrast, the *state as a prize* or *rapacity mechanism* predicts that the higher national wealth, the higher are expected returns from rebellion (Grossman, 1995; Fearon, 2007).

This study focuses on economic growth instead of income in levels. Chassang and i Miquel (2009) argue that opportunity costs—rather than the rapacity mechanism—drive the relationship between economic growth and conflict, since income is more volatile than wealth in the short run. Intuitively, while the "prize" remains more or less equally attractive during an economic crisis, opportunity costs are substantially lower.

Dal Bó and Dal Bó (2011) link the opportunity cost and rapacity mechanisms by developing a formal model of an economy with a labor-intensive, a capital-intensive and an unproductive appropriation sector. The model suggests that positive income shocks which predominantly affect capital-intensive industries increase conflict risk by reducing relative wages and thereby the opportunity cost of rebellion. The rainfall and temperature instruments are expected to identify exogenous variation in economic growth that is related to labor-intensive production (in particular agriculture), but is unrelated to capital-intensive industries (including extractive industries). Thus, a negative coefficient on economic growth instrumented by climate variables would support the idea of the opportunity cost mechanism.

Another channel through which income may affect conflict stresses the importance of the *state's capacity* to prevent or repress insurgence which is argued to be inversely related to national income via state revenues (Fearon and Laitin, 2003). Bazzi and Blattman (2013) point out that, if state revenue depends highly on natural resource rents, a rise in prices for extractive commodities diminishes conflict risk, which is in direct contrast to the rapacity idea.

Buhaug and Gleditsch (2008) discuss mechanisms through which spill-over effects of conflict may operate. First, conflicts in spatially close areas may increase awareness of own grievances and raise expectations towards the feasibility of insurgence (Kuran, 1998; Lake and Rothchild, 1998). The latter effect could be particularly strong, if there exist ethnic ties between these areas (Forsberg, 2008; Gleditsch, 2007). Secondly, cross-border refugee movements may increase the likelihood of violence in the receiving country by putting pressure on economic conditions and creating tensions between host and refugee population. Thirdly, conflict spill-overs may operate through economic spill-overs. Murdoch and Sandler (2004) have shown that conflict substantially affects economic growth in nearby countries. Other potential sources for spill-over effects are diseases and illicit trade of drugs and arms (Blattman and Miguel, 2010).

3 Previous empirical studies

It is well known that the economic growth-conflict relationship suffers from reverse causality. While economic shocks may trigger conflicts, violence or even the prospect thereof are likely to adversely affect economic growth.

In a seminal study, Miguel et al. (2004) instrument GDP growth with rainfall shocks which they define as the percentage change of rainfall from the previous year. The authors find significantly positive coefficients on contemporaneous and lagged rainfall shocks in the first stage with GDP growth as the dependent variable. Results from IV estimation using a sample of African countries in 1981-1999 suggest that a 10 percentage point GDP drop causes the likelihood of a civil war to increase by 0.5. This approach is critically discussed by Ciccone (2011, 2013) who argues that, because rainfall is strongly mean-reverting, a specification using rainfall in levels is more appropriate. In a response, Miguel and Satyanath (2010, 2011) justify the use of rainfall shocks, arguing that economic actors often react to changes in economic conditions, and also show that main results do not change when using rainfall in levels. Brückner and Ciccone (2010) show that the identification strategy in Miguel et al. (2004) is not robust to the inclusion of time effects. Jensen et al. (2009) point out that the exclusion of countries involved in civil wars in other states alters the results.

A more recent study using a similar identification strategy is given by Bergholt and Lujala (2012) who exploit climate-related natural disasters to identify the causal effect of growth on conflict. Estimation results suggest that natural disasters have a strong effect on economic growth, but economic shocks induced by disasters are unrelated to conflict. Koubi et al. (2012) analyze both the climate-economic growth and the economic growth-conflict link, but find that precipitation and temperature variation do not affect economic growth.[3]

[3]Although the instruments fail to be relevant, Koubi et al. (2012) also look at the second

A number of studies focus on the direct impact of climate on conflict. Burke et al. (2009) predict that the increase in conflict due to global warming will results in 390,000 additional battle deaths in sub-Saharan Africa by 2030. Interestingly, they find that temperature is a much stronger predictor than rainfall. These results are contested by Buhaug (2010) who argue that the association between climate and conflict is not robust. Hsiang et al. (2011) demonstrate that El Niño cycles are associated with conflict. Hsiang et al. (2013) conduct a meta-analysis of 60 studies and find a substantial effect of temperature and rainfall on conflict.

Another strand of literature exploits commodity price shocks to investigate the link between economic conditions and conflict. The identification strategy relies on the assumption that international commodity prices are not affected by civil wars in a single country. Brückner and Ciccone (2010) construct an export-weighted commodity price index for sub-Saharan African countries in 1981-2006. 3-year commodity price growth is shown to be significantly related to conflict; both when used as a regressor in a fixed effect estimation and when used as an instrument for economic growth. Dube and Vargas (2013) examine coffee and oil prices shocks in Columbia and show that a coffee price drop increases conflict risk, while a negative oil price shock reduces conflict risk, consistent with the view that conflict risk is decreasing in the price of labour-intensive commodities, but increasing in the price for capital-intensive goods (Dal Bó and Dal Bó, 2011). Cotet and Tsui (2013) do not find a link between oil abundance and violence. According to Bazzi and Blattman (2013), commodity price shocks do not trigger new conflicts, but there is some evidence that positive shocks may promote the likelihood of conflict ending.

The spatial dimension of violence has attracted much less attention. Buhaug and Gleditsch (2008) investigate spill-over effects and find transnational-ethnic ties to be particularly important, but do not control for country fixed effects, and income is treated as an exogenous control variable. Jensen et al. (2009) re-estimate the model from Miguel et al. (2004), but include a spatial conflict lag. The authors find that the estimated effect of economic growth on conflict is smaller when accounting for spill over effects.

4 Econometric Specification

The spatial autoregressive panel model considered in this study is

$$y_{ict} = \lambda \sum_{j=1}^{N} w_{ij} y_{jct} + \beta \hat{g}_{ict} + \gamma p_{ct} + \mu_{ic} + \delta_t + \psi_c t + u_{ict} \tag{1}$$

where i, c and t are the area, country and time index, respectively. y is a binary conflict indicator, $\hat{g}$ is economic growth estimated using night-time lights (discussed in Section 6) and p is the growth rate of an export-weighted commodity price index (defined in Section 5). In addition, the model allows for area-specific unobserved heterogeneity (μ_{ic}), common time effects (δ_t) and country-specific time trends ($\psi_c t$).[4]

stage where economic growth is instrumented by precipitation and temperature. This approach is certainly misleading as the model is under-identified, if the excluded instruments are not significant in the first stage.

[4] Another popular spatial model is the spatial error model where the error term follows a spatial autoregressive process. Kapoor et al. (2007) and Mutl and Pfaffermayr (2011) derive moment

The dependent variable, y_{ict}, is a binary conflict *onset* indicator. The use of a conflict *onset* instead of a conflict *incidence* indicator accounts for temporal persistence in violence (Beck and Katz, 2011; Bazzi and Blattman, 2013). The *onset* indicator is set to unity, if the number of casualties in a area-year is above a to-be-specified threshold, zero otherwise, but observations for which there is a conflict in the previous area-year are discarded. Although there is no consensus as to how a conflict is defined (Sambanis, 2004), it is standard in country-level conflict studies to employ a casualty threshold of 25. Since the unit of observations in this study are sub-national areas, it is unclear whether a threshold of 25 is appropriate. For this reason, a low threshold of at least 1 casualty per area-year (which is equivalent to at least 1 event) as well as a threshold of at least 25 casualties is considered.

The first term on the right-hand side of equation (4) is the spatially lagged dependent variable. The model assumes that conflict risk in area i depends on conflict risk in other areas through a weighted average. The spatial weights, w_{ij}, are specified below. λ is the spatial autoregressive parameter and reflects the strength of spill-over effects. Since y_{it} and y_{jt} are simultaneously determined, the spatial lag of the dependent variable is endogenous. Kelejian and Prucha (1998) suggest spatially lagged exogenous explanatory variables as instruments for the spatial lag. In this application, estimation of (4) is further complicated by the fact that the main regressor, economic growth, is endogenous. Thus, spatial lags of economic growth are no suitable instruments for the spatial conflict lag. Instead first and second order spatial lags of climate variables are used as instruments.

As demonstrated by Bound et al. (1995), the IV/GMM estimator may be severely biased in finite samples if the correlation between endogenous regressors and instruments is weak. For this reason, weak-identification robust inference which accounts for the uncertainty arising from weak instruments is applied (see Anderson and Rubin, 1949; Kleibergen, 2002, 2005; Finlay et al., 2013).

Spatial weights are specified based on geographic, political and ethnic distance. All specifications account for the fact that, *ceteris paribus*, it is expected that the impact of area j on area i is greater, the higher the population size of area j. First, the inverse distance matrix is defined as $w_{ij} = p_j/d_{ij}$ where d_{ij} is the geographic distance between area-centroids and p_j is the population count of area j. The interaction between i and j is decreasing in geographic distance, but increasing in the population size of area j. Note that the weight matrix is closely related to the gravity model of trade (due to Tinbergen, 1962). The squared inverse distance matrix puts a higher weight on geographically close areas: $w_{ij} = p_j/d_{ij}^2$. Second, since civil wars are often fought on the national level, strong within-country spill-over effects are expected. The country matrix captures these spill-overs effects: $w_{ij} = p_j$, if i and j are in the same country, 0 otherwise. The neighbor weight matrix is a slight modification of the country matrix: $w_{ij} = p_j$, if i and j are in the same country or in contiguous countries, 0 otherwise. Hence, the neighbor weight matrix also captures spill-over effects across country borders. Finally, an ethnic weight matrix is considered: If i and j are populated by at least one common ethnic group, $w_{ij} = p_j$, 0 otherwise. The binary ethnic matrix is obtained based on the

conditions under the random and fixed effects assumption for a spatial error model, but assume homoskedasticity. The assumption of homoskedasticity is violated in the above model due to the binary dependent variable. Therefore, only the spatial model in considered. For an overview of spatial panel models, see Elhorst (2014).

