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The Persistent Consequences of Civil Conflict

Evidence from a New Measure for Subnational Conflict Exposure

Tobias Korn*

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Abstract

This paper presents a novel approach to accounting for subnational conflict exposure and provides new insights into the causal medium-run effects of conflict on economic development. The existing literature has not reached a consensus on whether civil conflict can permanently alter economic growth trajectories. This study identifies the source of this disagreement as differing methodologies in measuring conflict exposure. Commonly, researchers rely on subnational aggregates of conflict intensity, overlooking crucial intra-regional variation. To provide a more accurate assessment, this paper proposes measuring conflict exposure as the share of economic activity in proximity to conflict events. Estimating a Bartik-like IV model at the district level across 70 countries, I provide causal evidence that conflict exposure significantly decreases economic activity in the medium run. As potential channels, I identify persistent diversions of investments and human capital.

Keywords: civil conflict, conflict exposure, economic development, Bartik IV

JEL Classification: D74, O15, O43

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1 Introduction

Economies that are prone to civil conflict are also more likely to experience high levels of poverty (Fearon and Laitin, 2003, Collier and Hoeffler, 2004), unstable institutions (Besley and Persson, 2010), disrupted trade flows (Bayer and Rupert, 2004), and out-migration (Salehyan, 2014). But how long do the consequences of conflict plague a society? The evidence on this question is mixed. In macroeconomic theory, the Solow model postulates that economies quickly converge back to their balanced growth paths after conflict if the structural parameters, in particular the savings rate, remain unaffected. Empirically, results based on (sub)national entities as the unit of observation back up this claim, while evidence from individual-level survey data points to persistent negative effects on conflict victims, bystanders, and their relatives. This paper argues that using a proper measure for local conflict exposure is key to solving this puzzle. The convention to aggregate distinct battle locations to higher spatial resolutions by counting the number of conflict events inside (sub)national borders ignores the spatial variation of battle locations *inside* these borders. To address this spatial variation in the aggregation process, we must account for where conflict locations lie with respect to an area’s economic activity. This further emphasizes an important heterogeneity that is otherwise lost in aggregation: violent clashes that occupy an area’s economic center are more damaging than battles taking place in the periphery.

Figure 1 illustrates the key idea of this paper. The figure shows the distribution of visible lights at night in Ukraine and Yemen from the year 2000. Red crosses indicate all conflict locations registered in either country between 2010 and 2018.¹ While the Ukrainian conflict mainly took place in the Eastern Donbas region, in Yemen almost all light-omitting locations are subject to conflict. This difference in intra-regional conflict exposure translates into heterogeneous effects of conflict on economic activity. Indeed, between 2013 and 2018, both countries experienced a similar number of battle events per year. But whereas Ukraine recovered rapidly after conflict onset, Yemen has suffered under negative growth rates ever since its civil war broke out.² This relationship is not restricted to the national level. Figure A2 shows a similar comparison for two districts in Uganda. While the town of Jinja recorded only one violent event between 1995 and 2010, the spatially vast district of Chua recorded 72 events during the same period. The one conflict event in Jinja however occurred close to the town’s economic center, whereas in Chua several populated places are located outside the battle zone. Again, even though both locations followed parallel trends in economic activity up to 2002 when Jinja recorded its one battle event, Jinja shifted to a lower path for several years afterwards.

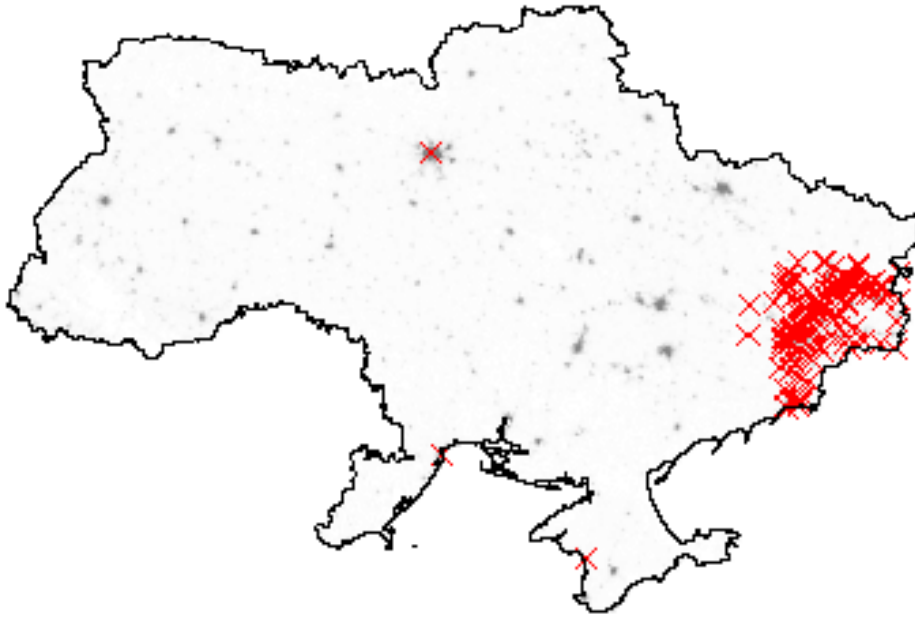
This paper tests whether this relationship holds for a sample of 21,259 subnational

¹Conflict events in Ukraine refer to the Russian-backed insurgency in the Donbas region that erupted in 2014, not the events of the Russian invasion in 2022.

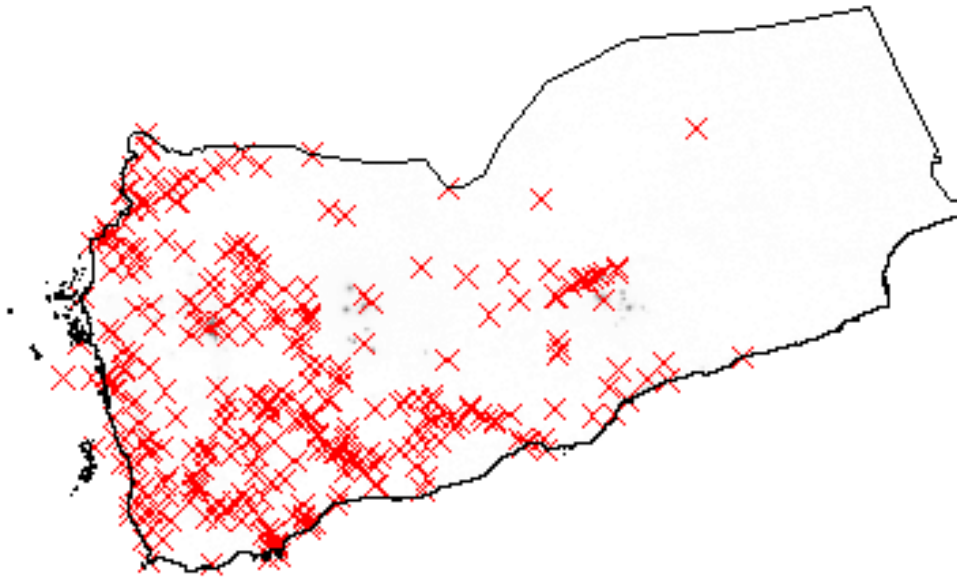
²See Appendix, Figure A1, for conflict and growth trends in the two countries.

Figure 1 – Two similar but different civil conflicts

Conflict in Ukraine



Conflict in Yemen



Notes: This Figure plots the distribution of nightlights and conflict events in Ukraine and Yemen, respectively. Nightlight intensity is indicated by inverted grey-scale and based on average visible lights during the year 2000. The locations of all conflict events in both countries since 2010 are indicated by red crosses.

areas at the second administrative layer (ADM2, or district level) across 70 countries for the 1992–2013 period.³ I propose a new way to measure conflict exposure with aggregated

³The availability of the DMSP nightlight dataset limits the yearly range of the panel dataset.

data, which takes account of the spatial variation of conflict events inside a district. Using either the pre-sample population distribution or visible lights at night as proxies for economic activity (Henderson et al., 2012, 2017, Bluhm and Krause, 2022), I compute the share of each district’s economic activity that is in close proximity to a conflict event in any given year. I then investigate whether differences in settlement patterns lead to heterogeneity in conflict exposure. Theoretically, an area whose economic activity concentrates in one location faces a higher risk that a large proportion of its population is affected by violent clashes than an area whose settlements are geographically dispersed. I provide evidence that areas with a higher spatial concentration of economic activity, measured by the spatial Gini of nightlights following Achten and Lessman (2020), exhibit higher values of conflict exposure for a given number of conflict events. Several other geographic determinants, e.g., mountainous terrain or gemstone deposits, affect conflict exposure only marginally and often insignificantly.

To test for a causal effect of conflict exposure on medium run economic development, I estimate 2SLS regressions in a Bartik-like IV (or shift-share) framework for a subsample of oil-producing countries following Autor et al. (2013), Nunn and Qian (2014), and Dreher et al. (2021). This 2SLS design relies on the interaction between a time-invariant local average (or “share”), which proxies a location’s likelihood to be affected by some external shock, and an exogenous time-series (or “shifter”), which each year takes the same value for all locations. As a local share, I use a location’s average economic concentration, and weight it by the average number of conflict events in that location. Robustness checks following Christian and Barrett (2017), Goldsmith-Pinkham et al. (2020), and Adão et al. (2019) support the validity of this share. As the global shifter, I use the international price of crude oil. For countries with access to on-shore oil production, oil revenues constitute one of rebel groups’ most important income sources, as well as the main motivation to fight (Andersen et al., 2022). At the same time, no single country in my sample, let alone one of their districts, is important enough an exporter to affect the global oil price. I find that exposure to conflict significantly decreases a location’s overall economic activity, both in the same year and when lagging conflict exposure for up to twelve years. This effect stems from the new measure for conflict exposure, as robustness checks rule out the identification method and sample selection as alternative explanations.

What is more, I find evidence that conflict exposure displaces economic activity to neighboring districts. OLS results that allow for spatial spillovers by interacting conflict exposure with a spatial weighting matrix demonstrate that high conflict exposure in close-by locations *increases* a location’s economic activity. This effect likely accrues due to people and capital moving away from conflict-locations towards less exposed areas. Finally, a panel analysis at the country level demonstrates that the subnational results based on nightlights as a proxy for economic activity also hold at the national level looking at GDP per capita as the outcome variable. The country-level analysis further

allows testing potential diversion channels. My results suggest that high conflict exposure reduces Foreign Direct Investments (FDIs) in the medium run and causes higher rates of external instead of internal migration. In addition, the fact that the negative results aggregate to the country level suggests that internal migration does not fully cushion the shock of local conflict episodes. Instead, migration frictions lead to productivity losses if people and businesses move to alternative, peaceful locations within their country's borders.

These findings shed new light on the persistent effects of conflict exposure. Recent studies using micro-level survey data show that the effects of civil conflict can last decades (see [Verwimp et al., 2019](#), for an excellent review). Studies found persistent effects on capital ownership ([Justino and Verwimp, 2013](#), [Mercier et al., 2020](#)), inequality ([Bircan et al., 2017](#)), education ([Brück et al., 2019](#)), displacement ([Verwimp and Muñoz-Mora, 2018](#), [Verwimp et al., 2020](#)), trust ([Tur-Prats and Valencia Caicedo, 2020](#)), and health ([Bundervoet et al., 2009](#), [Akresh et al., 2011, 2012](#)). Results at the aggregated level, e.g., towns, districts, or countries, oppose this view ([Blattman and Miguel, 2010](#), [Blattman, 2012](#)). In line with macroeconomic models, which assume that short term shocks do not affect long term outcomes ([Barro and Sala-i-Martin, 1992](#), [Mankiw et al., 1992](#)), they find that locations rapidly overcome the destruction from war ([Davis and Weinstein, 2002](#), [Brakman et al., 2004](#)). Some findings go one step further, arguing that in the very long run, conflict may even have positive effects for economic growth, at least in Europe ([Dincecco and Onorato, 2016](#), [Dincecco et al., 2019](#)).⁴ Even when analyzing the same conflict, studies disagree on the persistence of conflict's detrimental effects ([Miguel and Roland, 2011](#), [Singhal, 2019](#)). By accounting for the variation in conflict locations inside geographic areas, my results support the evidence from individual-level data that conflict has lasting negative effects. To bridge the gap between individual-level data and aggregated empirical questions, this paper suggests a simple but coherent way to measure conflict exposure. Researchers often use binary variables indicating the presence of civil conflict in some geographic area ([Braithwaite et al., 2016](#), [Berman et al., 2017](#)), or count variables based on the number of conflict events or battle related deaths inside that area's boundaries ([Bellows and Miguel, 2009](#), [Chamarbagwala and Morán, 2011](#), [Dube and Vargas, 2013](#)). Such measures disregard where exactly civil conflict takes place inside an area, and how many people are affected by it. Weighting conflict events by the economic activity close to them generates a more accurate image. This way of aggregating local shocks to higher geographic entities further has relevant implications for measuring other types of shocks, e.g. floods ([Kocornik-Mina et al., 2020](#)).

Finally, my findings contribute to the growing literature on locational fundamentals

⁴According to [Dincecco and Onorato \(2016\)](#), regular conflict episodes induced urbanization and hence economic growth in Europe as towns fortified and people gathered behind city walls to escape violent raids.

and how they affect long-run economic growth. Recent findings suggest that much of the allocation of today's economic activity is predetermined by fixed geographic fundamentals (Henderson et al., 2012, Alix-Garcia and Sellars, 2020). Still, sudden shocks may, under some circumstances, lead to diverging paths of development (Allen and Donaldson, 2022). The finding that the degree of geographic concentration of economic activity affects conflict vulnerability sheds new light on this discussion. As this geographic concentration is largely pre-determined by locational fundamentals (Achten and Lessman, 2020), it constitutes an important heterogeneity that might explain why civil conflict changes the path of development for some locations, but not for others.

The rest of this paper is structured as follows: Section 2 outlines the theoretical considerations and main hypotheses. Section 3 introduces a new way to measure conflict exposure and presents OLS results that investigate its heterogeneity towards the spatial concentration of the economy. Section 4 then presents the results from OLS and IV regressions that point to a causal medium-run effect of conflict exposure on economic activity. Section 5 tests these findings for robustness and Section 6 investigates various extensions to the main estimations, before Section 7 concludes.

2 Theory

The literature disagrees whether civil conflict harms economies in the long run. While various papers provide evidence of long-lasting effects on individuals affected by civil conflict, this persistent effect seems not to pass through to the aggregated level. Similarly, a number of theoretical contributions support the idea that economies recover rapidly from short-term shocks like civil conflict. This disagreement, I argue, accrues for two reasons. On the empirical side, we need to re-think how to measure conflict exposure at the geographically aggregated level, and whether geographic characteristics provoke a heterogeneous response to civil conflict. Regarding theory, we need to reconsider whether the assumption holds that short-run shocks like civil conflict do not affect locational fundamentals.