Geo-referencing of ethnic groups (GREG) dataset by Weidmann et al. (2010) who use the classical *Atlas Narodov Mira* (1964) to generate maps of ethnic groups.[5] Note also that, as standard in the spatial econometrics literature, all spatial weight matrices are row-standardized prior to generating spatial lags.

5 Data

Data for the dependent variable is taken from the Uppsala Conflict Data Program's Georeferenced Event Dataset (UCDP GED) v.1.5-2011 (Melander and Sundberg, 2011; Sundberg et al., 2010). The UCDP GED provides a list of geo-coded violent events in Africa covering 1989-2010. An event is defined as:

> The incidence of the use of armed force by an organised actor against another organized actor, or against civilians, resulting in at least 1 direct death in either the best, low or high estimate categories at a specific location and for a specific temporal duration. Sundberg et al. (2010, p. 4)

The UCDP has collected information on the location and timing for each event, as well as a high, a low and a best casualty estimate and the conflict type. Conflict type can be either state-based, non-state based or one-sided. If a formally organized group is involved in a violent incident with a state-based actor, the conflict type is denoted as state-based (11,137 events in the UCDP GED). If none of the actors are state-based, but both actors are formally organized, the conflict type is coded as non state-based (3,382 events). Accordingly, if one actor is not formally organized, the conflict is denoted as one-sided (6,838 events). The precision of geo-referencing varies from exact coordinates to "event can only be related to the whole country" (Sundberg et al., 2010, p. 12). Events that cannot be related to first order administrative units are discarded. This affects 1,283 of 21,357 events (6.0%) over the 1992-2010 period.

[Table 1 about here.]

The precipitation and temperature data is from Willmott and Matsuura (2013) and provided by NOAA/ESRL/PSD (2013) in a suitable data format (i.e., NetCDF). The authors have generated a 0.5 degree $\times$ 0.5 degree global dataset based on 20,782 weather stations which record monthly total precipitation throughout 1901-2010.[6] Precipitation is measured in cm and temperature in °C.

Night-time light data is made publicly available by the NOAA National Geophysical Data Center (2010, NOAA-NGDC). The NOAA-NGDC processes raw satellite data from the United States Air Force Defense Meteorological Satellite Program's Operational Linescan System (DMSP-OLS). The DMSP-OLS's satellites collect data at every location on a daily basis between 7 pm and 9 pm local time. The light intensity is measured on a scale from 0 to 63. However, only a negligible fraction of observations in low income countries is censored. Only 6 area-year observations in the African dataset are equal to 63 and only 36 observations are above 60. Observation distorted by sunlight, moonlight, clouds, auroral activity and forest fires are identified and excluded, and the remaining observations are used to obtain annual

[5] For a critical discussion see Bridgman (2008).

[6] See `http://climate.geog.udel.edu/~climate/html_pages/Global2_Ts_2009/Global_t_ts_2009.html` for a visualization of the data set (accessed on January 26, 2014).

averages for each 30 arc second $\times$ 30 arc second pixel[7] and each satellite-year.[8] The final product is a raster image in TIF format for each satellite-year, covering -180 to 180 degree longitude and -65 to 75 latitude. Satellite night-time light data is available for 1992-2012. There is data from one satellite per year for 1992-1993, 1995-1996 and 2008-2012, and two satellites for the remaining years. Light intensity as measured by satellites is not directly comparable across time and satellites, due to different, time-varying satellite settings. The framework by Henderson et al. (2012) accounts for this by the use of year dummies, which will be discussed in the next section. For further information on night-time light data see Henderson et al. (2012), Doll (2008) and Elvidge et al. (2009).

The construction of the export-weighted commodity price index follows Brückner and Ciccone (2010). International commodity prices are from the International Monetary Fund (2013). Prices are standardised with 1992 as the base year. Country-level export shares are obtained from UNCTAD Statistics (2013) and averaged across 1995-2012. The effect of commodity price shocks on conflict through economic conditions is likely to substantially differ across commodity groups. While it is expected that some commodities have a strong impact on low-income households (e.g. annual crops), other commodities may disproportionally affect capital owners and state rents (Dal Bó and Dal Bó, 2011; Bazzi and Blattman, 2013; Dube and Vargas, 2013). For this reason, commodities are divided into extractive (e.g. oil, minerals) and non-extractive commodities (e.g. food crops).[9] Specifically, the commodity price indices are defined as $\sum_j \omega_{cj} P_{jt}$ where ω_{cj} is the time-invariant export share of commodity j and country c. To account for the possibility that international commodity are influenced by conflict risk in Africa, a 3% and 10% threshold is considered such that ω_{cj} is set to zero if the world market share of country j is greater than 3% or 10%. Since the interest lies in commodity price shocks, the annual percentage change is used in all regressions.[10]

Climate, conflict and light data is matched with first order administrative boundaries from the Natural Earth (NE) dataset (2013).[11] The NE map reflects the present state of political boundaries on the earth. Thus, the NE dataset does not account for boundary changes over time. While this is clearly a limitation, it is unlikely to have a significant effect on results. There are in total 849 first-order administrative units for mainland Africa and Madagascar in the NE map. Areas without neighbors (i.e., islands) are discarded.

[7] 30 arc seconds corresponds to approximately 0.86 kilometres at the equator.

[8] Another source of background noise arises from gas flaring which occurs during oil production. The NOAA-NGDC does not exclude observations affected by gas flaring from the dataset. Elvidge et al. (2009) provides a polygon dataset that can be used to exclude the locations where light emissions are predominantly from gas flaring. The correlation coefficient between average light intensity with and without excluding gas flaring is however close to one which is why, for simplicity, only average light intensity including gas flaring is considered.

[9] Non-extractive commodities: coffee, chocolate, tobacco, cotton, tea, sugar, wheat, fish; extractive commodities: iron, copper, aluminium, nickel, oil, uranium, gold, wood. The list of commodities is almost identical to Brückner and Ciccone (2010), but does not include bananas, livestock, phosphates and ground nuts which are not included due to missing data.

[10] Brückner and Ciccone (2010) use percentage change across a 3-year period. However, annual average performed much better in this data set.

[11] The data generation process was carried out in `R 3.0.2` (R Core Team, 2013), in particular using the package `raster` (Hijmans and van Etten, 2014).

Worldwide GDP data for the prediction of GDP for African first-order administrative units is from the World Bank[12] and in local constant currency. Population count estimates used for the construction of spatial weight matrices are from CIESIN/FAO/CIAT (2005) and refer to the pre-sample year 1990.

Table 1 provides information about the distribution of conflict and night-time light data. Table 2 shows summary statistics. Figure 1 shows the development of rainfall, temperature, conflict and night-time light data over time.

[Table 2 about here.]

[Figure 1 about here.]

6 Predicting GDP with Night-time Light Data

The method for prediction of GDP using night-time light data from satellites is based on Henderson et al. (2012). The authors (eq. 13) consider different flavours of

$$n_{ct} = \psi l_{ct} + k_c + d_t + e_{ct} \tag{2}$$

where n is the logarithm of GDP in levels as measured by national accounts and l is the logarithm of average light intensity. c and t are the country index and year index, respectively. d_t accounts for variations in satellite settings across time as well as time-specific economic and technological conditions. k_c controls for country-specific unobserved heterogeneity due to cultural and economic characteristics.

[Table 3 about here.]

Table 3, Model 1 corresponds to Table 2, column 2 in Henderson et al. (2012).[13,14] The coefficient on average light intensity is 0.280 which suggests that a 1% increase in light intensity is associated with a 0.280% rise in GDP. Note that the point estimate is very close to the point estimate in HSW (0.277, with a standard error of 0.031).[15] Model 2 shows that the coefficient on light emission is substantially higher in African countries.

The interest of this study lies in the effect of income growth on conflict. It seems therefore more natural to consider equation (2) in first differences,

$$\Delta n_{ct} = \psi' \Delta l_{ct} + d'_t + e'_{ct} \tag{3}$$

where Δn_{ct} is the log-difference of GDP and Δl_{ct} is the log difference of luminosity. A major advantage of using (3) rather than (2) is that the latter does not require estimating the fixed effects. Hence, it is possible to obtain estimates for countries or areas for which no GDP data is available. Table 4 shows estimation results. Model 1 uses the full sample. Model 2-5 are based on Africa only. The coefficient on the

[12]Obtained using `wbopendata` (Azevedo, 2011) on December 2, 2013.

[13]All regression results in this study are obtained using Stata 12 and `xtivreg2` (Schaffer, 2012).

[14]Following Henderson et al. (2012, fn. 16), Bahrain, Singapore, Equatorial Guinea and Serbia and Montenegro are excluded from the sample. In addition, Norway and Estonia are excluded due to data reliability issues.