Most of the conflict literature assumes that short run economic disruptions due to violence have no lasting effect on the economy (Blattman and Miguel, 2010). Even though economies move away from their structural growth path in the short run (Barro and Sala-i-Martin, 1992, Mankiw et al., 1992), they rapidly converge back to pre-conflict levels afterwards (Blattman, 2012). Hence, civil conflicts should have no effect on economic activity in the long run as long as conflicts do not affect locations' structural determinants of growth (Davis and Weinstein, 2002, Gupta et al., 2004, Gates et al., 2012). A nascent literature investigating these structural determinants argues that locational fundamentals are pre-determined by nature (Henderson et al., 2017, Alix-Garcia and Sellars, 2020). Still, relative agglomeration forces across locations play a significant

role for the distribution of economic activity (Redding, Redding). This is, locations attract people and capital away from other places dependent on their *current* economic standing relative to other close locations. Hence, a civil conflict can persistently affect a location's agglomeration forces and hence lessen its attractiveness compared to other locations (Allen and Donaldson, 2022). Evidence abounds that people escape conflict by migrating to peaceful locations (Czaika and Kis-Katos, 2009). This can shift economic activity towards close and similar, but peaceful regions (Poot, 1995, Lewer and Van den Berg, 2008), hence reducing a location's capacity to recover from conflict. It therefore matters to what extent a location is exposed to a civil conflict to evaluate its chances of economic recovery. If, for example, all settlements in a sub-national region directly experience violence, people likely leave this region entirely and therefore shift economic activity persistently out of the region. If, on the other hand, only some part of that region is affected by conflict, economic activity can shift *within* that region. In this case, economic centers that are not subject to violence can cushion the economic downturn and preserve a region's overall production capacity. It is therefore essential to empirically account for heterogeneous conflict exposure.

Recent findings based on disaggregated individual-level data, often collected in surveys among the affected population, provide evidence for a persistent effect of conflict on various outcomes (Verwimp et al., 2019). Among other things, civil conflict has been shown to cause endured poverty (Bundervoet et al., 2009, Akresh et al., 2011, 2012, Justino and Verwimp, 2013, Mercier et al., 2020), mental health problems (Derluyn et al., 2004), deteriorating trust (Tur-Prats and Valencia Caicedo, 2020), and a lack of education (Brück et al., 2019). Furthermore, conflict-related crises like food insecurity, forced displacements and reductions in production and trade leave permanent imprints on the economy (Verwimp and Muñoz-Mora, 2018, Verwimp et al., 2020). These findings are however contrasted by studies that use geographic aggregates, e.g., towns, districts or countries, as the unit of observation. Empirical evidence from Japan (Davis and Weinstein, 2002), Vietnam (Miguel and Roland, 2011), or Germany (Brakman et al., 2004) emphasize that, despite large destruction and economic interruptions, affected places recover rapidly. Why do the persistent individual effects not translate to the aggregated level?

I argue that one essential reason for this disagreement is that the common ways to aggregate conflict data to higher geographic units neglect an important heterogeneity in how locations cope with civil conflict. Geographic conflict data usually come in the form of point data - i.e., information on perpetrators and victims associated with a specific location in space defined by geographic coordinates. To aggregate this information to a higher geographic level like districts or countries, researchers overlay these point data with (sub)national borders and then count the number of conflict events or fatalities that fall inside each spatial entity. While this concept follows the main idea of measuring

conflict exposure by indicating how active a civil conflict was in a given area, it does not yet take full advantage of the spatial component of conflict data. All conflict events receive the same weight. It makes no difference whether a conflict takes place in a highly populated and economically active location, or in the unpopulated hinterland. In both cases, a spatial entity would receive the same coding of conflict exposure. Therefore, these unweighted spatial aggregates ignore how many people were directly exposed to fighting.

Weighting conflict events by the population they affect leads to the question whether differences in settlement patterns induce heterogeneity in conflict exposure. Take the extreme case of a district where the economic activity is highly concentrated to one city and the hinterlands are sparsely populated. Such an area is more likely to see a large share of its economic activity affected by violence as (i) civil conflict tends to cluster in space (Buhaug and Gleditsch, 2008, Aas Rustad et al., 2011, Schutte and Weidmann, 2011), preferentially in places where the potential loot is high (Berman et al., 2017), and (ii) the (peaceful) rest of the area shows only low economic activity. Alternatively, one may also want to assume that more densely populated areas are better fortified and therefore make less attractive targets for insurgent groups with limited fighting capacity. Either way, geographically concentrated areas may respond differently to civil conflicts than less concentrated ones. Note that this paper does not equate spatial concentration of economic activity with income inequality (see Alesina et al., 2016, for a discussion of this issue). Instead, I focus on the mechanical relationship between settlement patterns and conflict locations to develop a way to aggregate spatial conflict data that takes account of this heterogeneity. This way of aggregation helps to connect findings from spatial conflict analysis to evidence from individual-level survey data, which themselves suffer from severe restrictions. First, despite recent efforts to encourage and facilitate survey data collection in conflict zones (Brück et al., 2013), such survey data remain as of yet too scarce. Second, surveys induce an inherited survivor bias to the analysis. Enumerators can only interview people who were neither severely wounded during the conflict nor fled to safer locations. Inference then relies on the assumption that those people available for interviews are not structurally different from people who cannot be interviewed anymore in a conflict location. We hence require a measure of conflict exposure that combines the availability of conflict event data with the accuracy of individual-level survey data.

3 Measuring Local Conflict Exposure

I use subnational data for 70 economies during the 1992–2013⁵ period to develop a new measure for local conflict exposure based on the UCDP Georeferenced Event Dataset (GED) Version 19.1 provided by [Sundberg and Melander \(2013\)](#). Countries enter the sample if the UCDP GED dataset documents violent clashes that occur predominantly between organized rebel groups and state governments, or between two or more organized non-governmental groups during the sample period.⁶ The benchmark unit of observation is the second administrative area (ADM2 level), which is similar to districts in the United States.

To aggregate the conflict event data to administrative areas, I calculate the share of an area’s population or economic activity close to a conflict event. My preferred conflict exposure measure uses the pre-sample population from 1990 to relate conflict locations to local settlement patterns. As an alternative, I use the lagged amount of light emitted at night. Using pre-sample or lagged measures ensures that an ongoing conflict does not affect the underlying population or light distribution. I prefer the 1990 population over the lagged nightlights as my main measure for conflict exposure as the nightlights, while allowing for a more detailed and contemporary picture of subnational settlement patterns, might themselves be affected by civil conflict and hence lead to endogeneity in my main analysis.⁷ I use data on local population counts in 1990 from the Gridded Population of the World (GPW) dataset. GPW aggregates information from local housing censuses to grid cells of 2.5 arc-minutes size, i.e., about 5km at the equator. The National Oceanic and Atmospheric Administration (NOAA) provides yearly data on nightlight emissions. Nightlights were introduced by [Henderson et al. \(2011, 2012\)](#) as a consistent proxy for economic activity in places where subnational economic accounts are not available. For information on conflict locations, I use the UCDP Georeferenced Event Dataset (GED), version 19.1, provided by [Sundberg and Melander \(2013\)](#).⁸ Conflict events included in the UCDP dataset constitute “an incident where armed force was used by an organized actor against another organized actor, or against civilians, resulting in at least 1 direct death at a specific location and a specific date.” An organized actor can be a national government or an (in)formally organized group of non-governmental actors. I restrict the sample to conflict events for which the exact geographic coordinates are available

⁵My sample stops in 2013 due to the availability of consistent nightlights data. New satellites introduced after 2013 make the younger, high-resolution data uncomparable to the earlier nightlights data.

⁶For example, Afghanistan and Iraq are excluded because for most of the sample period, violence occurred between organized groups and international actors. Such conflicts differ in how they affect the local population due to the nature of targets (i.e. military bases or personnel of international actors). Further, e.g. Somalia is excluded because accurate information on conflict locations is hardly available.

⁷All results are robust to using nightlights instead of population data.

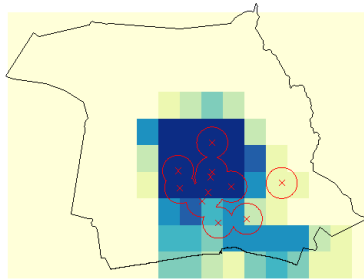
⁸UCDP conflict data can be downloaded free of charge at <https://ucdp.uu.se>.

(these are around 41% of the overall dataset).⁹ While UCDP conflict events constitute the benchmark for my regression analysis, I provide comparisons and robustness checks for African countries using conflict data provided by the Armed Conflict Location & Event Dataset (ACLED) as introduced by Raleigh et al. (2010).¹⁰ I restrict the ACLED data to conflict events with the highest precision, i.e., events that can be associated with a particular town (64.3% of observations). The benchmark unit of observation for my analysis constitutes the second administrative (ADM2) area based on GADM version 3.6. With either UCDP or ACLED, I define conflict exposure in ADM2 area i as follows:

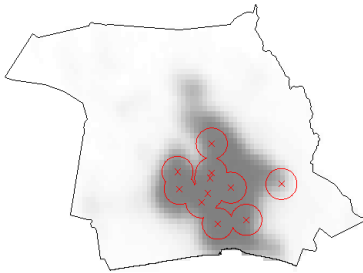
$$ConflictExposure_{i,t} = \frac{\sum_{j=1}^n Pop_{ij,t} \times \mathbb{1}(Conflict_{ij,t})}{\sum_{j=1}^n Pop_{ij,t}} \quad (1)$$

Figure 2 – Construction of Conflict Exposure Measure

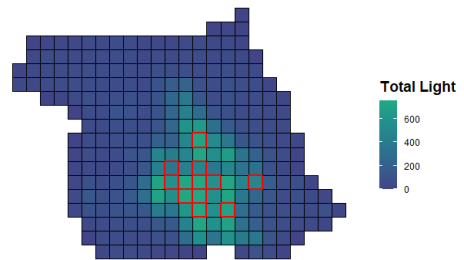
(a) Population 1990, 3km Buffers (Benchmark)



(b) Light 2010, 3km Buffers



(c) Light 2010, 3 × 3km Grid Cells



Notes: This Figure demonstrates the construction of the conflict exposure measure based on the Abidjan district, Ivory Coast, in 2011. Figure (a) demonstrates the construction of the population-based exposure measure, plotting conflict events (indicated by red crosses) with 3km Buffers over the population distribution in 1990 based on data from GPW. Figure (b) uses the same buffer sizes, but plots conflict over nightlights (in inverse grey-scale). Buffers were combined to represent the total area close to a conflict event. Figure (c) plots these data aggregated to 3 × 3km grid cells, where the color scheme indicates the total DN of nightlights. Red boxes indicate grid cells that include at least one conflict event. Conflict exposure estimated in these three panels is 33.7%, 35.5%, and 58.8%, respectively

Figure 2 illustrates the construction of three different conflict exposure measures

⁹My results are robust to including events of lower accuracy (available upon request).

¹⁰ACLED started by collecting data on conflicts in Africa and the Middle East, so data availability is best for this region. The data are freely available online at <https://acleddata.com>.

for the Abidjan district in Ivory Coast. The UCDP dataset registered eleven conflict locations in Abidjan in 2011. Whereas most of these conflict locations lie close to the population center, some events occurred rather outside in the periphery. My conflict exposure measure will give relatively little weight to the remote events, but high weight to events close to the center. Panel (a) illustrates the computation of the population-based exposure measure. Here, I identify all grid cells as “treated” if they touch a buffer around a conflict event. As a baseline, I use buffers of 3km radius, while all results presented below are robust to smaller and larger buffer sizes. I then sum the population over all “treated” cells and divide this number by the total population recorded for Abidjan in 1990.

This yields a conflict exposure of 33.7%. Panels (b) and (c) demonstrate two possibilities to construct the measure based on nightlights. To compute conflict exposure for the year 2011, I use nightlights recorded in 2010. For the buffer-method illustrated in Panel (b), I combine all conflict-buffers to a closed area and compute the share of nightlights emitted in this buffer-area vs. the total light emitted in Abidjan in 2010. This yields an exposure measure of 35.5% that is slightly higher than the population-based measure. Finally, Panel (c) illustrates the gridded lights approach. Here, I first aggregate nightlights to $3km \times 3km$ grid cells and then record which grid cells also hosted at least one conflict event. Again taking the share of light in “treated” cells vs. the overall light, we receive an exposure measure of 58.8%.

Note three things here. First, the nightlight-based measure on average produces higher values than the population-based measure. This likely reflects agglomeration effects that occurred since 1990 and are hence not detectable in the stable settlement patterns we can identify in the GPW dataset. Second, the gridded light-approach here produces larger exposure shares. This goes back on the (random) allocation of grid cells. In the case here, we have a number of central, high-population cells which are almost all “treated,” while small, bright pixels that end-up slightly outside a buffer in Panel (b) are blurred away by the aggregation to grid cells. This is however no general observation – the gridded light-approach might produce systematically higher or lower exposure shares than the buffer light-approach, depending on how the grid in a given location is arranged. Finally, my measure assigns the same weight to treated cells irrespective of whether they experience one or multiple conflict events during a given year. The exposure measures hence constitute conservative, lower-bound measures of conflict exposure which would bias estimates towards zero assuming that multiple conflict events in one region mean a higher treatment intensity. I abstain from additionally weighting cells by the number of conflict events in order to bound the exposure measure at a maximum of one, and to focus on the extensive margin of identifying insecure conflict locations. That being said, I assign to each district a grid that is stable over time such that within-district comparisons are not susceptible to grid differences. The three exposure measures are

highly correlated with each other, and different buffer sizes lead to qualitatively similar measures (see Table 1 for a comparison).¹¹

Table 1 – Correlation across Exposure Measures

	Exp	Exp_Light	Exp_Grid	Exp_5km	Exp_1km
Exposure	1.00	0.90	0.68	0.92	0.86
Exposure_Light	0.90	1.00	0.70	0.88	0.79
Exposure_Grid	0.68	0.70	1.00	0.68	0.54
Exposure_5km	0.92	0.88	0.68	1.00	0.79
Exposure_1km	0.86	0.79	0.54	0.79	1.00

Notes: This table displays the correlations among different conflict exposure measures. The first three measures (“Exposure”, “Exposure_Light”, and “Exposure_Grid”) refer to the three main measures using 3km buffers (Columns 1 & 2) and grid cells (Column 3). Columns (1) and (3) use population, Column (2) uses nightlights to identify settlement patterns. Columns (4) and (5) repeat the population-buffer measure from Column (1), but instead use 5km and 1km buffers, respectively.

Using the ACLED conflict data allows to compare the exposure measure over different types of civil unrest. I follow ACLED’s categorization and construct separate exposure measures for (i) battles between rebels and government forces, (ii) remote violence via explosives, (iii) violence against civilians, (iv) riots, and (v) protests. Figure A6 shows that on average, “low-cost” types of unrest like protests and riots exhibit a higher conflict exposure. This likely stems from the fact that protests and riots are more likely to occur in cities rather than in the periphery, and that it is easier to bring protesters to the streets across towns than projecting violent force across larger parts of an area. Additionally, violence against civilians is slightly more likely to spread across populated places inside an area than are battles between rebels and government troops. This observation is in line with, e.g., Kalyvas (2006), who argues that it is costly for armed forces to spread their reach geographically away from their center of control.

Centralization and Conflict Exposure. Differences in economic geography can induce heterogeneity in how districts cope with civil conflicts. I expect a location’s degree of economic concentration to be an additional determinant of how conflict exposure affects economic growth. Hence, I investigate whether my conflict exposure measure takes higher values for locations with higher spatial economic concentration, holding the number of conflict events fixed. This will also provide the first stage for this paper’s

¹¹See also Figure A3 in the Appendix, which illustrates the relationship between the “common” conflict measure and my exposure measure. It also shows that my measure picks up conflict exposure from events that occur close to the border in neighboring districts, which would be omitted in the usual count-based measures.

subsequent analysis.

I estimate OLS regressions of the form:

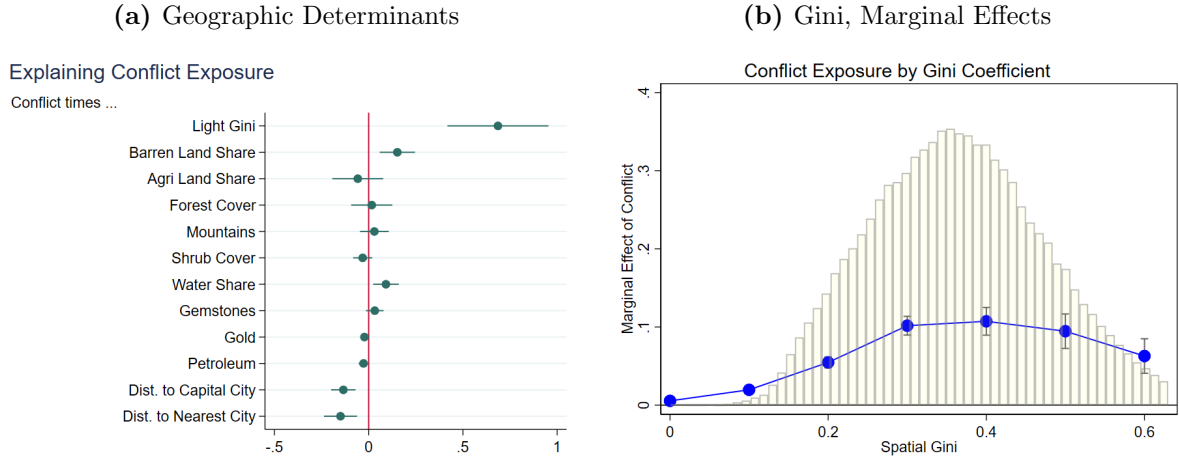
$$Exposure_{ic,t} = \beta_1 G_{ic,t} + \beta_2 \ln(C_{ic,t}) + \beta_3 G_{ic,t} \times \ln(C_{ic,t}) + X'_{ic,t} \phi + \delta_i + \lambda_{ct} + \epsilon_{ic,t} \quad (2)$$

where conflict exposure of spatial entity i in country c at year t constitutes the dependent variable. The main explanatory variables are the natural logarithm of conflict events, $\ln(1+C_{ic,t})$, and various geospatial covariates, indicated by $G_{ic,t}$. My main spatial variable of interest is economic concentration. For this, I follow [Achten and Lessman \(2020\)](#) and calculate the yearly spatial Gini coefficient of nighttime lights for each unit of observation. Just as a regular Gini coefficient, the spatial Gini coefficient takes on values between 0 and 1, where a value of 0 would indicate a perfectly equal distribution of light, and a value of 1 would indicate a perfectly concentrated distribution in only one pixel. Note that the number of conflict events is obviously endogenous to conflict exposure, such that it comes at no surprise that the correlation between conflict exposure and the number of conflict events, β_2 , should be highly significant. However, the main purpose of this analysis is to determine whether the *marginal effect* of an additional conflict event varies with the degree of spatial concentration. Therefore, I am mainly interested in β_3 , i.e. the coefficient from the interaction term of the number of conflict events and the Gini coefficient (or other geographic variables, respectively). A significantly positive value for β_3 would indicate that for a given number of conflict events, a location's conflict exposure increases with the value of this geographic variable. Note further that the purpose of this first-stage estimation is not to establish causality, but to test whether spatial concentration in fact significantly moderates the marginal effect of an additional conflict event on conflict exposure. All specifications control for population density, the total amount of nightlights, and climate indicators ($X'_{ic,t}$), along with location (δ_i) and country-year (λ_{ct}) fixed effects.

Figure 3, Panel (a), summarizes the standardized estimates for this β_3 coefficient for various geographic variables.¹² All variables are constant over time (the Gini coefficient is based on the nightlight distribution in 1992), and hence controlled for by location fixed-effects. Most coefficients are either statistically insignificant or exhibit a small gradient. Only the Gini coefficient moderates the effect of conflict events on conflict exposure significantly, with a 1SD increase in the Gini coefficient being associated with a 0.7SD increase in conflict exposure for each additional conflict event. Panel (b) of Figure 3 plots the marginal effects of conflict events on conflict exposure, moderated

¹²Table B2 in the Appendix displays detailed results for the Gini Coefficient as the explanatory variable.

Figure 3 – Geographic Determinants of Conflict Exposure



Notes: Figure (a) plots the coefficients from regressing conflict exposure on the interaction terms of the number of conflict events and various geographical variables. All variables are centered and standardized to account for distributional differences. The regression controls for the number of conflict events as well as climate shocks, and includes country-year and district fixed effects, the latter of which account for the interaction terms’ base variables. Lines depict 95% Confidence Intervals. Figure (b) plots the marginal effects of conflict events on conflict exposure conditional on the spatial Gini coefficient. The Gini coefficient is here categorized into 0.1-bins, with $Gini < 0.1$ as the reference category. The histogram in the background displays the distribution of the continuous Gini variable.

by the Gini coefficient. Here, I repeat the main specification according to Equation (1) but using a categorical variable instead of the continuous Gini coefficient. For this, I assign observations to different bins of the Gini coefficient, each of size 0.1. The category of the least centralized locations with a Gini coefficient between 0 and 0.1 constitute the reference category. This figure illustrates again the relevance of economic geography as a moderator for conflict exposure: A high level of economic concentration makes areas more vulnerable to conflict. This result is robust across different specifications. In the Appendix, I provide estimates from the same regression specifications, but based on nightlights (Tables B3 and B4), lights from the year 1992 (Table B5), or for lights averaged across the whole sample period (Table B6). All these alternatives deliver almost exactly the same picture. Using the contemporaneous Gini coefficient or fixing it to the year 1992 does not change the results (Table B7). The results are further robust to the usage of smaller (1km) or bigger (5km) buffer sizes (see Tables B8 & B9), as well as for omitting the bottom ten percent and the top ten percent brightest observations from the sample (see Table B10).

4 Conflict Exposure and Economic Activity

To investigate the medium-run effect of conflict exposure on local economic activity, I regress the natural logarithm of a location’s sum of nightlights as a proxy for local

economic activity on my measure for conflict exposure. I follow the general set-up of [Kocornik-Mina et al. \(2020\)](#), who test for a medium-run effect of floods on economic activity, and lag my explanatory variable by one additional year in each column moving to the right. All regressions include ADM2- and country-year fixed effects, and control for population density and climate indicators. What is more, I include the spatial Gini of lights and the yearly number of conflict events as additional control variables to estimate the effect of conflict exposure on economic activity *holding the number of conflict events constant*.

Various papers raise concern of endogeneity between conflict and economic activity. For example, conflict traps impose a feedback-loop between conflict and deteriorating economic activity ([Braithwaite et al., 2016](#)), and sudden economic windfalls may cushion reasons for war ([Miguel and Satyanath, 2011](#), [Dube and Vargas, 2013](#), [Bazzi and Blattman, 2014](#), [Berman and Couttenier, 2015](#)) or spur insurgency via higher expected gains ([Angrist and Kugler, 2008](#), [Nunn and Qian, 2014](#), [Bluhm et al., 2021](#), [Berman et al., 2017](#)). Also international donors take civil conflict into consideration when they allocate development assistance to certain locations ([Dreher and Lohmann, 2015](#), [Bluhm et al., 2020](#)). Therefore, I employ a 2SLS Bartik-IV (or “shift-share”) strategy to test for a causal effect of conflict exposure on economic activity.¹³ This 2SLS strategy was recently employed across various fields, see e.g., [Autor et al. \(2013\)](#), [Nunn and Qian \(2014\)](#) and [Dreher et al. \(2021\)](#). The idea is to interact a local average that is constant over time (a so-called “share”), with an arguably exogenous time series that is the same for all locations (a so-called “shifter”). The local shares are then meant to identify how much a local entity is affected by a (global) shock. I use the interaction of two related variables as the local share. These are (i) a location’s average number of conflict events, and (ii) a location’s average Gini coefficient of lights at night.¹⁴ The decision to interact two local shares relies on the results presented in [Figure 3](#) above, which show that the *interaction* of conflict and economic concentration has the highest predictive power for conflict exposure. This interacted share hence proxies for the propensity that large parts of a location’s economic activity may be exposed to conflict in any given year. Note that this share, while possibly endogenous, is controlled for by ADM2 fixed effects. As a shifter, I use the one-period lagged value of the international crude oil price, an important determinant of conflict intensity ([Andersen et al., 2022](#), [Basedau and Lay, 2009](#), [Dube and Vargas, 2013](#), see, e.g.).

¹³Table [B11](#) in the Appendix provides OLS results for comparison.

¹⁴In the Appendix, I provide results using the Gini coefficient based on 1992 lights instead of the average coefficient. The results are almost identical.

Table 2 – 2SLS: Conflict Exposure and Economic Activity, 1992-2013

	(1)	(2)	(3)	(4)	(5)
	ln(light)	ln(light)	ln(light)	ln(light)	ln(light)
<i>Exposure</i>	-8.089** (3.441)	0.303 (0.302)	-0.469** (0.220)	-0.171 (0.173)	-0.442*** (0.166)
<i>Exposure</i> _{<i>t</i>-1}		-8.077*** (2.626)	0.104 (0.161)	-0.600** (0.264)	-0.246 (0.163)
<i>Exposure</i> _{<i>t</i>-2}			-4.638*** (1.253)	0.00677 (0.159)	-0.762** (0.330)
<i>Exposure</i> _{<i>t</i>-3}				-4.747*** (1.164)	-0.116 (0.180)
<i>Exposure</i> _{<i>t</i>-4}					-5.155*** (1.191)
First Stage:	<i>Exposure</i>				
<i>IV</i>	0.00116*** (0.000418)	0.00019*** (0.0000377)	0.000276*** (0.0000664)	0.000308*** (0.0000737)	0.000294*** (0.000116)
ADM2 FE	✓	✓	✓	✓	✓
Country-Year FE	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓
Obs.	190,624	180,902	171,178	161,458	151,738
<i>F</i> _{1st stage}	15.82	21.85	21.13	18.63	36.20
Nbr. Countries	27	27	27	27	27

Notes: This table provides the second stage results for the 2SLS estimates. The unit of observation is the second administrative area (ADM2) for countries with active on-shore oil production. The endogenous variable is the share of lights at night within 3km to a conflict event and is instrumented by a triple-interaction of *i*) the regional average of conflict events *ii*) the regional average of the Gini of lights and *iii*) the yearly world price for crude oil. All regressions include a control variables population density, precipitation, precipitation squared, temperature, temperature squared, as well as ADM2 and Country-Year Fixed Effects. All regressions also control for the endogenous exposure variable in year *t* (column 1 aside) as well as for the yearly number of conflict events and the yearly Gini of lights in year *t* – *s*, where *s* indicates the lag of the endogenous variable.

Standard errors clustered at the ADM2 region in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Of course, the yearly oil price itself is not unconditionally independent of local growth trajectories. It is for example straightforward to assume that a higher oil price would increase the output of oil-producing districts.¹⁵ However, I argue that the interaction term between both local shares and the global oil price is conditionally independent of local

¹⁵This however would bias my results towards zero.

economic activity as long as one controls for the two constituting two-way interactions of the oil price with either of the local shares.

I therefore estimate 2SLS regressions of the following form:

$$Exp_{ic,t} = \beta_1 \overline{G_{ic}} \times \overline{C_{ic}} \times \$Oil_{t-1} + \gamma_1 \overline{G_{ic}} \times \$Oil_{t-1} + \gamma_2 \overline{C_{ic}} \times \$Oil_{t-1} + \delta X'_{ic,t} + \pi_i + \lambda_{ct} + \epsilon_{ict} \quad (3)$$

$$\ln(light)_{ict} = \beta_2 \widehat{Exp_{ict-s}} + \gamma_1 \overline{G_{ic}} \times \$Oil_{t-s-1} + \gamma_2 \overline{C_{ic}} \times \$Oil_{t-s-1} + \delta X'_{ict} + \pi_i + \lambda_{ct} + \mu_{ict} \quad (4)$$

where $Exp_{ic,t}$ denotes the exposure to conflict of ADM2 area i in country c in year t . The subscript $(t - s)$ in the second stage indicates the various lags across specifications. $\overline{G_{ic}}$ is the local average of the Gini coefficient, and $\overline{C_{ic}}$ denotes the average number of conflict events in area i . The international price for crude oil, $\$Oil_{t-1}$, is the yearly average of international oil prices in the prior year and is constant across locations. In countries with abundant oil resources, oil constitutes both a motivation and financing resource for rebel groups (Ross, 2008, Basedau and Lay, 2009, Dube and Vargas, 2013, Koubi et al., 2014). This is especially the case for countries with on-shore oil production, whereas the effect might run in the opposite direction in countries with mainly off-shore oil production, where governments exert the main control over the oil deposits and hence enjoy a financial advantage over insurgents (Andersen et al., 2022). For this instrument to have enough power to predict national conflict trends, I therefore subset my sample to countries with abundant on-shore oil resources that rebels could potentially attempt to capture. These are a total of 27 countries, which I illustrate in Figure A7 in the Appendix.¹⁶

For countries that began oil production during the sample period, I exclude the pre-production years. Note that, while Bazzi and Blattman (2014) show that natural resources do not significantly predict conflict onset at the national level, I control for social disputes at the national level with country-year fixed effects. I use the lagged oil price to avoid concerns that conflict in an oil-producing location may affect the global oil-price, and to allow violent actors to observe changes in the oil price and react to it. However, as shown in Appendix Table B12, my results are robust to using contemporary oil prices, whereas the first stage loses predictive power when leading the oil price or lagging it by more than one year. What is more, my results are further robust to subsetting the sample to countries in Sub-Saharan Africa, none of which has the market power to significantly affect the global oil price, let alone anyone of these countries' ADM2 districts. The control variables $X'_{ic,t}$ include local population density and a number of climate variables, all of which have been shown to be associated with civil conflict (see notes to Table 2). The

¹⁶Even though this limits the external validity of my findings (albeit only marginally as there is no significant difference in the OLS estimates between oil and non-oil countries as discussed below), I prefer this subsample for my main analysis to clearly establish a causal relationship between conflict exposure and medium-run economic activity. The advantage of limiting the analysis to the oil-producing subsample is that this allows for valuable falsification tests of the IV, as discussed in the robustness section below.