[15]One reason for the difference is that NOAA and Worldbank have revised and updated their data. In addition, minor differences due to the use of different GIS software are likely.

log-difference of night-time light in Model 2 is significantly larger, suggesting that in Africa night-time lights are more responsive to changes in income than in the rest of the world. For this reason, estimates of economic growth are based on the African sample only.

[Table 4 about here.]

A concern for the purpose of this study is that the relationship between income and light growth is, due to fixed installation costs, asymmetric in the sense that light is more responsive to positive growth than to negative economic growth. Model 3 in Table 4 shows that the coefficient on negative light growth is not significantly different from the coefficient on positive light growth (see also Table 3, column 4 in Henderson et al. 2012). Model 4 includes squared light growth and Model 5 includes the logarithm of light emission in levels to account for non-linearities. However, both variables are insignificant. Therefore, Model 2 is the preferred model for estimating economic growth using night-time lights. Specifically, estimated economic growth is defined as

$$\hat{g}_{ict} \equiv \Delta\hat{n}_{ict} = \hat{\psi}' l_{ict} + \hat{d}_t'.$$

7 Results

7.1 Conflict and night-time lights

It is well known that conflicts and economic growth measured by national accounts are negatively correlated. If economic growth estimated by night-time lights is a good proxy for true growth in economic activity, violence should also be reflected in night-time lights and estimated economic growth. Henderson et al. (2012, Fig. 4) show that the Rwandan genocide was associated with a drop in GDP as estimated by night-time light data. However, the Rwandan genocide, as one of the bloodiest events in the recent African history, is certainly not a representative example.

[Table 5 about here.]

The fixed effects estimation in Table 5 can be interpreted as a formal test of whether the estimated economic growth is, conditional on fixed effects and year effects, significantly different in conflict years. A significant different mean in conflict years may be interpreted as evidence that violence is reflected in night-time lights, which in turn supports the use night-time lights as a predictor for economic growth. The dependent variable in Model 1-3 is conflict *incidence* with a conflict threshold of 1, 25 and 50 battle deaths, respectively (as indicated in brackets). In all four specifications, the null hypothesis that the conditional mean in conflict years is equal to the conditional mean in peace years is rejected. The results suggest that average income growth in conflict years is lower by between 0.96% and 1.93% percentage points.

7.2 Economic growth, temperature and rainfall

It is insightful to examine the relationship between economic growth estimated using night-time lights and climate variables. With respect to rainfall, it is expected that, all other things equal, higher rainfall levels are associated with higher output due to favorable conditions for agricultural production. However, most studies neglect that very high rainfall levels may reflect extreme, adverse weather conditions which suggests a concave relationship between economic growth and rainfall in levels. In Model 1 in Table 6, the coefficient on rainfall is significantly positive and the coefficient and squared rainfall is significantly negative, consistent with the notion that very high rainfall levels are associated with adverse weather conditions. Model 2 controls for year effects and fixed effects which renders rainfall in levels insignificant. Model 3 includes country-specific time trends. The F-tests indicate that rainfall and squared rainfall are jointly significant in all three specifications.

[Table 6 about here.]

The economic rationale for the relationship between temperature and economic growth is less obvious. Heal and Park (2014) argue for an inverted-u shaped relationship with a single peak around the agricultural and physiological optimum temperature. Physiological studies have shown that human performance significantly deteriorates if temperatures are very high (e.g. Wendt et al., 2007). Looking at the estimation results, temperature and squared temperature are separately insignificant in Model 1. The F-test however shows that temperature and squared temperature are jointly significant at the 1% level. Temperature is also significant in Model 2, but not in Model 3 which accounts for country-specific time trends.

A useful feature of spatial econometric methods is that additional instruments become available. Weather conditions in spatially close areas may capture some of the weather variability that affects economic growth. Some areas, may not be directly affected by climate shocks, but indirectly through the adverse effect on output in spatially close areas. For instance, areas with high population density but negligible agricultural production (i.e., cities and metropolitan areas) are likely to be predominantly affected through the impact on spatially close areas with relevant agricultural production. Models 4 and 5 regress economic growth on spatially lagged climate variables where the inverse distance matrix is used. The F-tests indicate that spatial climate lags significantly affect economic growth in Africa.

It is interesting to note that the effect of rainfall on economic growth is predominantly driven by the adverse effect of extreme rainfall levels, and the effect of temperature on economic growth is predominantly driven by the positive effect of temperature. The latter is in contrast to Dell et al. (2008) who consider a linear specification and find that a 1°C increase in the average temperature reduces economic growth by 1.1 percentage points in a sample of poor countries. However, as pointed out, the relationship is likely to be concave and whether the positive or the negative effect dominates may depend on the data sample. As stated by Hsiang et al. (2013, p. 8), 'the curvature is not apparent in every study, probably because the range of temperatures [...] contained within a sample may be relatively limited'. Another explanation for the positive effect of temperature on predicted economic growth is that the relationship between temperature and night-time light growth may be different to the relationship between temperature and economic growth measured by national accounts. Specifically, high temperatures may lead individuals to shift social and economic activities from day-time to night-time, causing an increase in night-time light emissions.

There is overall strong evidence that economic growth is affected by climate variables. Rainfall and squared rainfall are jointly and highly significant in all specification. Temperature is jointly significant in all specifications, but Model 3. Temporally lagged climate variables do not significantly affect economic growth (results not shown). There is evidence that the relationship between rainfall and economic growth as well as the relationship between temperature and economic growth is concave. Furthermore, the climate-growth relationship is mainly driven by squared rainfall—i.e., extreme weather conditions—and temperature in levels.

7.3 Conflict, temperature and rainfall

[Table 7 about here.]

Against the background of climate projections predicting higher average temperatures and more extreme weather conditions (Stern, 2007; IPCC, 2007), the direct effect of climate variables on conflict is of intrinsic interest. An extensive literature looks at the effect of climate changes on conflict (for an overview, see Hsiang et al., 2013). Table 7 shows results from the regression of conflict against climate variables. The results suggest that lagged temperature and lagged squared temperature have a strong impact on conflict. The coefficient on temperature is significantly negative and the coefficient on squared temperature is positive, supporting the hypothesis of a concave relationship. According to Model 1, at a below-average annual temperature of 15°C, a 1°C rise in temperature reduces conflict risk by 3.03 percentage points in the same year. At an above-average temperature of 30°C, a 1°C temperature shock leads to an increase in conflict risk by 3.48 percentage points in the same year. The optimal (i.e. conflict-minimizing) annual average temperature is 21.98°C (with a standard error of 1.38). Results are similar in Model 2 which applies a threshold of 25 battle deaths, but the coefficient estimates are smaller in absolute value.

7.4 Conflict, economic growth and commodity prices

Estimation in this section is by two-step efficient GMM with fixed effects, time effects and country-specific time trends. Estimated economic growth is treated as endogenous and climate variables as well as spatial lags thereof are exploited as instruments. Commodity price growth is treated as exogenous, but not as an instrument for economic growth (as in Brückner and Ciccone 2010). The reason is that, as pointed out by Bazzi and Blattman (2013), commodity price growth may affect conflict through channels other than income, in particular through state revenues. The dependent variable is conflict onset, and the threshold employed is either 1 or 25 (as indicated in brackets). Tables 8 and 9 report two F-tests: The first test reports the p-value from the null hypothesis that commodity price growth does not affect conflict. The second F-test is from the the null hypothesis that all endogenous regressors (i.e. the spatial lag and income growth) are unrelated to conflict. The latter test is not robust to weak-identification, but the corresponding weak-identification robust Kleibergen p-value which uses the same null hypothesis is also reported (Kleibergen, 2002, 2005).

Model 1 and 2 in Table 8a are non-spatial (i.e., $\lambda = 0$). Estimated economic growth is insignificant in all specifications and the coefficient is close to zero. The Kleibergen 95% weak-identification robust confidence interval for Model 1 is given by

$[-0.0153, 0.0173]$ whereas the classical Wald confidence interval is $[-0.0113, 0.0092]$.[16] As exptected, the Kleibergen confidence interval is wider as it accounts for weak identification.

The subsequent models in Tables 8 and 9 include a spatial conflict lag. Economic growth is significant in none of the specifications. The coefficients on the ethnic lag in Model 3-4, Table 8a, are relatively small at 0.37 and 0.24, but highly significant. As shown in Table 8b, within-country spill-over effects are much stronger, with coefficients of 0.845 and 0.644, respectively. While the country weight matrix captures only within-country spill-over effects, the neighbor matrix also captures spill-over effects across country borders. The spatial lags on the neighbor matrix are again highly significant, but smaller, indicating that spill-over effects are stronger within than across country borders. The models reported in Table 9a are based on the inverse distance and squared inverse distance matrix. The spatial weight matrices based on geographic distance support the view of strong and significant spill-over effects.

Figure 2 and 3 display the 60%, 95% and 99% weak-identification robust confidence intervals in a two-dimensional space. The confidence interval for economic growth is in general much wider, suggesting that temperature and rainfall identify the causal effect of economic growth on conflict weakly. The spatial lag, on the other hand, is much more precisely estimated.

[Table 8 about here.]

[Table 9 about here.]

It is certainly problematic that geographic, political and ethnic distances are highly correlated, making it impossible to test the different channels of conflict diffusion against each other. For example, the correlation coefficient between the spatial country lag and spatial ethnic lag of conflict incidence (using a threshold of 1) is 0.773. However, the estimation results show that all specifications are consistent in that they provide evidence for strong and significant spill-over effects.