ADM2 fixed effects π_i account for time-invariant characteristics, while country-year fixed effects λ_{ct} control for common shocks at the country-year level. Note again that, since my instrumental variable consists of a triple interaction, I control for the interactions of the oil price with the average Gini coefficient and the average number of conflict events, respectively. The base-levels of these variables as well as the interaction term of the average Gini coefficient and average conflict are absorbed by the location fixed effects. The results are robust to not including these baseline-interactions (see Appendix, Table B13). In addition, the triple-interaction has much higher explanatory power than interacting the international oil price with either of the local shares alone. Neither the number of conflict events nor the Gini coefficient alone constitute a strong instrument as shown in Tables B14 and B15 in the Appendix.

Table 2 presents the 2SLS results for up to four lags of conflict exposure, while Figure 4 summarizes the causal estimates for longer lag structures of up to 12 years. Across all specifications, the coefficients for the lagged conflict exposure variables are statistically as well as economically highly significant. The first-stage F-statistics and second-stage t-values for all twelve lagged regressions are large enough to interpret the estimates as significant at the 5 percent level according to Lee et al. (2022)¹⁷ On average, a one-standard deviation increase in the share of the local population affected by conflict decreases local nightlights by around 17.3 percent in the same year.¹⁸ Even though the point estimates slightly decrease when lagging conflict exposure by one or more years, the negative effects on economic activity remain significant. A one standard-deviation increase of conflict exposure is associated with a decrease of about 11.6 percent of nightlights still four years later. Even twelve years later, local nightlights remain 5.8 percent lower. These results are robust to computing conflict exposure based on 1km or 5km buffers (Tables B16 & B17), or based on nightlights instead of population (Tables B18 and B19). These results are hence in line with the recent micro-level findings and suggest that conflict exposure significantly harms economic activity, both in the short- and the medium run.

Causal Interpretation. The causal interpretation of estimates recovered from shift-share 2SLS regressions is subject to several caveats. As I discuss in more detail in Section 5 below, the identifying assumption I require states that the local share, i.e., the interaction between a location’s average conflict propensity and its pre-sample economic concentration, is conditionally exogenous to the outcome variable of interest, i.e., contemporary lights at night (Goldsmith-Pinkham et al., 2020). Note that all specifications control for either level component of the local share, interacted with the

¹⁷Lee et al. (2022) provide a table with minimal F- and t-values needed for 5-percent significance. For example, the F-Statistic of 36.2 in Column (5) requires a t-value of at least 2.27. Hence, the t-value of my IV estimate of 4.33 allows to interpret the coefficient as significant at least at the five percent level.

¹⁸According to $(e^{\beta \times \sigma_x} - 1) \times 100\%$, for a standard deviation of conflict exposure of $\sigma_x = 0.024$.

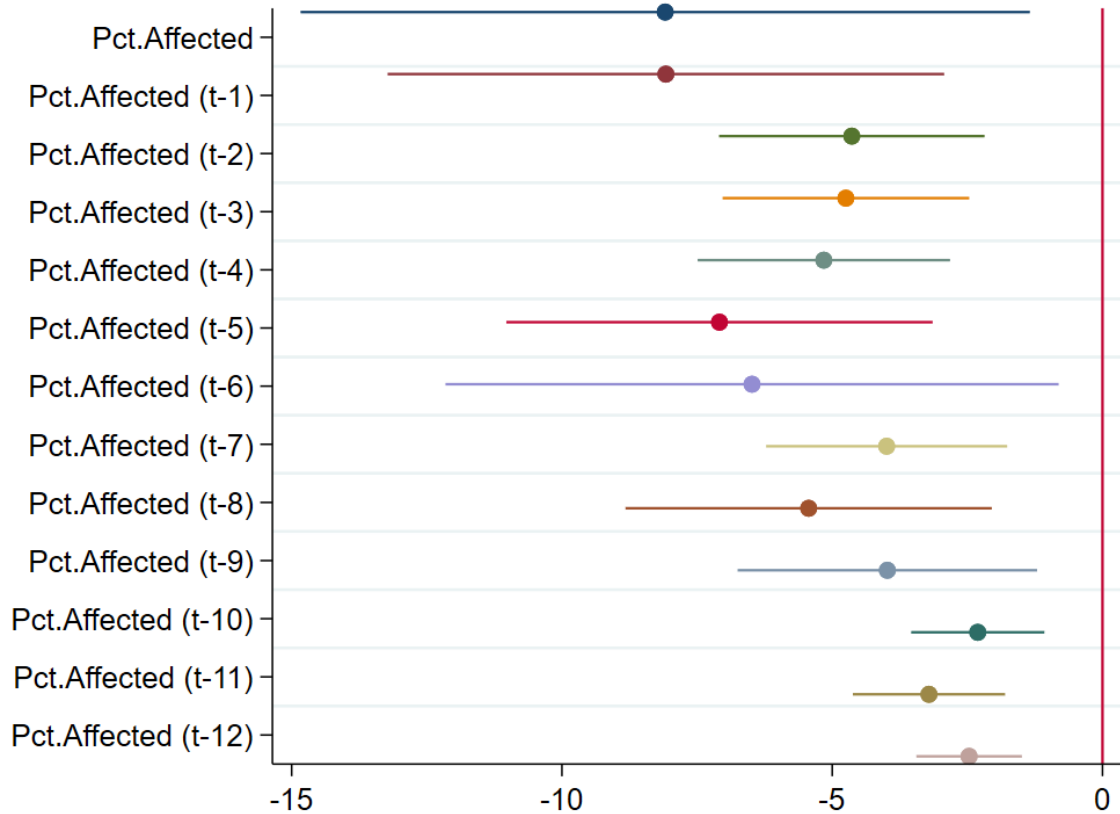
global oil price. Hence, all specifications acknowledge the endogeneity of locations' conflict propensity and economic concentration by directly controlling for it. Below, I provide a number of tests that suggest that the conditional independence assumption for the interaction term between economic concentration and conflict propensity is plausible.

Note further the difference in interpretation to Staggered Difference-in-Differences designs as discussed, among others, in [Callaway and Sant'Anna \(2021\)](#). Staggered Difference-in-Differences or event study designs compare entities that receive a treatment at some time period and *stay treated* for the rest of the sample to other entities that are not (yet) treated. Causal inference then requires the standard parallel trends assumption as well as avoiding negative weighting of observations by, e.g., comparing newly treated to already treated entities. Shift-share 2SLS estimations also require the parallel trends assumption to hold, following the idea of a two-period Difference-in-Differences setting ([Christian and Barrett, 2017](#)). In the case of this paper, this assumption implies that locations with high values of the interaction term between conflict propensity and economic concentration follow parallel trends in nightlight emissions as locations with lower values of the interaction term in years without a change in the oil price, conditional on the levels of conflict propensity and economic concentration. I test these assumptions for plausibility in Section 5 below. However, differently to Staggered Difference-in-Differences designs, observations cannot receive negative weights because the weights are explicitly assigned by the shifter in the specification, here the global oil price. Hence, the identifying variation stems from estimating the slope of my interaction between conflict propensity and economic concentration on lights at night, while observations in years with higher oil prices receive higher weights ([Borusyak et al., 2022](#)).

The interpretation therefore comes close to an Average Causal Response of the outcome on the treatment intensity (i.e., the value of the interacted shares) as recently discussed for Continuous Difference-in-Differences settings in [Callaway et al. \(2021\)](#). Finally, one last concern could be that oil price increases have persistent effects on conflict likelihood, hence inducing a bias from prior periods in the first stage estimation. However, I find the global oil price to have a rather short-run effect on conflict occurrence. As shown in Table B12, lagging and leading the oil price by several years demonstrates that the oil price only has significant predictive power when lagging it one year or using contemporaneous oil prices. Leads or longer lags of the oil price do not significantly correlate with conflict exposure.

There remains the question whether the evidence in favor of the micro-level studies indeed accrues due to the new measure introduced here, or whether the findings are driven by my identification approach. To investigate this possibility, I repeat the 2SLS regressions, but use the number of conflict events as the endogenous variable. The results in Table 3 indeed match the macro-level evidence. Conflict has strong detrimental effects in the short run, but the effect turns around for later years. While insignificant for

Figure 4 – 2SLS Regression Outcomes, further Lags



Notes: This Figure plots the 2SLS coefficients from regressing nights at light on conflict exposure. The regression follows the specifications in Table 2. Each plotted coefficient is derived from a separate 2SLS regression including all smaller lags as controls. The number of observations ranges from 190,624 in specification 1 to 74,969 in specification 13

the second lag (although here a weak instrument problem is an issue), regions that were exposed to conflict three or four years before show higher economic activity today. Hence, the main results in Table 2 accrue due to the new way to measure conflict exposure. Therefore, it is essential to take intra-regional variation in conflict locations into account.¹⁹

5 Instrument Validity & Robustness

Shift-share instruments are subject to several caveats. Two recent discussions from Goldsmith-Pinkham et al. (2020) and Borusyak et al. (2022) focus on the canonical sector-

¹⁹The results in Table 3 focus on countries in Sub-Saharan Africa due to weak IV issues. In Appendix Table B20, I provide results for the whole sample. Whereas the results are similar, the F-Statistics for the whole sample are not large enough to rule out a weak IV problem. Note further that the main 2SLS results reported in Table 2 are robust to subsetting the sample to Sub-Saharan Africa (see Appendix, Table B21).

Table 3 – 2SLS with Conflict Events as Endogenous Variable, 1992-2013

	(1)	(2)	(3)	(4)	(5)
	ln(light)	ln(light)	ln(light)	ln(light)	ln(light)
$\ln(\text{conflict})$	-0.517*** (0.149)	0.299** (0.116)	-0.431 (0.994)	0.0608 (0.0374)	0.0214 (0.0259)
$\ln(\text{conflict})_{t-1}$		-1.086*** (0.401)	-2.662 (6.169)	-0.0594* (0.0306)	0.0676 (0.0438)
$\ln(\text{conflict})_{t-2}$			11.16 (26.01)	-0.316** (0.136)	-0.0415 (0.0285)
$\ln(\text{conflict})_{t-3}$				1.496** (0.659)	-0.326** (0.153)
$\ln(\text{conflict})_{t-4}$					1.581** (0.755)
ADM2 FE	✓	✓	✓	✓	✓
Country-Year FE	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓
Obs	27,210	25,772	24,331	22,896	21,461
$F_{1st\ stage}$	34.04	13.87	0.187	9.963	7.699

Notes: This table reproduces the main results from Table 2 with the number of conflict events as the endogenous variable. Only African countries are used due to a weak IV problem with the worldwide sample – results for the complete sample are reported in the Appendix for comparability. The instrument is constructed by interacting a time-invariant indicator variable for positive conflict propensity with the international crude oil price. The controls include the Gini of light, population, precipitation, temperature, precipitation squared, and temperature squared.

Standard errors clustered at the ADM2 level in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

level shift-share approach and argue that either the conditional exogeneity of the local shares, or a large enough number of exogenous temporal shocks is a sufficient condition for Bartik-IV estimates to be unbiased. [Goldsmith-Pinkham et al. \(2020\)](#) suggest to focus on one of those assumptions, because the chances that both are fulfilled is very low. Therefore, I will follow their assumption of conditionally exogenous shares, especially because the alternative assumption from [Borusyak et al. \(2022\)](#) is unlikely to hold in my setting with a rather short sample period of only 20 years. Another relevant critique with specific focus on the non-industry setting comes from [Christian and Barrett \(2017\)](#). Their point is that a spurious correlation between the exogenous time-series and the endogenous variable can create falsely significant results, especially if the parallel-trends assumption fails. Similar to a Difference-in-Differences analysis, a valid shift-share estimation requires that locations with zero or very low propensity of being “treated” follow a trend parallel to those locations with a high treatment propensity. Finally, [Adão et al. \(2019\)](#) raise caution for inference in the shift-share framework. They show that locations with similar shares

likely underlie similar unobserved shocks, independent of their geographic proximity to each other. Hence, standard errors should be clustered in a way that accounts for correlated residuals across similar locations.

Table 4 – 2SLS: Oil vs. Non-Oil Countries

First Stage						
<i>Contemporaneous</i>			<i>Lagged</i>			
Sample:	All	Oil	Non-Oil	All	Oil	Non-Oil
	(1)	(2)	(3)	(4)	(5)	(6)
	Exposure	Exposure	Exposure	Exposure	Exposure	Exposure
IV	0.00531 (0.00537)	0.0166*** (0.00418)	0.00404 (0.00512)	-0.00303 (0.00409)	0.0197*** (0.00423)	-0.00503 (0.00401)

Second Stage						
<i>Contemporaneous</i>			<i>Lagged</i>			
	(1)	(2)	(3)	(4)	(5)	(6)
	ln(light)	ln(light)	ln(light)	ln(light)	ln(light)	ln(light)
<i>Exp</i>	-3.342 (4.030)	-8.089** (3.441)	0.458 (5.302)	-14.32 (16.43)	-5.155*** (1.191)	92.49 (1138.8)

Sample	All	Oil	Non-Oil	All	Oil	Non-Oil
FE	✓	✓	✓	✓	✓	✓
<i>N</i>	370,943	190,624	178,408	297,311	151,738	142,614
<i>F</i> _{1st}	0.978	15.82	0.622	0.537	36.20	0.00689

Notes: This table repeats the 2SLS regressions presented in Table 2, but for different samples. Columns (1)-(3) reproduce the results from 2, column (1), using contemporaneous conflict exposure, Columns (4)-(6) reproduce the results from 2, column (5), lagging conflict exposure 4 years. Columns (2) and (5) mirror the original estimates using the same oil-country sample as Table 2. Columns (1) and (4) use the full sample of African countries, columns (3) and (6) include non-oil producing countries only. The unit of observations is the second administrative area (ADM2) for countries with active on-shore oil production. The endogenous variable is the share of lights at night within 3km to a conflict event and is instrumented by a triple-interaction of *i*) the regional average of conflict events *ii*) the regional average of the Gini of lights and *iii*) the yearly world price for crude oil. All regressions include a control variables population density, precipitation, precipitation squared, temperature, temperature squared, as well as ADM2 and Country-Year Fixed Effects. All regressions also control for the endogenous exposure variable in year t (column 1 aside) as well as for the yearly number of conflict events and the yearly Gini of lights in year $t - s$, where s indicates the lag of the endogenous variable.

Standard errors clustered at the ADM2 region in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Christian and Barrett (2017) and Goldsmith-Pinkham et al. (2020) suggest to run a placebo-test to check whether the time series generates weak instruments in constellations where we would not expect it to affect the endogenous variable. As my 2SLS sample focuses on oil-producing countries for identification, I repeat my main regressions for non-oil producing countries. As the international oil prices should only affect the capacity

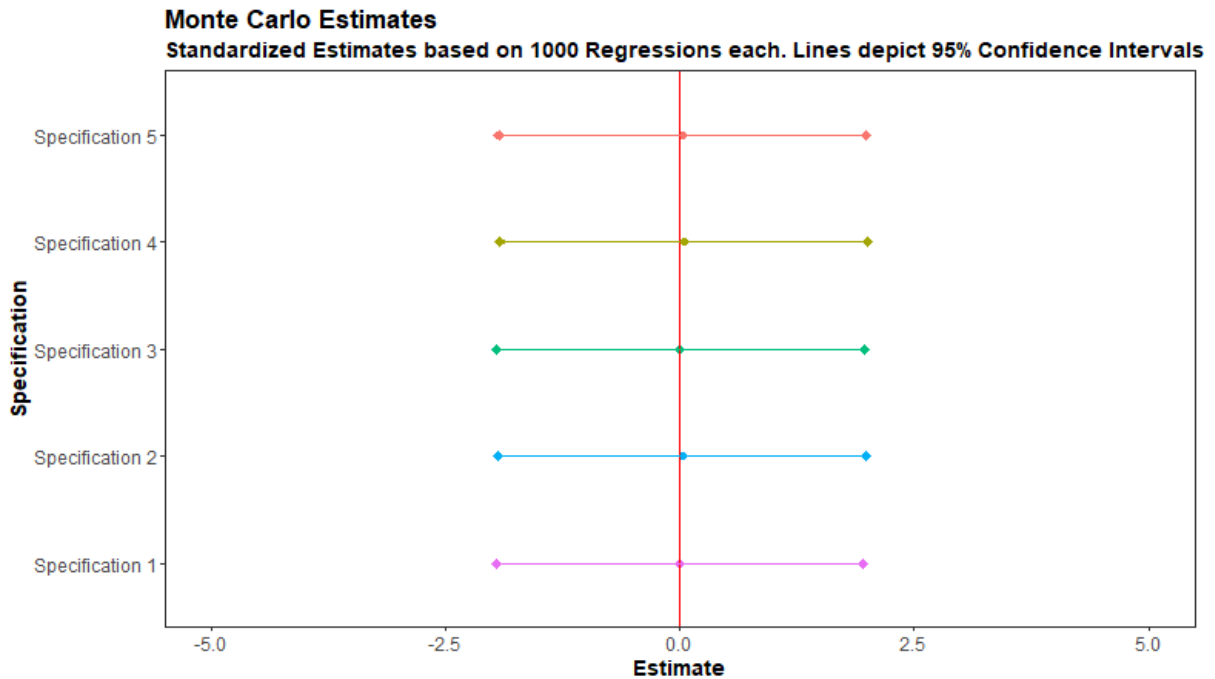
and motivation to fight for rebels in oil-producing countries, we would expect no effect in this alternative sample. Table 4 presents results from the same regressions as in Table 2, Columns (1) and (5), but based on samples of either (i) all countries, (ii) only oil-producing countries as for my main 2SLS regressions, or (iii) only non-oil producing countries. Indeed, the IV only works if I restrict the sample to oil-producing countries. The Kleibergen-Paap F-Statistic is exceptionally low for the complete sample as well as the non-oil sample. It is hence unlikely that a spurious correlation between the oil price and local conflict waves drives my results. Another important assumption in Goldsmith-Pinkham et al. (2020) and Christian and Barrett (2017) is that locations with higher odds of conflict and locations with lower odds of conflict should follow parallel trends in the dependent variable. In essence, shift-share IVs rely on a Difference-in-Differences estimation in the first stage. Instead of comparing the two groups across two periods, my shift-share instrument assumes that the treatment effect shows up in years when the oil price is high and vice-versa. This is, the identifying variation must come from short-term fluctuations in “treated” locations compared to “control” locations, while there should be no difference in the long-term trends between the two groups. In Figure A9, I compare the trends of never treated and sometimes treated, as well as the trends of the non-zero propensity locations below median to those above median conflict propensity.²⁰ These locations follow an astonishingly similar trend. I interpret this as support that the parallel trends assumption holds.

Next, Goldsmith-Pinkham et al. (2020) argue that a central assumption is the exogeneity of local shares conditional on covariates. In my case, this means that the *interaction* of the average Gini and the average number of conflict events must be uncorrelated with the compound error term when controlling for both, the average Gini and the average number of conflict events along with the other control variables. As a formal check for the plausibility of this assumption, the authors suggest to regress the shares on a number of potential confounders. Figure A8 in the Appendix reports the estimates from regressing the local shares on various potential confounders, conditional on the control variables used in the 2SLS main regressions. This demonstrates that a number of variables that may co-determine local economic activity and conflict exposure, e.g., drug cultivation or petrol production, are not significantly related to the local shares. While some geographic variables like mountainous area or the share of agricultural land are significantly related to the local shares, it is unlikely that these temporally constant variables are correlated with the error term in my 2SLS panel regressions once ADM2 fixed effects are accounted for.

As a final check, Christian and Barrett (2017) recommend randomly re-allocating the non-zero values of the endogenous variable within each year, and then re-estimating the

²⁰Never treated, or zero-propensity, locations would be those ADM2 locations for which no conflict event was recorded over the whole sample period.

Figure 5 – Monte Carlo Estimates



Notes: This Figure plots the confidence intervals based on 1000 estimations following the main specifications from Table 2. Specification 1 follows Column 1 and regresses lights on contemporary conflict, while Specification 5 follows Column 5 and lags conflict exposure 4 years. For each estimation, the endogenous variable was re-allocated among all observations with non-zero conflict exposure in a given year. All estimates are standardized to ease display.

2SLS regressions. If the identification indeed relies on a non-spurious correlation with the time-series, randomly re-allocated values of the endogenous variable should on average produce results around zero. I produce 1000 randomly re-arranged conflict exposure variables and re-estimate the main regressions presented in Table 2. The confidence intervals for the second-stage estimates based on any of the five specifications are all centered around zero (see Figure 5). This further encourages a causal interpretation of my main results.²¹ To test for the concern of correlated residuals according to Adão et al. (2019), I repeat my main regressions with standard errors clustered at the (i) conflict-propensity level, (ii) average Gini coefficient-level, or (iii) with two-way clustered errors in both aforementioned dimensions. The results depicted in Figure A11 show that my results are unaffected by different levels of clustering.

My 2SLS results are further robust to various alternative specifications. The results remain similar when varying the lag of the global oil price within a short period of time (Table B12), controlling for province-year fixed effects (Table B22), holding the sample constant over the lag structures (Table B23), or using the Gini-coefficient based on lights

²¹For further inspection, the time series of the oil price and the global number of conflict events is plotted in the Appendix, Figure A10.

in 1992 instead of the mean Gini for the local shares (Table B24). Moreover, restricting my sample to conflict events with at least five casualties and hence more accurate media coverage (see Weidmann, 2015, for a discussion) leaves the results mostly unaffected (see Table B25).

6 Extensions

I conduct a couple of extensions to the main findings. Below, I present alternative analyses at different spatial resolutions, tests for potential channels as well as spatial spillover effects, and relate the conflict exposure measure developed in this paper to findings based on alternative measures in the prior literature.

Country level analysis. First, to extrapolate my main findings to a higher spatial aggregation and to explore potential mechanisms, I construct the conflict exposure measure at the country level using 5km, 10km, and 15km buffers. At the country level, more moderating variables are available, and I can extend the sample period to the years 1989–2019, as I am no more constrained by the availability of nightlights data. Table 5 provides the results from regressing various dependent variables on (lagged) conflict exposure. Note that all regressions control for the (lagged) number of conflict events, so the conflict exposure coefficients provide the effect of conflict exposure *conditional on* the number of conflict events inside a country. Note further that I abstain from using nightlights as an outcome variable as they were only validated as good proxies at the local level and are therefore barely used at the country level. Column (1) constitutes a robustness check to the main regressions discussed above. Here, I regress the natural logarithm of GDP per capita on lagged conflict exposure. Across all five specifications, the results suggest a negative relationship between GDP per capita and conflict exposure. This relationship is statistically significant for the first, second, and third lag, hinting at a medium-run, persistent effect of conflict exposure on economic activity. The next four columns test for potential mechanisms. Two reasons for persistent effects of conflict exposure can be the diversion of investments and/or people away from the affected location. In Columns (2) and (3), I test for these potential channels by regressing the ratio of Foreign Direct Investments (FDI) to GDP and the share of the externally vs. internally displaced people on conflict exposure. Column (2) suggests a slightly delayed but persistent negative effect of conflict exposure on FDI. While all specifications report negative coefficients, these coefficients are only statistically significant for the second, third, and fourth lags. These results suggest that international investors react (slowly) to high conflict exposure and divert their investments away from the conflict country. These findings are further in line with the results in Korn and Stemmler (2022), who find that civil conflict has a persistent effect on international economic cooperation.

Table 5 – Country-Level OLS Regressions, 1989-2019

	(1)	(2)	(3)	(4)
	ln(GDP p.c.)	FDI/GDP	Ext.Displaced	ln(US Aid)
<i>Exposure</i>	-0.0650 (0.0650)	-1.375 (1.982)	0.184** (0.0799)	0.290 (0.503)
<i>Exposure_{t-1}</i>	-0.111** (0.0498)	-1.805 (1.891)	0.256*** (0.0951)	0.248 (0.469)
<i>Exposure_{t-2}</i>	-0.125** (0.0561)	-2.368** (1.080)	-0.0295 (0.0910)	0.421 (0.277)
<i>Exposure_{t-3}</i>	-0.0972** (0.0469)	-2.430* (1.249)	0.0988* (0.0572)	0.185 (0.248)
<i>Exposure_{t-4}</i>	-0.0297 (0.0581)	-2.428* (1.294)	0.0970 (0.0737)	0.248 (0.269)
Country FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Controls	✓	✓	✓	✓
<i>N</i>	4,335	4,329	2,360	3,500
<i>R_{adj}²</i>	0.981	0.217	0.588	0.839

Notes: This table displays OLS results with conflict exposure as the main explanatory variable. The unit of observation are countries. All regressions control for log(Population), the number of conflict events, IO membership, and political rights, along with country- and year-fixed effects. Standard errors clustered at the country-level in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

In Column (3), the dependent variable is the share of externally displaced people over the total number of externally *and* internally displaced people. I chose this dependent variable because in theory, high conflict intensity with a low spatial radius of conflict (i.e. low conflict exposure) on the one hand displaces people from their homes, but allows them to stay inside the borders of their home country. Only if conflict exposure increases, i.e. if more parts of the country are subject to conflict, then people must exit the country entirely to escape from violence. The results in Column (3) support this argument. Holding the number of conflict events constant, a higher conflict exposure is associated with a higher rate of external displacement. Contrary to the FDI-results, this effect appears immediately. Conflict exposure in the same year as well as the year before is significantly associated with a higher share of external displacement, whereas later lags do not lead to estimates that are significant at the five percent level or below. Finally, Column (4) evaluates whether the US as a donor considers conflict exposure as a relevant variable to allocate development aid. The throughout-insignificant coefficients suggest that this is not the case. Whereas the number of conflict events during the same year is slightly related to a higher amount of development aid (not shown), the actual

exposure to conflict by the local population seems not to be taken into account in the aid allocation decision.

Spatial Spillovers. A second extension concerns spatial spillovers. Table B26 reports OLS estimates which account for two different spatial dimensions. First, Column (2) introduces a spatial lag of conflict exposure as an additional explanatory variable. This spatial lag interacts conflict exposure in close locations with a spatial decay function and allows conflict exposure in proximate locations to affect nightlight activity in the observed location, weighted by the inverse distance to the observed location. I find that the direct effect of conflict exposure on nightlights remains significantly negative, while spatial spillovers of conflict exposure have a significantly *positive* effect on local economic activity. This likely hints at displacement effects: when conflict exposure forces people and capital to leave one location, close-by locations absorb this displaced economic activity. Yet, despite economic activity spilling over to neighboring locations as people avoid civil conflict, the results in Table 5 above suggest that at the aggregate, countries still experience a decrease in economic output. Hence, movement frictions seem to create a loss in productivity. As people and businesses switch to neighboring locations they increase output in these new locations, but not enough to compensate the loss in their location of origin.

As a final test for spatial spillovers, I introduce lagged spatial residuals to account for clustered shocks across close locations in Column (3). Whereas the introduction of lagged residuals noticeably decreases the point estimate of conflict exposure, hinting at spatially correlated shocks, the coefficients of both the direct and lagged effects of conflict exposure remain statistically significant.

7 Conclusion

Civil conflict leaves a persistent imprint on (local) economies. Whereas prior evidence on this question is mixed, this paper confirms results from mostly individual-level data by leveraging a new measure for conflict exposure that takes account of intra-regional variation in conflict locations. I find that spatially concentrated economies are more vulnerable to civil conflict, and that accounting for this heterogeneity uncovers a robust negative relationship between economic activity and conflict exposure in the medium run. There remain open questions about what role economic centralization plays for conflict vulnerability. We are still far from understanding what determines the capacity of post-conflict reconstruction, and how economic centralization plays a role in that. First and foremost, the results presented here do only test the medium run effects for up to twelve years after conflict. However, there remains the question whether the detrimental effect of conflict extends to the (very) long run. For this, it is essential to understand

better how conflict exposure affects local reconstruction capabilities. More work is hence needed to discover the actual channels driving the results found here, e.g. by investigating whether migration, trade, or FDIs respond differently to conflict in centralized locations than in decentralized ones. What is more, the natural question arises how regions can improve their post-war reconstruction capabilities, and how the international community can assist them in this task. Incentives to migrate or invest back in the affected locations seem a helpful approach, but need more evaluation to find out what helps and what does not.