There is limited evidence that growth in extractive commodity prices affect conflict risk. Temporally lagged extractive commodity price growth is significant in all specification, but the coefficients are very small in magnitude. Note however that, with a standard deviation of 19.02 percentage points, commodity price growth of extractive commodities exhibit a strong variation. According to the Model (1) in Table 8b, a 10 percentage point increase in the export-weighted price for extractive commodities, increases conflict risk by 0.36 percentage points with a one-year delay. In contrast, there is no evidence that non-extractive commodity prices affect conflict risk. This finding supports the rapacity mechanism which suggest that increase in wealth provide an incentive for deprivation and is in contrast to the state capacity mechanism discussed by Bazzi and Blattman (2013).

[Figure 2 about here.]

[Figure 3 about here.]

[16] Weak identification robust inference was conducted using the `weakiv` command in Stata (Finlay et al., 2013).

7.5 Extension: Spatial heterogeneity

The analysis in the previous sections assumes that the effect of economic growth on conflict is the same across the African continent. However, as causes of conflicts are diverse and complex, the role of economic growth is likely to vary substantially across the continent. This section explores parameter heterogeneity across space using geographically weighted regression (GWR; McMillen, 1996; Brunsdon et al., 1996; Fotheringham et al., 2002). In order to approximate the effect of economic shocks on conflict in area i, the model is estimated with the Gaussian weighting function

$$a_{ij} = \exp\left(-0.5(d_{ij}/b)^2\right) \quad \text{for } i, j = 1, \ldots, N$$

where b is the bandwidth parameter and d_{ij} is the distance between the centroids of area i and area j in kilometers. Note that the weight for observation i is $a_{ii} = 1$.

[Figure 4 about here.]

[Figure 5 about here.]

Figure 4 and 5 display estimates of the effect of economic shocks on conflict for bandwidths of $b = 500$, 700 and 1,000. Black and dark gray areas indicate a positive effect of economic growth on conflict, while white and light gray areas indicates a negative effect. Hence, GWR allows to determine areas which are dominated by the rapacity mechanism (black, dark gray) or the opportunity cost mechanism (white, light gray). At a bandwidth of $b = 500$, parameter heterogeneity is substantial and the distribution of estimates is centered around zero as shown in the histogram. As the bandwidth increases, parameter heterogeneity declines. At a bandwidth of $b = 1{,}000$, Southern Africa stands clearly out as a region that is dominated by the rapacity mechanism. The substantial parameter heterogeneity may explain why the impact of growth on conflict is insignificant in the IV/GMM estimation of the previous section. The identification strategy identifies the average effect of growth shocks on conflict in Africa, but does not account for local effects which may be positive in some and negative in other regions.

8 Conclusion

Night-time light data and the framework proposed by Henderson et al. (2012) is valuable in that it allows for examining social and economic phenomena at a sub-national level, which is likely to provide new insights—not only in conflict research. The use of night-time lights as a predictor for economic growth is supported by the observation that violence is significantly reflected in night-time light emissions.

For the sample of African sub-national areas in 1992-2010, rainfall and temperature significantly determine economic growth estimated by night-time lights. While previous studies assume a linear relationship between climate and income, results suggest a non-linear form. In particular, very high rainfall levels have a strong negative impact on growth.

The reduced form regression shows that lagged temperature significantly affects conflict onset, but rainfall does not. The marginal effect of temperature on conflict risk is 3.48 percentage points at an above-average temperature of 30°C. However, the IV/GMM estimation which treats economic growth as an endogenous regressor provides no evidence of a significant impact of growth shocks on conflict risk. This is possibly because rainfall and temperature identify the causal effect of growth on conflict only weakly, stressing the need for new identification strategies. There is limited evidence that commodity price shocks of extractive products (such as oil and minerals) increase conflict risk.

Conflict in spatially close areas has a strong causal effect on conflict risk. In particular, the country weight matrix suggests strong within-country spill-over effects. Finally, geographically weighted regression reveals substantial parameter heterogeneity, suggesting that some regions are driven by the rapacity mechanism and other regions by the opportunity cost mechanism. Future research should account for parameter heterogeneity and estimate local treatment effects.

References

Anderson, T. W. and H. Rubin (1949). Estimation of the Parameters of a Single Equation in a Complete System of Stochastic Equations. *The Annals of Mathematical Statistics 20*, 46–63.

Azevedo, J. P. (2011). WBOPENDATA: Stata module to access World Bank databases.

Barrios, S., L. Bertinelli, and E. Strobl (2010). Trends in Rainfall and Economic Growth in Africa: A Neglected Cause of the African Growth Tragedy. *Review of Economics and Statistics 92*, 350–366.

Bazzi, S. and C. Blattman (2013). Economic Shocks and Conflict: Evidence from Commodity Prices.

Beck, N. and J. N. Katz (2011). Modeling Dynamics in Time-Series–Cross-Section Political Economy Data. *Annual Review of Political Science 14*, 331–352.

Becker, G. S. (1968). Crime and Punishment: An Economic Approach. *Journal of Political Economy 76*(2), 169–217.

Bergholt, D. and P. Lujala (2012). {C}limate-related natural disasters, economic growth, and armed civil conflict. *Journal of Peace Research 49*(1), 147–162.

Blattman, C. and E. Miguel (2010). Civil War. *Journal of Economic Literature 48*, 3–57.

Bound, J., D. A. Jaeger, and R. M. Baker (1995). Problems with Instrumental Variables Estimation when the Correlation between the Instruments and the Endogenous Explanatory Variable is Weak. *Journal of the American Statistical Association 90*, 443–450.

Bridgman, B. (2008). What Does the Atlas Narodov Mira Measure? *Economics Bulletin 10*(6), 1–8.

Brückner, M. and A. Ciccone (2010). International commodity prices, growth and the outbreak of civil war in Sub-Saharan Africa. *Economic Journal 120*, 519–534.

Brückner, M. and A. Ciccone (2011). Rain and the Democratic Window of Opportunity. *Econometrica 79*(3), 923–947.

Bruk, S. I. and V. S. Apenchenko (1964). *Atlas Narodov Mira.* Moscow: Glavnoe upravlenie geodezii i kartografii.

Brunsdon, C., A. S. Fotheringham, and M. E. Charlton (1996). Geographically weighted regression: A method for exploring spatial nonstationarity. *Geographical Analysis 28*, 281–298.

Buhaug, H. (2010). Climate not to blame for African civil wars. *Proceedings of the National Academy of Sciences of the United States of America 107*, 16477–16482.

Buhaug, H. and K. S. Gleditsch (2008). Contagion or confusion? Why conflicts cluster in space. *International Studies Quarterly 52*, 215–233.

Burke, M. B., E. Miguel, S. Satyanath, J. A. Dykema, and D. B. Lobell (2009). Warming increases the risk of civil war in Africa. *Proceedings of the National Academy of Sciences of the United States of America 106*, 20670–20674.

Burke, P. J. and A. Leigh (2010). Do Output Contractions Trigger Democratic Change? *American Economic Journal: Macroeconomics 2*, 124–157.

Chassang, S. and G. i Miquel (2009). Economic Shocks and Civil War. *Quarterly Journal of Political Science 4*(3), 211–228.

Ciccone, A. (2011). Economic shocks and civil conflict: A comment. *American Economic Journal: Applied Economics 3*, 215–227.

Ciccone, A. (2013). Estimating the Effect of Transitory Economic Shocks on Civil Conflict. *Review of Economics and Institutions 4*(2).

CIESIN, FAO, and CIAT (2005). *Gridded Population of the World, Version 3 (GPWv3): Population Count Grid.* Palisades and NY: NASA Socioeconomic Data and Applications Center (SEDAC).

Collier, P. and A. Hoeffler (1998). {O}n economic causes of civil war. *Oxford Economic Papers 50*(4), 563–573.

Collier, P. and A. Hoeffler (2004). Greed and grievance in civil war. *Oxford Economic Papers 56*(4), 563–595.

Collier, P., A. Hoeffler, and D. Rohner (2009). Beyond greed and grievance: Feasibility and civil war. *Oxford Economic Papers 61*, 1–27.

Cotet, A. M. and K. K. Tsui (2013). Oil and conflict: What does the cross country evidence really show? *American Economic Journal: Macroeconomics 5*, 49–80.

Dal Bó, E. and P. Dal Bó (2011). Workers, warriors, and criminals: Social conflict in general equilibrium. *Journal of the European Economic Association 9*, 646–677.

Dell, M., B. F. Jones, B. A. Olken, and I. National Bureau of Economic Research (2008). Climate change and economic growth: Evidence from the last half century.

Djankov, S. and M. Reynal-Querol (2010). Poverty and Civil War: Revisiting the Evidence. *Review of Economics and Statistics 92*, 1035–1041.

Doll, C. (2008). CIESIN Thematic Guide to Night-time Light Remote Sensing and its Applications.

Dube, O. and J. F. Vargas (2013). Commodity price shocks and civil conflict: Evidence from Colombia. *Review of Economic Studies 80*, 1384–1421.

Elhorst, J. (2014). *Spatial Econometrics: From Cross-Sectional Data to Spatial Panels.* Springer.

Elvidge, C. D., E. H. Erwin, K. E. Baugh, D. Ziskin, B. T. Tuttle, T. Ghosh, and P. C. Sutton (2009). Overview of DMSP Nightime Lights and Future Possibilities. In *2009 Joint Urban Remote Sensing Event*. Urban Remote Sensing Joint Event.

Elvidge, C. D., D. Ziskin, K. E. Baugh, B. T. Tuttle, T. Ghosh, D. W. Pack, E. H. Erwin, and M. Zhizhin (2009). A fifteen year record of global natural gas flaring derived from satellite data. *Energies 2*, 595–622.

Fearon, J. and D. Laitin (2003). Ethnicity, Insurgency, and Civil War. *American political science review 97*, 75–90.

Fearon, J. D. (2007). Economic Development, Insurgency, and Civil War. In E. Helpman (Ed.), *Institutions and Economic Performance*. Harvard University Press.

Finlay, K., L. Magnusson, and M. E. Schaffer (2013). WEAKIV: Stata module to perform weak-instrument-robust tests and confidence intervals for instrumental-variable (IV) estimation of linear, probit and tobit models.

Forsberg, E. (2008). Polarization and Ethnic Conflict in a Widened Strategic Setting. *Journal of Peace Research 45*, 283–300.

Fotheringham, A. S., C. Brunsdon, and M. Charlton (2002). *Geographically Weighted Regression: The Analysis of Spatially Varying Relationships*. Wiley.

Gleditsch, K. S. (2007). Transnational Dimensions of Civil War. *Journal of Peace Research 44*, 293–309.

Grossman, H. I. (1995). Insurrections. *Handbook of defense economics 1*, 191–212.

Heal, G. M. and J. Park (2014). Feeling the Heat: Temperature, Physiology & the Wealth of Nations. *The Harvard Project on Climate Agreements Discussion*.

Hegre, H. (2006). Sensitivity Analysis of Empirical Results on Civil War Onset. *Journal of Conflict Resolution 50*, 508–535.

Henderson, J. V., A. Storeygard, and D. N. Weil (2012). Measuring economic growth from outer space. *American Economic Review 102*, 994–1028.

Hijmans, R. J. and J. van Etten (2014). raster: Geographic analysis and modeling with raster data.

Hsiang, S. M., M. Burke, and E. Miguel (2013). Quantifying the Influence of Climate on Human Conflict. *Science 341*(6151), 1235367.

Hsiang, S. M., K. C. Meng, and M. A. Cane (2011). Civil conflicts are associated with the global climate. *Nature 476*(7361), 438–441.

International Monetary Fund (2013). IMF Primary Commodity Prices. \url{http://www.imf.org/external/np/res/commod/index.aspx}.

IPCC (2007). Climate Change 2007: Synthesis Report: Fourth Assessment Report (AR4). \url{http://www.ipcc.ch/publications_and_data/publications_ipcc_fourth_assessment_report_

Jensen, P. S., K. Skrede Gleditsch, and P. Sandholt Jensen (2009). RAIN, GROWTH, AND CIVIL WAR: THE IMPORTANCE OF LOCATION. *Defence and Peace Economics 20*(5), 359–372.

Kapoor, M., H. H. Kelejian, and I. R. Prucha (2007, September). Panel data models with spatially correlated error components. *Journal of Econometrics 140*(1), 97–130.

Kelejian, H. H. and I. R. Prucha (1998). A Generalized Spatial Two-Stage Least Squares Procedure for Estimating a Spatial Autoregressive Model with Autoregressive Disturbances. *Journal of Real Estate Finance and Economics 17*, 99–121.

Kim, N. K. (2014). Revisiting Economic Shocks and Coups. *Journal of Conflict Resolution*.

Kleibergen, F. (2002). Pivotal Statistics for Testing Structural Parameters in Instrumental Variables Regression. *Econometrica 70*(5), 1781–1803.

Kleibergen, F. (2005). Testing Parameters in GMM Without Assuming that They Are Identified. *Econometrica 73*(4), 1103–1123.

Koubi, V., T. Bernauer, A. Kalbhenn, and G. Spilker (2012). Climate variability, economic growth, and civil conflict. *Journal of Peace Research 49*, 113–127.

Kuran, T. (1998). Ethnic dissimilation and its international diffusion. *The international spread of ethnic conflict*, 35–60.

Lake, D. A. and D. Rothchild (1998). Spreading fear: The genesis of transnational ethnic conflict. *The international spread of ethnic conflict: Fear, diffusion, and escalation*, 3–34.

Lanzafame, M. (2014). Temperature, rainfall and economic growth in Africa. *Empirical Economics 46*(1), 1–18.

Magnusson, L. M. (2010). Inference in limited dependent variable models robust to weak identification. *Econometrics Journal 13*(3), S56—-S79.

McMillen, D. P. (1996). One Hundred Fifty Years of Land Values in Chicago: A Nonparametric Approach. *Journal of Urban Economics 40*(1), 100–124.

Melander, E. and R. Sundberg (2011). Climate Change, Environmental Stress, and Violent Conflict – Test Introducing the UCDP Georeferenced Event Dataset.

Miguel, E. and S. Satyanath (2010). Understanding Transitory Rainfall Shocks, Economic Growth and Civil Conflict.

Miguel, E. and S. Satyanath (2011). Re-examining economic shocks and civil conflict. *American Economic Journal: Applied Economics 3*, 228–232.

Miguel, E., S. Satyanath, and E. Sergenti (2004). Economic Shocks and Civil Conflict: An Instrumental Variables Approach. *Journal of Political Economy 112*, 725–753.

Murdoch, J. C. and T. Sandler (2004). Civil Wars and Economic Growth: Spatial Dispersion. *American Journal of Political Science 48*(1), 138–151.

Mutl, J. and M. Pfaffermayr (2011). The Hausman test in a Cliff and Ord panel model. *The Econometrics Journal 14*(1), 48–76.

National Geophysical Data Center (2010). Version 4 DMSP-OLS Nighttime Lights Time Series.

Natural Earth (2013). Admin 1 – States, Provinces (10m v3.0.0). \url{http://www.naturalearthdata.com/downloads/10m-cultural-vectors/10m-admin-1-states-provinces/}.

NOAA/ESRL/PSD (2013). University of Delaware Air Temperature & Precipitation V3.01.

Nordhaus, W. D. and X. Chen (2012). Improved Estimates of Using Luminosity as a Proxy for Economic Statistics: New Results and Estimates of Precision.

R Core Team (2013). R: A Language and Environment for Statistical Computing.

Sambanis, N. (2004). What Is Civil War?: Conceptual and Empirical Complexities of an Operational Definition.

Schaffer, M. E. (2012). XTIVREG2: Stata module to perform extended IV/2SLS, GMM and AC/HAC, LIML and k-class regression for panel data models.

Siebert, S., P. Doll, S. Feick, J. Hoogeveen, and K. Frenken (2007). Global Map of Irrigation Areas (version 4.0.1).

Stern, N. (2007). *The Economics of Climate Change: The Stern Review*. Cambridge: Cambridge University Press.

Sundberg, R., M. Lindgren, and A. Padskocimaite (2010). UCDP GED Codebook version 1.5-2011.

The World Bank (2013). Fact Sheet: The World Bank and Agriculture in Africa. \url{http://go.worldbank.org/GUJ8RVMRL0}.

Tinbergen, J. (1962). *Shaping the World Economy: Suggestions for an International Economic Policy*. Twentieth Century Fund.

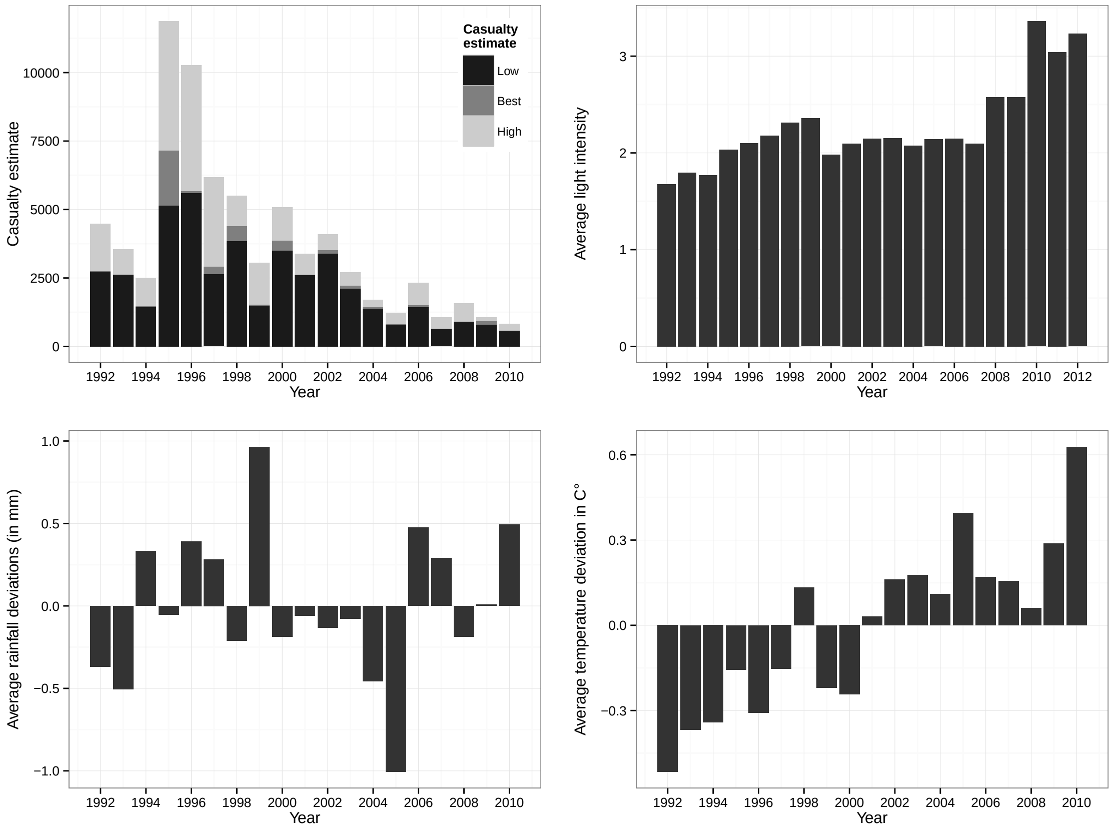
UNCTAD Statistics (2013). No Title. \url{http://unctadstat.unctad.org/}.