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Appendix

A Figures

Figure A1 – Conflict and Growth in Ukraine and Yemen

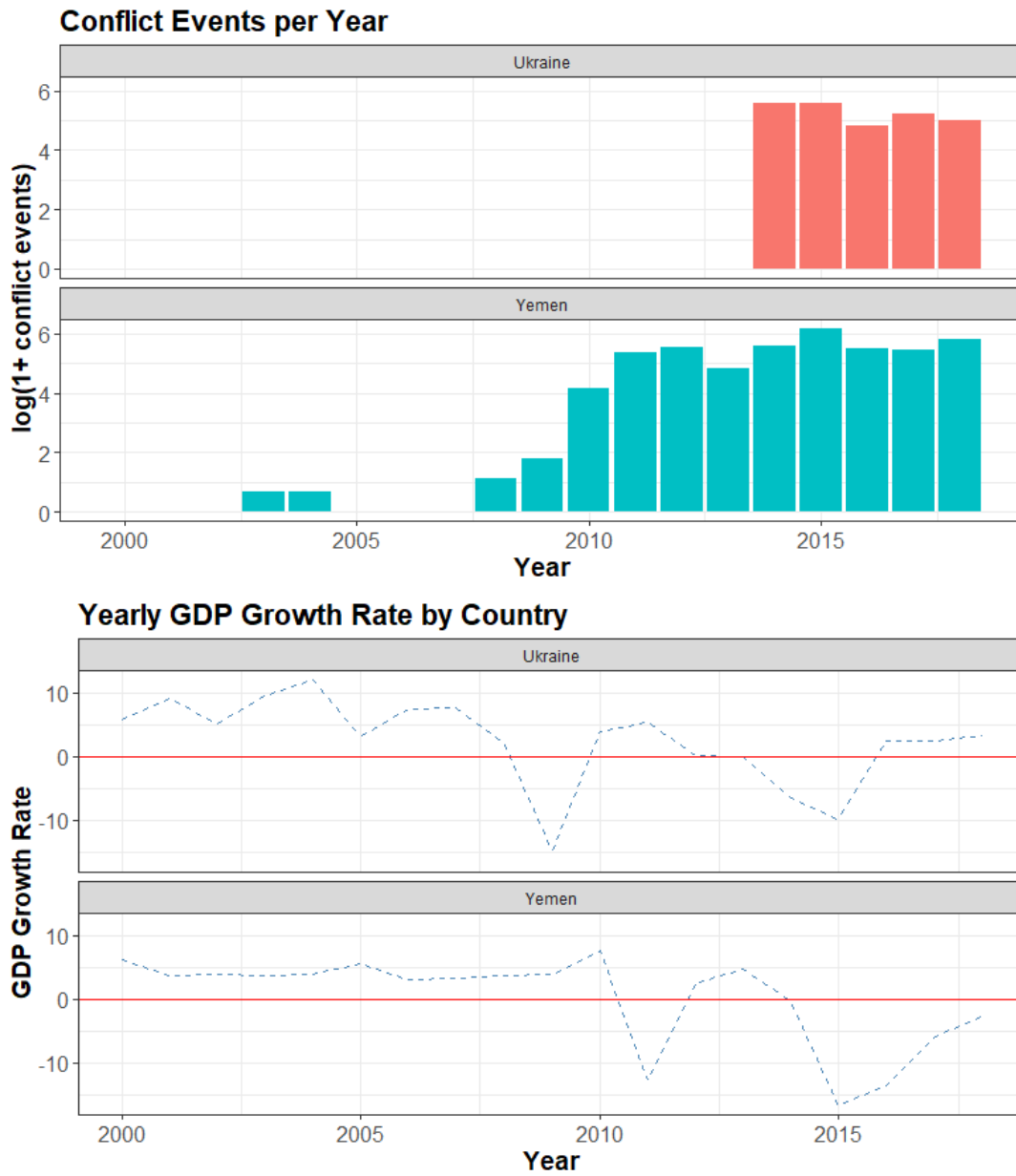
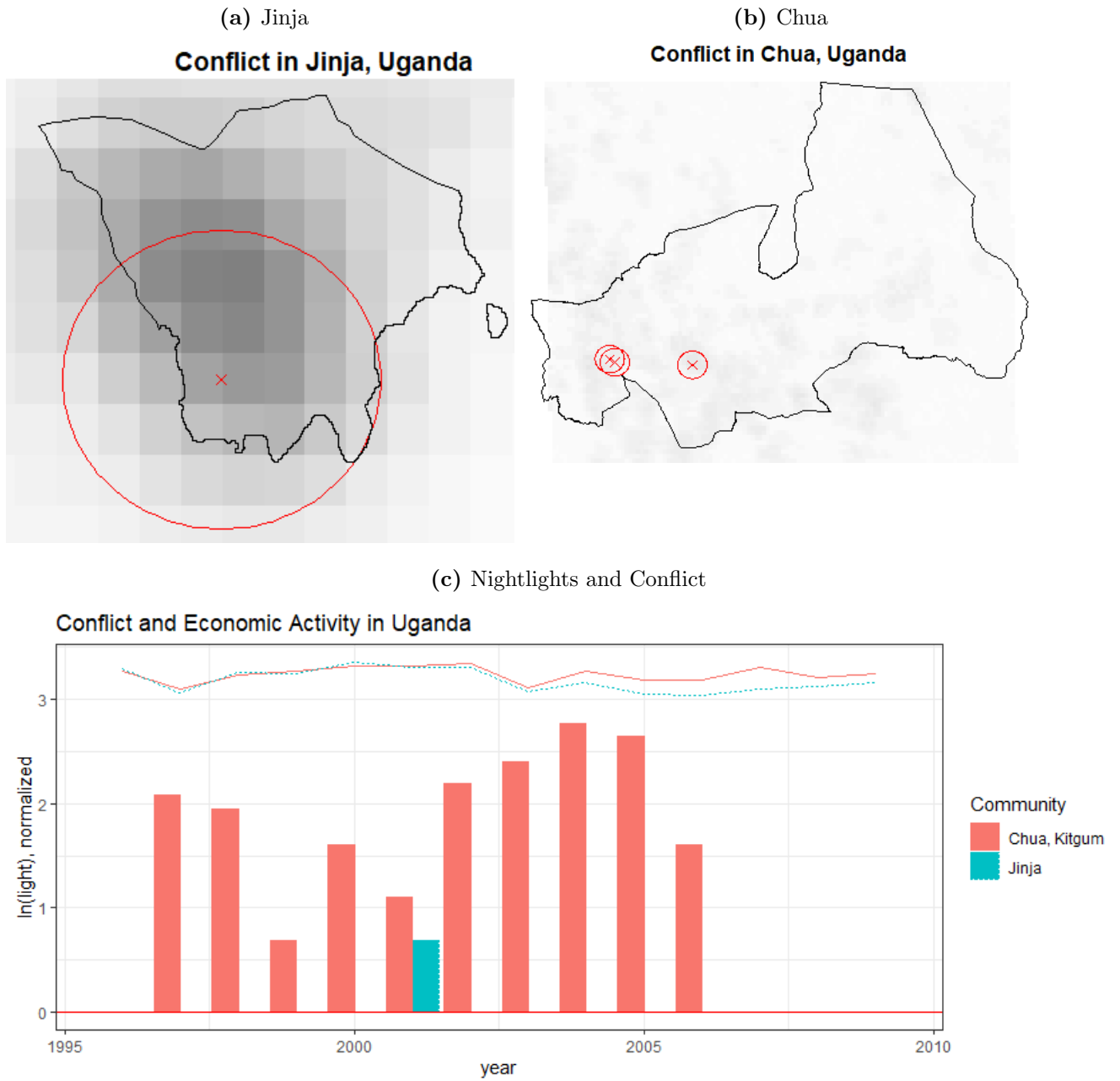


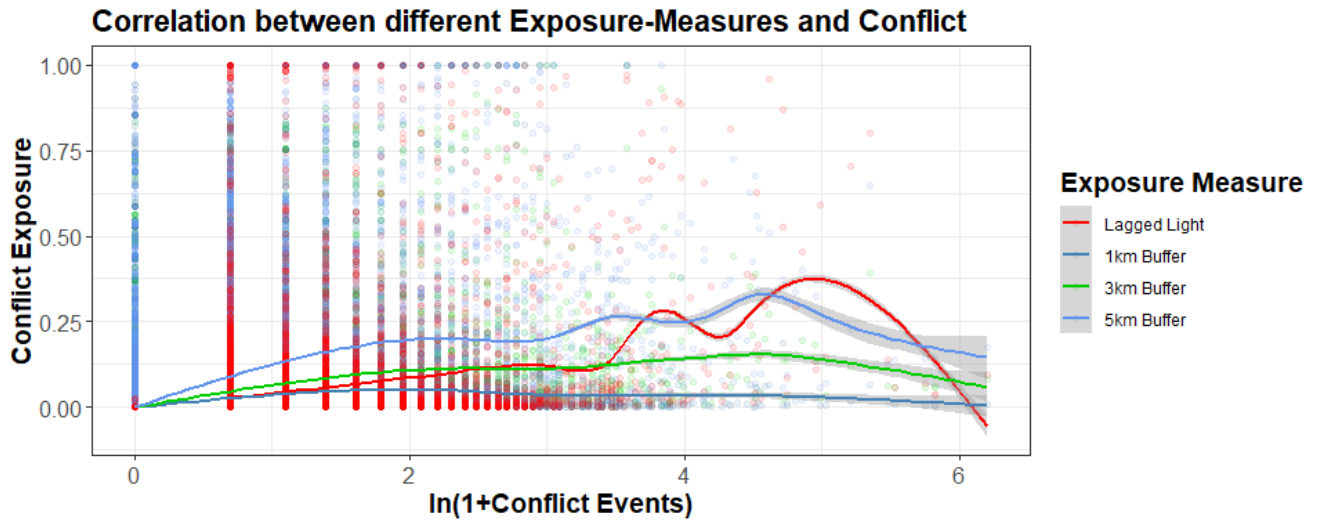
Figure A2 – Conflict and Growth in Uganda



Notes: This figure provides a subnational example for the intuition of this paper. Subfigure (a) displays the distribution of nightlights (in inverted grey-scale) in the South-Ugandan district Jinja, which includes Uganda’s fourth-biggest city of the same name. In Jinja, only one conflict event occurred during the sample period. This conflict event is indicated by a red cross and surrounded by a 3km-Buffer, also in red. However, this conflict event was located at a relatively central place in the rather small region and hence affected a large share (around 51%) of the region’s economic activity. Subfigure (b) shows the same relationship for Chua, a rather large but decentralized district in Northern Uganda. Here, a total of 72 conflict events occurred during the sample period, but the conflict locations cluster in only small parts of the region. On average, less than 1% of Chua’s economic activity was close to a conflict event in any given year. The chart in subfigure (c) compares the trends in economic activity (proxied by the normalized natural log of nightlights) and the natural log of civil conflict in both regions. Up to 2002, both regions followed a similar trend in economic activity. However, in the aftermath of the one conflict event in Jinja (dashed line), its total nightlight emissions drop noticeably below the output of Chua (solid line) and remains below for more than five years. 35

Figure A3 – Exposure Measures vs. Common Conflict Measures

(a) Conflict Events



(b) Fatalities

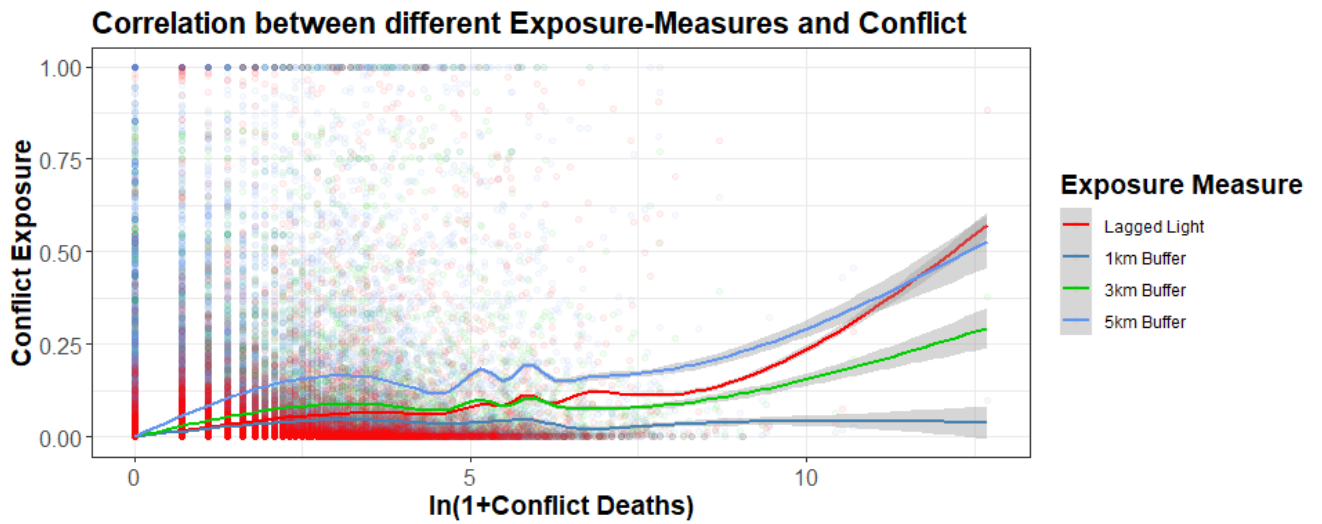
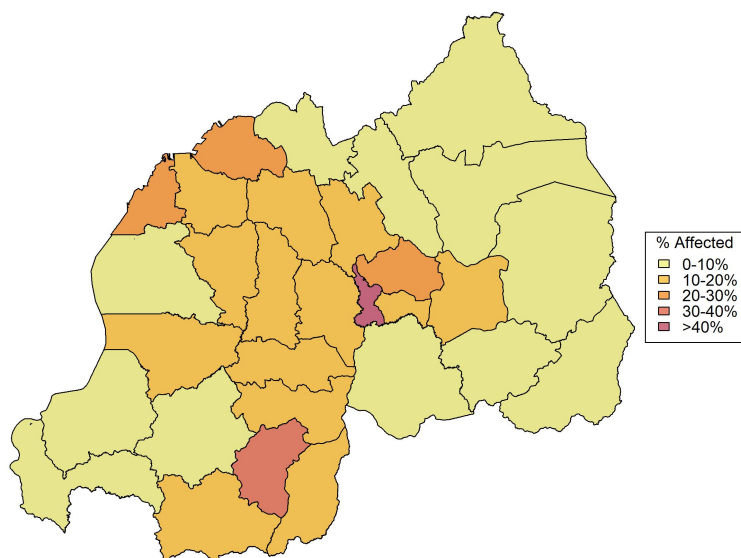