Weidmann, N. B., J. K. Rø d, and L.-E. Cederman (2010). Representing ethnic groups in space: A new dataset. *Journal of Peace Research 47*(4), 491–499.

Wendt, D., L. Loon, and W. Lichtenbelt (2007). Thermoregulation during Exercise in the Heat. *Sports Medicine 37*(8), 669–682.

Willmott, C. J. and K. Matsuura (2013). Terrestrial Air Temperature and Precipitation: Monthly and Annual Climatologies (Version 3.01).

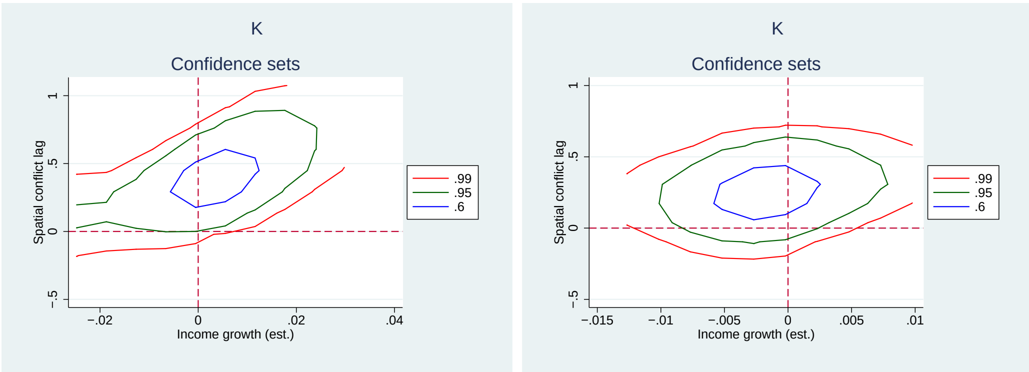
Figure 1: Descriptive graphs



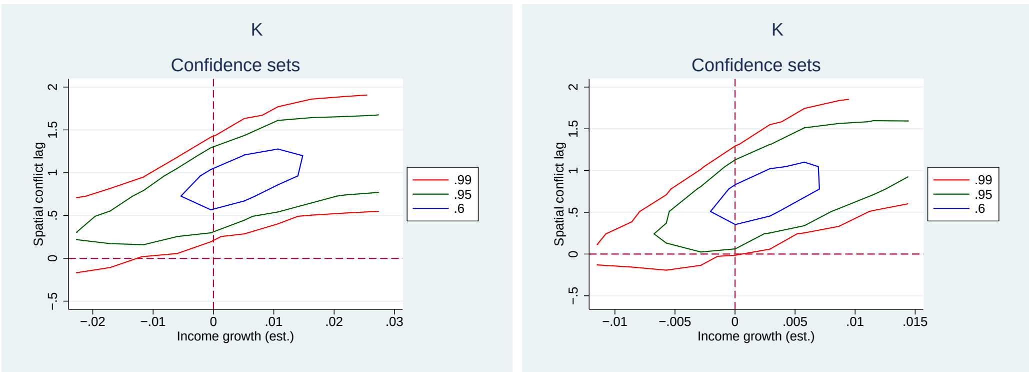
Top-left: Aggregate low, best and high casualty estimate. *Top-right:* Light intensity averaged across areas. *Bottom-left:* Rainfall deviations averaged across areas (in mm). *Bottom-right:* Temperature deviations averaged across areas (in C°).

Figure 2: Weak identification-robust confidence intervals

(a) Ethnic weight matrix with low (*left*) and high threshold (*right*)



(b) Country weight matrix with low (*left*) and high threshold (*right*)



(c) Neighbor weight matrix with low (*left*) and high threshold (*right*)

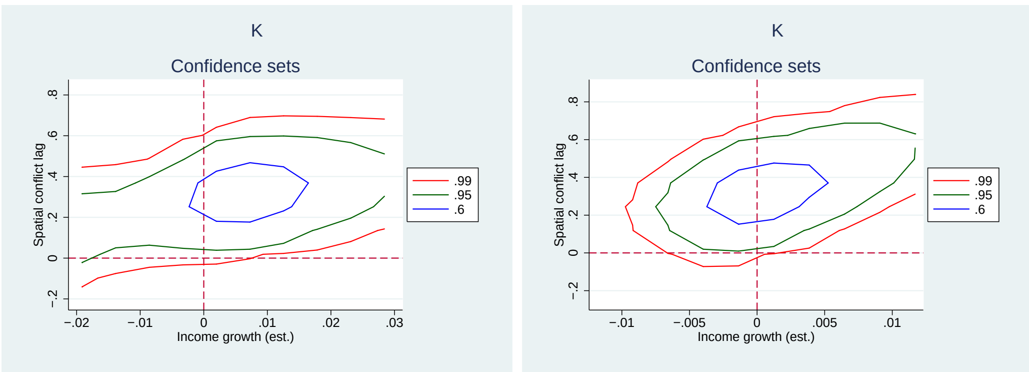
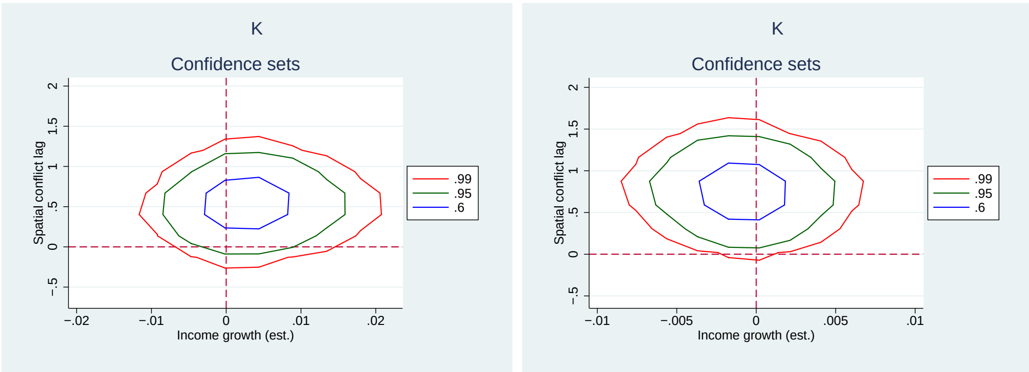


Figure 3: Weak identification-robust confidence intervals

(a) Inverse distance weight matrix with low (*left*) and high threshold (*right*)



(b) Inverse squared distance matrix with low (*left*) and high threshold (*right*)

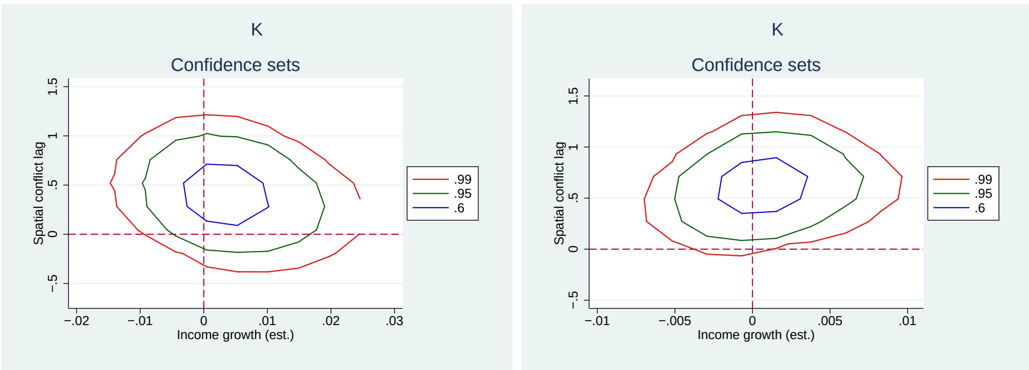
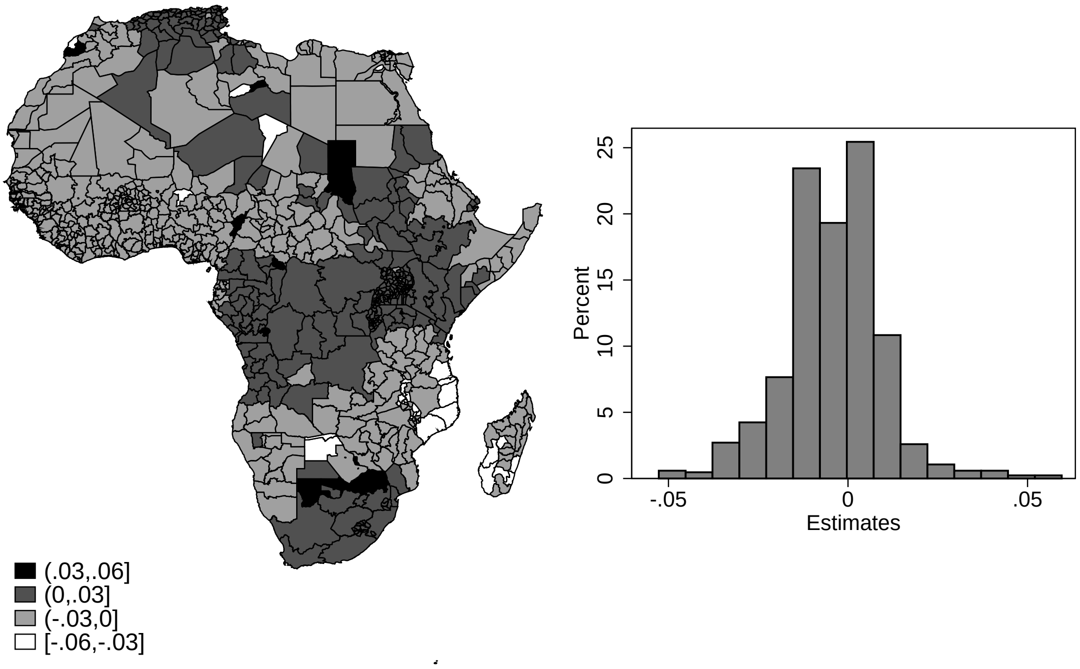