Figure A4 – Example: Rwanda

(a) Battle Shares

Average Battle Shares in Rwanda



(b) Light-Gini and Conflict Events

Rwanda: Light-Gini and Conflict Events

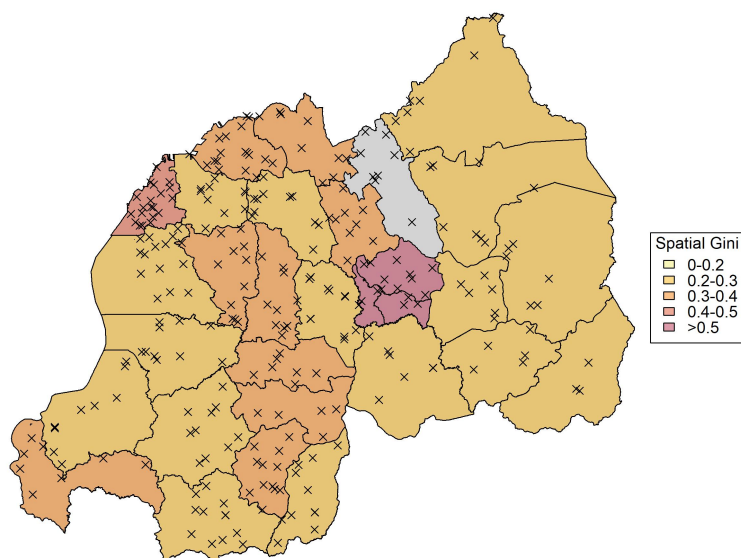
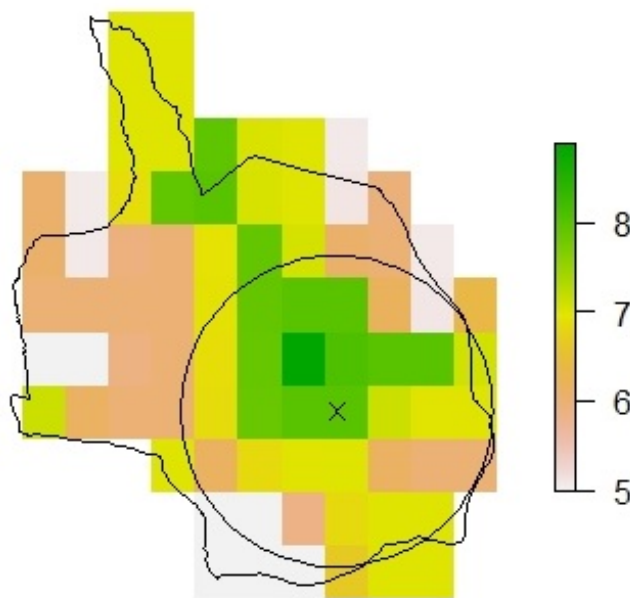
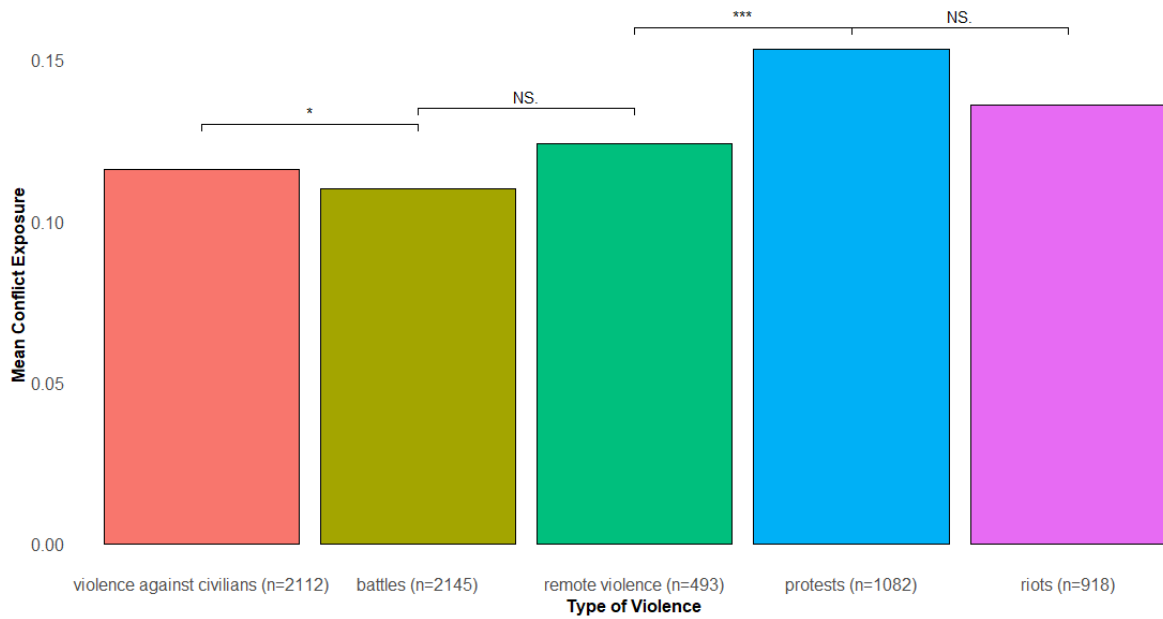


Figure A5 – Example: Conflict Exposure in Gulu, Uganda 2001



Notes: This figure provides another intuition for the construction of conflict exposure based on Gulu, Uganda in 2001. In this example, a total of six conflict events were associated with the same location inside Gulu, indicated by the cross. The buffer around these conflict events indicates which raster cells are located three kilometers or less away from these conflict events. Nightlight emissions are recorded in “Digital Numbers” (DN), where a higher DN refers to a brighter spot. In the example here, a total of 280DN fall inside the buffer around the conflict events. In Gulu region in total, nightlight emissions summed up to 444DN. Hence, the measure of conflict exposure in Gulu in 2001 amounts to $\frac{280}{444} = 63\%$.

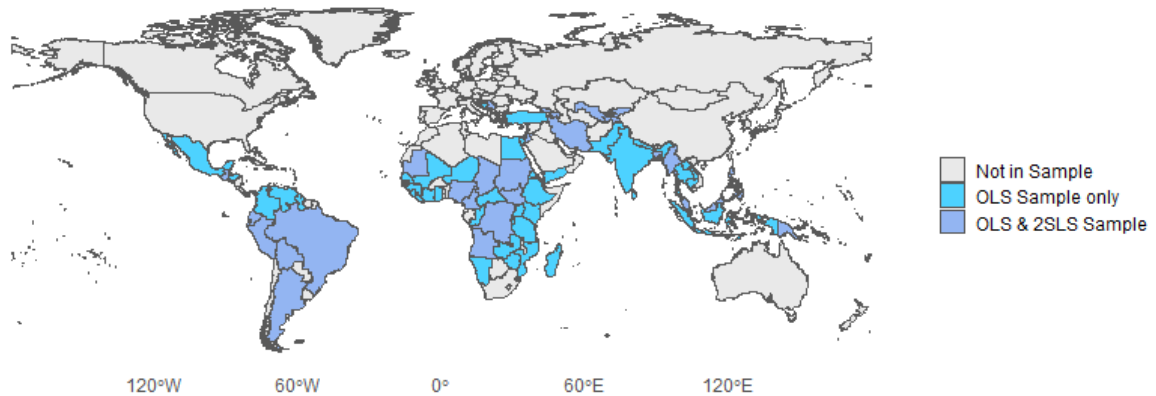
Figure A6 – Conflict Exposure Disaggregated by Type of Unrest



Notes: This figure plots the average conflict exposure across types of civil unrest for all observations with positive exposure measures. All conflict exposure measures are based on ACLED event data and calculated for subnational ADM2 regions in 33 countries in Sub-Saharan Africa, 1997–2013. Bars indicate the significance of inter-group differences, sym* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$, N.S. = “Not Significant”.

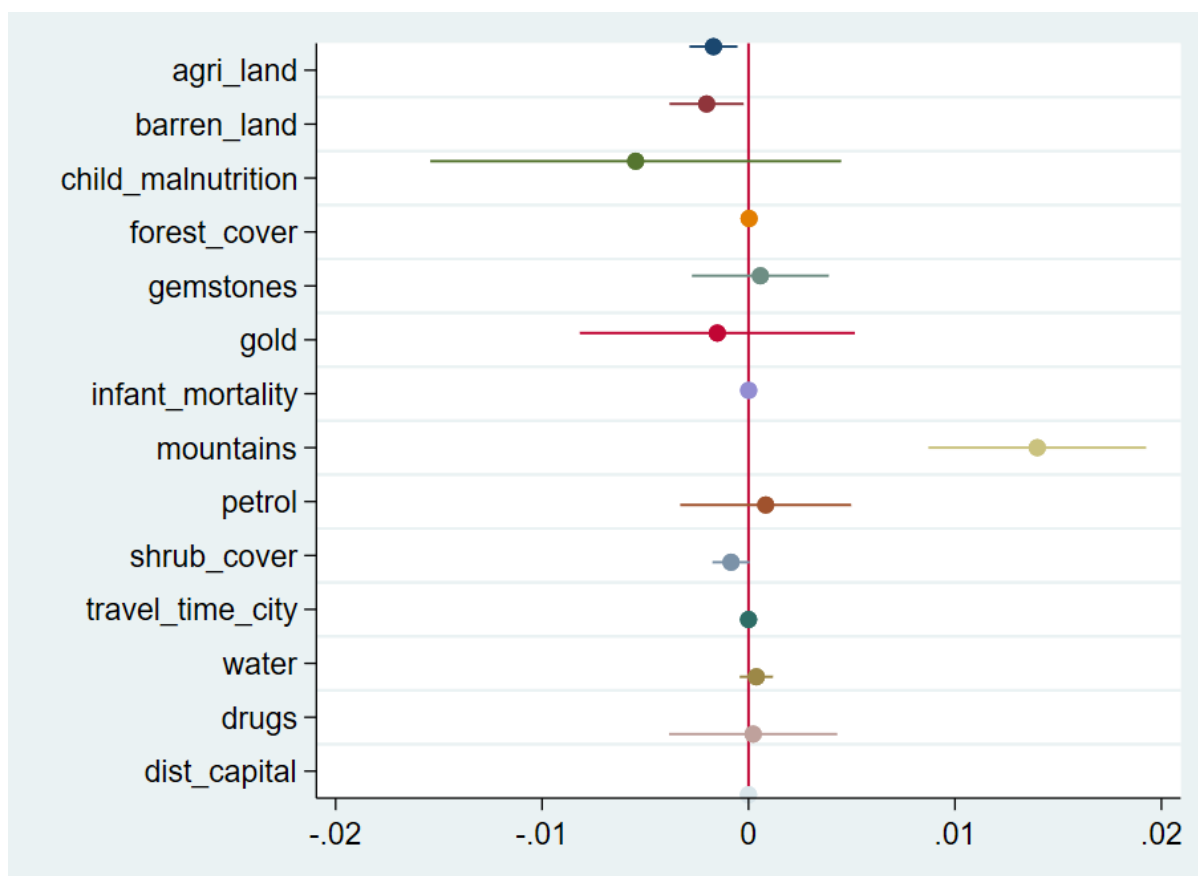
Figure A7 – Overview of Sample Countries

Overview of Sample Countries



Notes: This figure illustrates the sample compositions for the different specifications. Colored in dark-blue are conflict-countries with on-shore oil-resources, which are included in both the OLS and 2SLS estimates. Countries colored light-blue are part of the OLS sample, but excluded from the 2SLS sample as they did not produce on-shore oil during the sample period. Countries colored grey are not part of any sample.

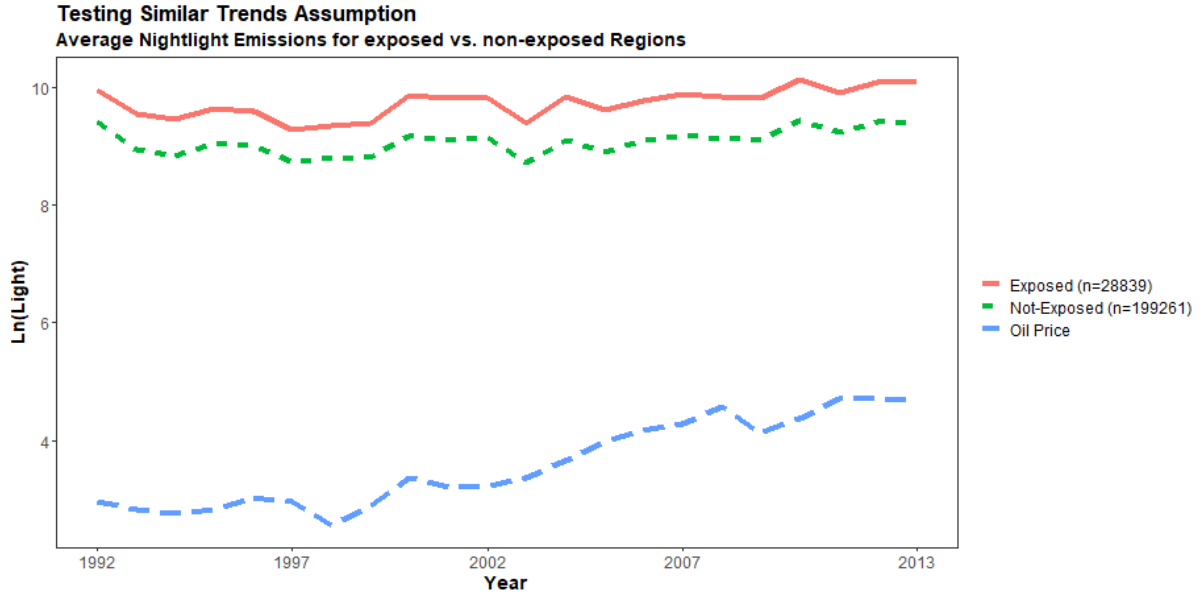
Figure A8 – Correlation of local Shares



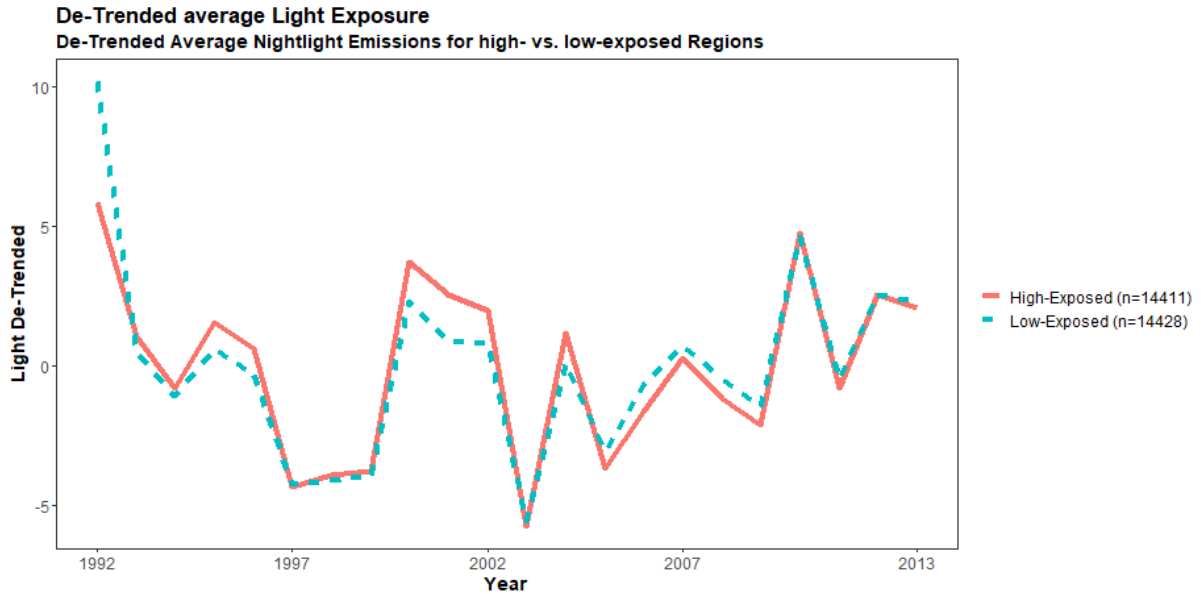
Notes: This figure reports the point estimates and the 90%-confidence intervals from regressing the local shares (i.e. the interaction of average conflict and the average Gini coefficient) on various potential confounders. All regressions control for average conflict, average Gini, average population density, average precipitation (squared), average temperature (squared), and province fixed effects.