Figure 4: Spatial heterogeneity

(a) Bandwidth: $b = 500$



(b) Bandwidth: $b = 700$

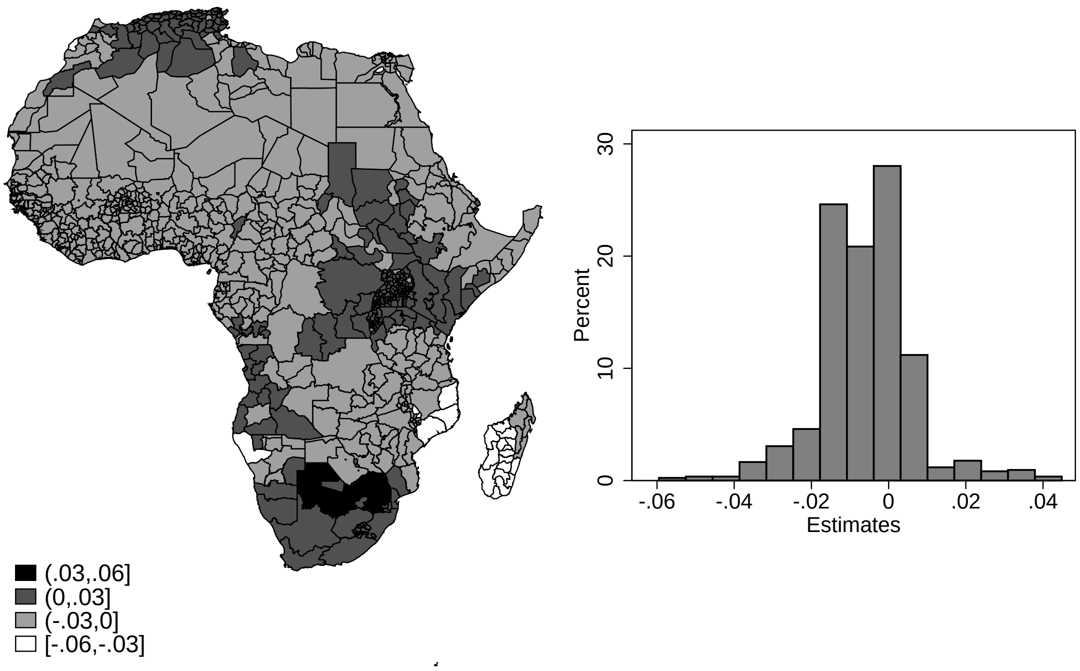


Figure 5: Spatial heterogeneity

(a) Bandwidth: $b = 1000$

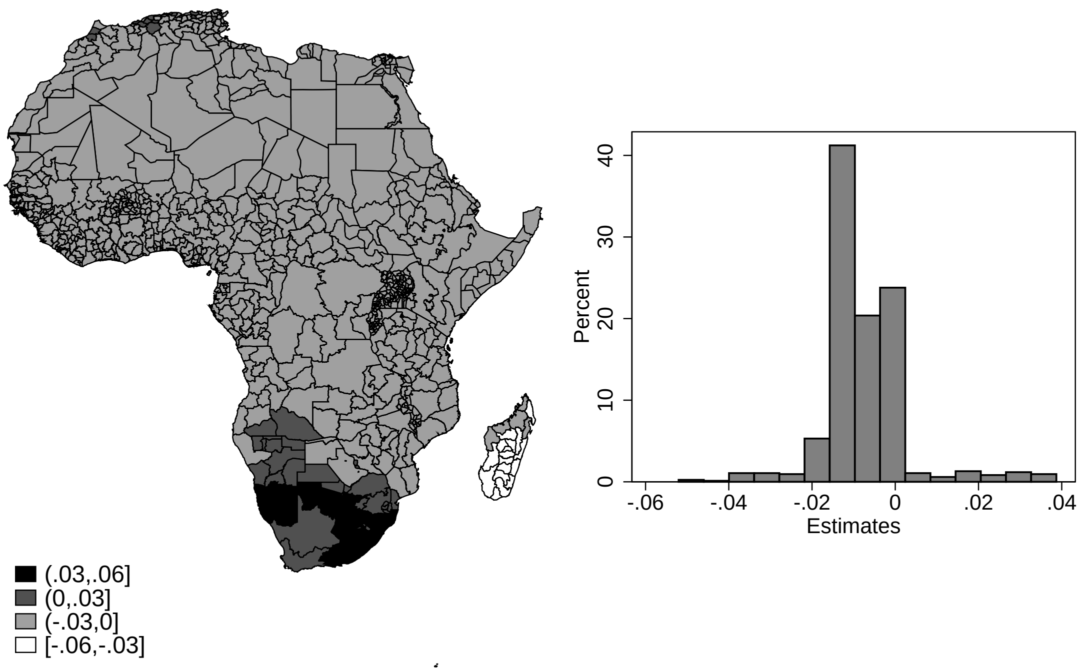


Table 1: Distribution table

	Relative frequency
$[1, \infty)$	13.3%
$[2, \infty)$	10.4%
$[3, \infty)$	8.4%
$[5, \infty)$	6.0%
$[10, \infty)$	3.9%
$[25, \infty)$	1.9%
$[50, \infty)$	1.0%

(a) Best casualty estimate

	Relative frequency	Cumulative rel. frequency
$[0, 1)$	79.6%	79.6%
$[1, 2)$	5.1%	84.7%
$[2, 5)$	6.2%	90.8%
$[5, 10)$	2.6%	93.4%
$[10, 20)$	3.0%	96.4%
$[20, 60)$	3.5%	99.8%
$[60, 63)$	0.2%	100.0%

(b) Average light intensity

Table 2: Summary statistics

	Obs.	Mean	Sd.	Min	Max	p50
Country-level						
	Obs.	Mean	Sd.	Min	Max	p50
Average light emissions	3862	4.40	8.13	0.00	61.79	1.29
Log. of average light emissions	3853	-0.02	2.05	-6.46	4.12	0.26
Light growth in %	3664	4.84	23.69	-200.15	237.95	2.66
Log. of GDP, constant LCU	3729	25.95	3.31	16.92	35.50	26.30
Growth in GDP in %	3541	3.62	5.62	-69.81	72.41	3.85
Income growth (estimated) in %	3664	3.68	3.32	-28.27	40.39	3.89
Area-level						
Incidence[1]	16131	0.13	0.34	0.00	1.00	0.00
Incidence[25]	16131	0.02	0.14	0.00	1.00	0.00
Onset[1]	13204	0.06	0.24	0.00	1.00	0.00
Onset[25]	14984	0.02	0.13	0.00	1.00	0.00
Best casualty estimate	16131	2.95	43.27	0.00	4000.00	0.00
Average light emissions	17472	2.32	7.38	0.00	63.00	0.05
Log. of average light emissions	14690	-1.94	2.67	-10.72	4.14	-2.25
Light growth in %	13565	6.83	41.15	-325.50	408.94	3.85
Income growth (estimated) in %	13565	4.04	6.18	-48.44	70.49	4.08
Rainfall	16014	7.73	4.95	0.00	31.16	7.69
Temperature	16017	23.25	4.25	0.95	31.51	23.78
Commodity price growth (non-extr.) in %	16980	3.81	17.77	-54.47	75.20	4.79
Commodity price growth (extractive) in %	16960	7.49	19.02	-44.99	71.53	8.32

Table 3: Estimating GDP

	(1) ln(GDP)	(2) ln(GDP)
ln(Light)	0.280***	0.425***
	(0.0413)	(0.0873)
Observations	3698	950
Countries	184	46
R^2 (within)	0.782	0.811

All models include country fixed effects and year effects. Standard errors are in parentheses. Standard errors are robust to both arbitrary heteroskedasticity and arbitrary within-region correlation.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Estimating economic growth

	(1) $\Delta\ln(\text{GDP})$	(2) $\Delta\ln(\text{GDP})$	(3) $\Delta\ln(\text{GDP})$	(4) $\Delta\ln(\text{GDP})$	(5) $\Delta\ln(\text{GDP})$
$\Delta\ln(\text{Light})$	0.0461***	0.161***	0.117***	0.161***	0.161***
	(0.0149)	(0.0544)	(0.0396)	(0.0546)	(0.0544)
$\Delta\ln(\text{Light})^-$			0.0970		
			(0.0891)		
$\Delta\ln(\text{Light})^2$				-0.108	
				(0.0817)	
ln(Light)					-0.000737
					(0.00125)
Observations	3509	904	904	904	904
Countries	184	46	46	46	46
R^2 (within)	0.0851	0.155	0.160	0.169	0.154

All models include year effects. Standard errors are in parentheses. Standard errors are robust to both arbitrary heteroskedasticity and arbitrary within-region correlation.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Conflict and economic growth estimated by night-time lights

	(1) Income growth (est.)	(2) Income growth (est.)	(3) Income growth (est.)
Incidence[1]	-0.953***		
	(-4.38)		
Incidence[25]		-1.620**	
		(-2.52)	
Incidence[50]			-1.926**
			(-2.20)
Observations	12099	12099	12099

All models include region fixed effects and year effects. Standard errors are in parentheses. Standard errors are robust to both arbitrary heteroskedasticity and arbitrary within-region correlation.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Economic growth, remperature and rainfall

	(1) Growth (est.)	(2) Growth (est.)	(3) Growth (est.)	(4) Growth (est.)	(5) Growth (est.)
Rainfall	0.102***	0.0947	0.0404		
	(0.0225)	(0.132)	(0.139)		
Rainfall^2	-0.00662***	-0.0161***	-0.0144**		
	(0.00129)	(0.00560)	(0.00584)		
Temperature	-0.0900	1.203**	0.870		
	(0.0985)	(0.510)	(0.602)		
Temperature^2	0.00361	-0.0203*	-0.0153		
	(0.00222)	(0.0116)	(0.0138)		
W×Rainfall				0.855*	0.669
				(0.513)	(0.548)
W×Rainfall^2				-0.0855***	-0.0784***
				(0.0230)	(0.0242)
W×Temp.				5.227***	4.062
				(1.802)	(2.576)
W×Temp.^{2}				-0.0818*	-0.0565
				(0.0431)	(0.0634)
F-test, p-value (Rainfall)	0.000	0.000	0.000	0.000	0.000
F-test, p-value (Temp.)	0.000	0.004	0.133	0.000	0.001
F-test statistic (all)	24.109	11.625	9.397	17.227	15.401
Fixed effects	No	Yes	Yes	Yes	Yes
Year effects	No	Yes	Yes	Yes	Yes
Country-trends	No	No	Yes	No	Yes
Spatial Matrix	N/A	N/A	N/A	Distance	Distance
Observations	11999	11988	11988	11988	11988

Standard errors are in parentheses. Standard errors are robust to both arbitrary heteroskedasticity and arbitrary within-region correlation.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 7: Reduced form: Conflict and climate

	(1) Onset[1]	(2) Onset[25]
Rainfall	-0.000230	0.00242
	(0.00377)	(0.00202)
Rainfall^2	0.000128	-0.0000726
	(0.000160)	(0.0000854)
Rainfall, $t-1$	0.00497	0.00191
	(0.00346)	(0.00205)
Rainfall^2, $t-1$	-0.000113	-0.0000508
	(0.000128)	(0.0000807)
Temperature	-0.0238	0.0120
	(0.0360)	(0.0148)
Temperature^2	0.000323	-0.000416
	(0.000788)	(0.000349)
Temperature, $t-1$	-0.0954***	-0.0271*
	(0.0311)	(0.0151)
Temperature^2, $t-1$	0.00217***	0.000750**
	(0.000695)	(0.000346)
Observations	13094	14872

All models include region fixed effects and year effects. Standard errors are in parentheses. Standard errors are robust to both arbitrary heteroskedasticity and arbitrary within-region correlation. F statistic is from the joint test that all climate variables are jointly insignificant.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 8: Conflict and spill-over effects

(a) Non-spatial and ethnic weight matrix

	(1) Onset[1]	(2) Onset[25]	(3) Onset[1]	(4) Onset[25]
Spatial conflict lag			0.370***	0.240**
			(0.137)	(0.117)
Income growth	-0.00106	-0.00167	0.00250	-0.00145
(estimated)	(0.00522)	(0.00223)	(0.00529)	(0.00218)
Commodity price	0.0000678	-0.0000246	-0.0000596	-0.0000669
growth (non-extr.)	(0.000295)	(0.000137)	(0.000285)	(0.000141)
Commodity price	-0.000324	-0.000144	-0.000362	-0.0000488
growth (non-extr.), $t-1$	(0.000252)	(0.000158)	(0.000255)	(0.000168)
Commodity price	0.0000103	-0.000123	0.0000838	-0.0000204
growth (non-extr.), $t-2$	(0.000281)	(0.000147)	(0.000285)	(0.000154)
Commodity price	-0.0000379	-0.0000257	0.0000663	-0.0000420
growth (extractive)	(0.000196)	(0.0000818)	(0.000204)	(0.0000779)
Commodity price	0.000372**	0.0000496	0.000400***	0.0000326
growth (extractive.), $t-1$	(0.000155)	(0.0000736)	(0.000155)	(0.0000731)
Commodity price	-0.000131	0.000246***	0.00000277	0.000261***
growth (extractive), $t-2$	(0.000156)	(0.0000830)	(0.000162)	(0.0000810)
Spatial Matrix	N/A	N/A	Ethnic	Ethnic
F-test, p-value (exog.)	0.0725	0.0950	0.0981	0.0557
F-test, p-value (endog.)	0.839	0.453	0.0193	0.0933
Kleibergen p-value	0.860	0.468	0.0255	0.120
Hansen-Sargan (Df.)	7	7	10	10
Hansen-Sargan (p-val.)	0.411	0.0708	0.549	0.378
Observations	9333	10587	9333	10587

All models include region fixed effects, year effects and country-specific time trends. Standard errors are in parentheses. Estimation is by two-step efficient GMM with fixed effects. Standard errors are robust to both arbitrary heteroskedasticity and arbitrary within-region correlation.

(b) Country and neighbor weight matrix

	(1) Onset[1]	(2) Onset[25]	(3) Onset[1]	(4) Onset[25]
Spatial conflict lag	0.845***	0.644***	0.310***	0.308***
	(0.206)	(0.235)	(0.102)	(0.110)
Income growth	0.00234	0.00146	0.00463	-0.0000625
(estimated)	(0.00486)	(0.00251)	(0.00462)	(0.00228)
Commodity price	-0.0000989	-0.00000855	0.000133	-0.0000369
growth (non-extr.)	(0.000285)	(0.000139)	(0.000282)	(0.000134)
Commodity price	-0.000262	-0.000157	-0.000254	-0.0000815
growth (non-extr.), $t-1$	(0.000264)	(0.000179)	(0.000252)	(0.000158)
Commodity price	0.0000745	0.0000495	0.000309	-0.0000498
growth (non-extr.), $t-2$	(0.000289)	(0.000162)	(0.000285)	(0.000151)
Commodity price	0.000113	-0.0000201	0.000103	-0.0000340
growth (extractive)	(0.000205)	(0.0000780)	(0.000206)	(0.0000773)
Commodity price	0.000356**	0.0000116	0.000486***	0.0000450
growth (extractive.), $t-1$	(0.000159)	(0.0000769)	(0.000162)	(0.0000730)
Commodity price	-0.0000758	0.000151*	0.0000756	0.000283***
growth (extractive), $t-2$	(0.000148)	(0.0000901)	(0.000170)	(0.0000828)
Spatial Matrix	Country	Country	Neighbor	Neighbor
F-test, p-value (exog.)	0.158	0.784	0.0461	0.0381
F-test, p-value (endog.)	0.0000177	0.0116	0.00943	0.0139
Kleibergen p-value	0.000186	0.00504	0.0104	0.0151
Hansen-Sargan (Df.)	10	10	10	10
Hansen-Sargan (p-val.)	0.347	0.740	0.215	0.671
Observations	9333	10587	9333	10587

See Table 8a.

Table 9: Conflict and spill-over effects

(a) Geographic weight matrices

	(1) Onset[1]	(2) Onset[25]	(3) Onset[1]	(4) Onset[25]
Satial conflict lag	0.536**	0.733***	0.402*	0.602***
	(0.232)	(0.249)	(0.208)	(0.192)
Income growth	0.00211	-0.000780	0.00285	0.000421
(estimated)	(0.00396)	(0.00170)	(0.00421)	(0.00195)
Commodity price	-0.00000590	-0.0000452	0.0000218	0.0000116
growth (non-extr.)	(0.000290)	(0.000135)	(0.000287)	(0.000136)
Commodity price	-0.000407	-0.000153	-0.000406	-0.000166
growth (non-extr.), $t-1$	(0.000249)	(0.000158)	(0.000255)	(0.000156)
Commodity price	-0.0000187	-0.000109	-0.00000112	-0.0000827
growth (non-extr.), $t-2$	(0.000277)	(0.000143)	(0.000278)	(0.000140)
Commodity price	0.0000805	-0.0000589	0.0000797	-0.0000289
growth (extractive)	(0.000189)	(0.0000786)	(0.000193)	(0.0000775)
Commodity price	0.000419***	0.0000265	0.000419***	0.0000309
growth (extractive.), $t-1$	(0.000155)	(0.0000727)	(0.000155)	(0.0000734)
Commodity price	-0.0000210	0.000215***	0.00000709	0.000218***
growth (extractive), $t-2$	(0.000157)	(0.0000792)	(0.000158)	(0.0000827)
Spatial Matrix	Distance	Distance	Distance^2	Distance^2
F-test, p-value (exog.)	0.0406	0.127	0.0545	0.182
F-test, p-value (endog.)	0.0656	0.0128	0.110	0.00725
Kleibergen p-value	0.0746	0.0119	0.141	0.00891
Hansen-Sargan (Df.)	10	10	10	10
Hansen-Sargan (p-val.)	0.720	0.540	0.731	0.812
Observations	9333	10587	9333	10587

See Table 8a.