Figure A9 – Parallel Trends of Dependent Variable by Regional Share

(a) Some conflict vs. never conflict

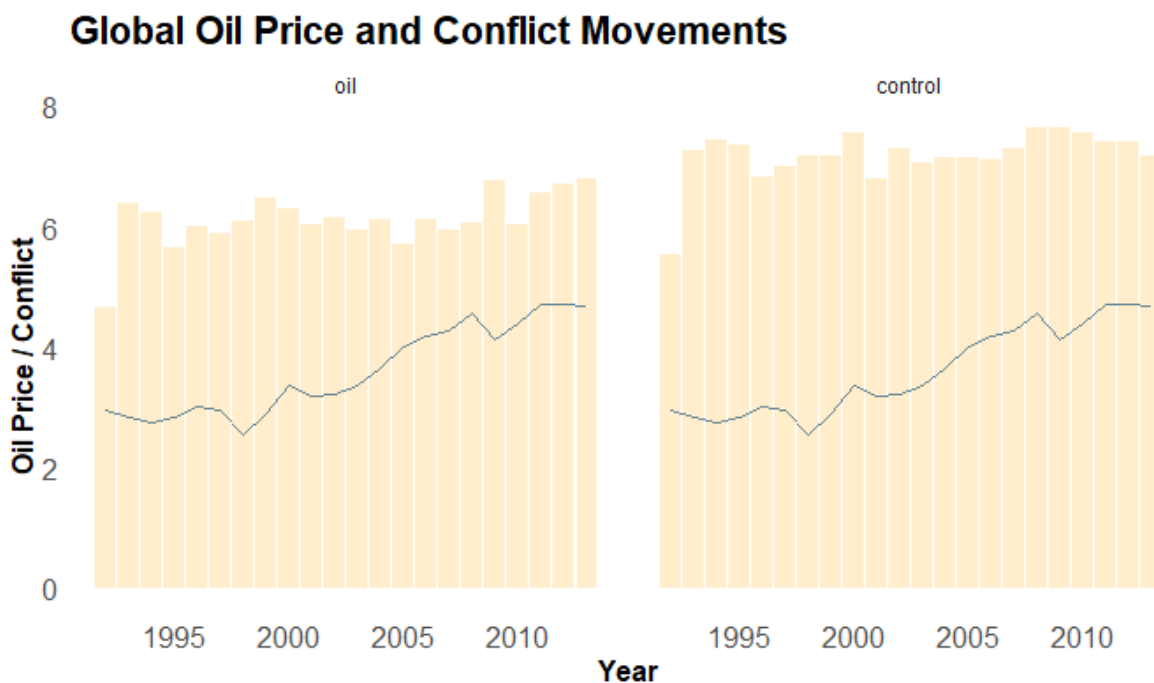


(b) Above-Median Conflict vs. Below-Median Conflict, de-trended



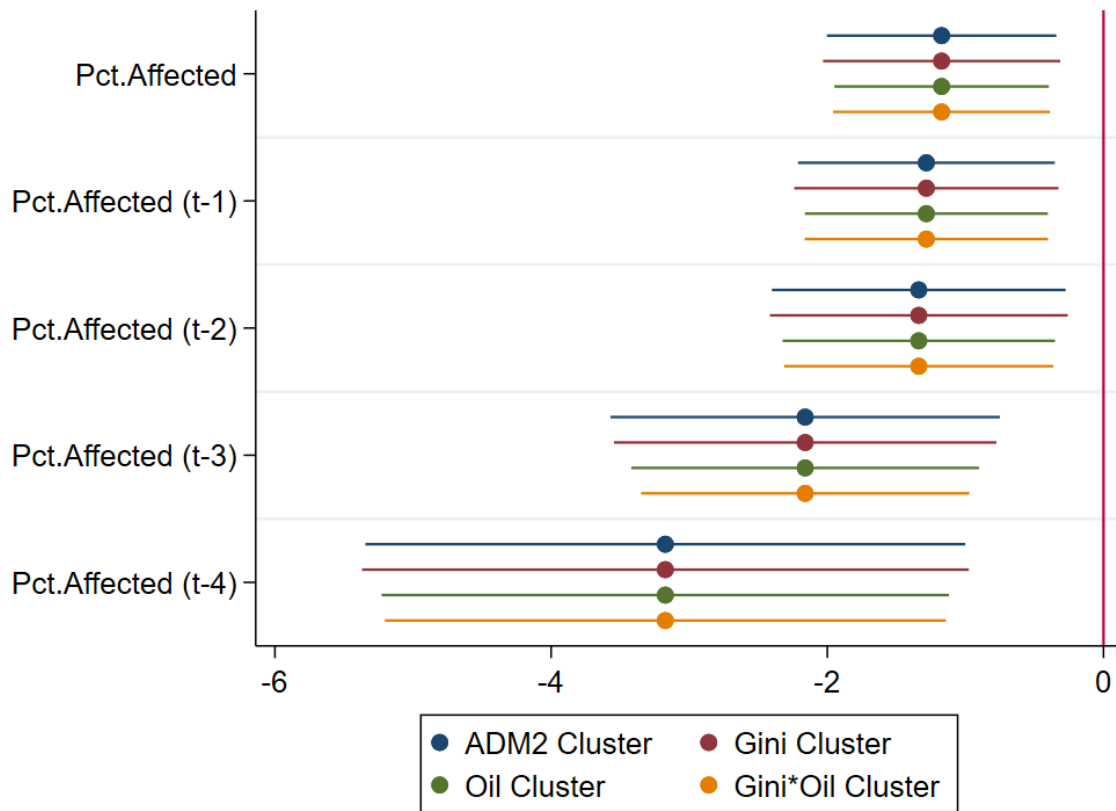
Notes: This figure plots the yearly group-level average nightlights omissions of ADM2-regions in the 2SLS sample. Panel (a) plots the yearly means of nightlights for locations with a Bartik-IV share bigger than zero (i.e., with more than one conflict event in the sample period) together with the yearly means of locations with zero share. The oil-price is included to allow for a comparison of overall trends. Panel (b) plots de-trended versions of the yearly mean-values, and further only considers locations with non-zero Bartik IV shares but splits the sample into above-median and below-median shares. Both graphs point to similar overall-trends across locations with different treatment-propensity and therefore suggest that the similar-trends assumption is likely to hold.

Figure A10 – Yearly Oil Price and Conflict Events in Logs.



Notes: This figure plots the time series for the global oil price (line) and total yearly conflict events (bars), separated for oil-producing and non-oil-producing countries.

Figure A11 – Different cluster dimensions following Adão et al. (2019)



Notes: This Figures plots the estimates and confidence intervals of the main 2SLS specifications with standard errors clustered at either the location-level, the conflict-propensity, the average Gini coefficient, or with two-way clusters at the conflict-propensity and Gini coefficient level. Lines depict 95% Confidence Intervals.

B Additional Tables

Table B1 – Descriptive Statistics

Statistic	N	Mean	Full Sample				
			St. Dev.	Min	Pctl(25)	Pctl(75)	Max
exposure	459,067	0.002	0.035	0	0	0	1
ln_light	461,487	8.160	1.527	0	7.101	9.188	14.221
light_gini	426,060	0.363	0.112	0.001	0.280	0.438	0.883
conflict_events	461,487	0.091	1.790	0	0	0	493
pop_dens	457,575	445.936	2,369.469	0	20.748	187.149	76,856
precipitation	435,175	920.646	3,180.088	0	90.732	776.561	181,425
temperature	444,090	22.243	5.173	-7.102	19.578	26.287	32.310
agri_land	450,597	44.465	29.797	0	17.231	69.901	99.985
barren_land	450,597	3.783	15.472	0	0	0.068	100
forest_cover	450,597	30.371	26.038	0	7.606	48.503	99.834
shrub_cover	450,597	9.266	13.820	0	0.438	12.552	98.577
water_share	450,597	5.440	12.694	0	0.015	2.515	95.599
gemstones	450,597	0.060	0.237	0	0	0	1
gold	450,597	0.016	0.124	0	0	0	1
petrol	450,597	0.042	0.200	0	0	0	1
dist_capital	450,597	599.089	499.601	4.387	202.507	860.737	3,776
dist_city	450,597	263.903	337.510	14.829	113.478	290.778	6,585

Statistic	N	Mean	2SLS Sample				
			St. Dev.	Min	Pctl(25)	Pctl(75)	Max
exposure	232,388	0.001	0.024	0	0	0	1
ln_light	232,410	8.000	1.553	0	6.914	9.032	13.972
light_gini	214,893	0.371	0.111	0.001	0.289	0.447	0.794
conflict_events	232,410	0.044	0.741	0	0	0	114
pop_dens	230,970	292.703	1,450.118	0	15.837	152.337	61,225
precipitation	217,226	963.377	3,980.622	0	96.971	626.525	181,425
temperature	221,665	22.288	4.936	-7.102	19.743	26.083	32.201
agri_land	227,130	49.997	28.359	0	28.290	73.670	99.917
barren_land	227,130	2.847	12.811	0	0	0.052	100
forest_cover	227,130	27.065	23.699	0	8.194	40.071	99.834
shrub_cover	227,130	10.080	14.437	0	0.775	13.157	96.079
water_share	227,130	5.676	13.019	0	0.015	2.552	92.056
gemstones	227,130	0.034	0.181	0	0	0	1
gold	227,130	0.012	0.107	0	0	0	1
petrol	227,130	0.047	0.212	0	0	0	1
dist_capital	227,130	759.277	505.502	4.387	340.144	1,110.527	2,873
dist_city	227,130	250.118	322.690	14.829	104.396	270.996	5,244

Table B2 – OLS: Economic Activity affected by Conflict

	(1)	(2)	(3)	(4)
	Exposure	Exposure	Exposure	Exposure
G_{Light}	-0.00864** (0.00386)	-0.0171*** (0.00353)	-0.00571 (0.00399)	-0.00741*** (0.00256)
$Conflict$	0.0549*** (0.00328)	-0.0157 (0.0113)	-0.0151 (0.0107)	-0.0249*** (0.00558)
$G_{Light} \times Conflict$		0.216*** (0.0372)	0.214*** (0.0332)	0.211*** (0.0215)
Country-Year FE	✓	✓	✓	✓
ADM2 FE			✓	✓
Geo Controls				✓
N	410,495	410,495	410,495	387,403
F	77.34	62.78	83.73	60.27
R_{adj}^2	0.158	0.184	0.399	0.403

Notes: This table shows OLS results with conflict exposure as dependent variable. The unit of observations is the second administrative area (ADM2) for the sample of 70 countries. The main explanatory variables constitute (a) the natural logarithm of the number of conflict events, denoted by “Conflict”, and (b) the Gini coefficient of nightlights, denoted by “ G_{Light} ”. Controls are the sum of lights, population, (squared) precipitation and (squared) temperature. Standard errors clustered at the ADM2 region in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table B3 – OLS: Economic Activity affected by Conflict, 3km Buffers Exposure

	(1)	(2)	(3)	(4)
	Exposure	Exposure	Exposure	Exposure
G_{Light}	-0.00639 (0.00431)	-0.0176*** (0.00397)	-0.000692 (0.00407)	-0.00350 (0.00288)
$Conflict$	0.0605*** (0.00337)	-0.0343*** (0.0116)	-0.0347*** (0.0109)	-0.0465*** (0.00647)
$G_{Light} \times Conflict$		0.291*** (0.0381)	0.293*** (0.0339)	0.299*** (0.0248)
Country-Year FE	✓	✓	✓	✓
ADM2 FE			✓	✓
Geo Controls				✓
N	412,596	412,596	412,596	389,364
F	88.44	76.40	107.2	72.03
R_{adj}^2	0.182	0.227	0.461	0.477

Notes: This table shows OLS results with conflict exposure as dependent variable following the specifications from Table B2, but using 3km buffers around each conflict event to construct the conflict exposure measure as dependent variable. The unit of observations is the second administrative area (ADM2). The main explanatory variables constitute (a) the natural logarithm of the number of conflict events, denoted “ $Conflict$ ”, and (b) the Gini coefficient of nightlights, denoted “ G_{Light} ”.

Standard errors clustered at the ADM2 region in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table B4 – OLS: Economic Activity affected by Conflict

	(1)	(2)	(3)	(4)
	Exposure	Exposure	Exposure	Exposure
G_{Light}	0.00479** (0.00201)	-0.00517*** (0.00119)	-0.00454 (0.00304)	-0.00716*** (0.00221)
$Conflict$	0.0475*** (0.00328)	-0.0355*** (0.0109)	-0.0353*** (0.0107)	-0.0477*** (0.00427)
$G_{Light} \times Conflict$		0.254*** (0.0335)	0.255*** (0.0316)	0.264*** (0.0169)
Country-Year FE	✓	✓	✓	✓
ADM2 FE			✓	✓
Geo Controls				✓
N	408,565	408,565	408,565	385,507
F	55.06	73.26	97.91	55.43
R_{adj}^2	0.196	0.288	0.465	0.528

Notes: This table shows OLS results with conflict exposure as dependent variable. The unit of observations is the second administrative area (ADM2) for the sample of 70 countries. The main explanatory variables constitute (a) the natural logarithm of the number of conflict events, denoted by “Conflict”, and (b) the Gini coefficient of nightlights, denoted by “ G_{Light} ”. Controls are the sum of lights, population, (squared) precipitation and (squared) temperature. Standard errors clustered at the ADM2 region in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table B5 – OLS: Economic Activity affected by Conflict, 1992 Lights Exposure

	(1)	(2)	(3)	(4)
	Exposure	Exposure	Exposure	Exposure
G_{Light}	0.00500** (0.00204)	-0.00502*** (0.00119)	-0.00838*** (0.00293)	-0.0109*** (0.00201)
$Conflict$	0.0468*** (0.00328)	-0.0367*** (0.0109)	-0.0365*** (0.0107)	-0.0496*** (0.00417)
$G_{Light} \times Conflict$		0.256*** (0.0337)	0.257*** (0.0314)	0.269*** (0.0165)
Country-Year FE	✓	✓	✓	✓
ADM2 FE			✓	✓
Geo Controls				✓
N	408,496	408,496	408,496	385,431
F	53.42	70.67	96.00	54.21
R_{adj}^2	0.190	0.283	0.464	0.526

Notes: This table shows OLS results with conflict exposure as dependent variable following the specifications from Table B2, but using lights from the year 1992 to construct the conflict exposure measure as dependent variable. The unit of observations is the second administrative area (ADM2). The main explanatory variables constitute (a) the natural logarithm of the number of conflict events, denoted “Conflict”, and (b) the Gini coefficient of nightlights, denoted “ G_{Light} ”. Standard errors clustered at the ADM2 region in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table B6 – OLS: Economic Activity affected by Conflict, Average Light Exposure

	(1)	(2)	(3)	(4)
	Exposure	Exposure	Exposure	Exposure
G_{Light}	0.00455** (0.00217)	-0.00552*** (0.00130)	-0.00999*** (0.00341)	-0.0127*** (0.00275)
$Conflict$	0.0484*** (0.00333)	-0.0333*** (0.0111)	-0.0333*** (0.0108)	-0.0457*** (0.00435)
$G_{Light} \times Conflict$		0.252*** (0.0343)	0.253*** (0.0319)	0.263*** (0.0172)
Country-Year FE	✓	✓	✓	✓
ADM2 FE			✓	✓
Geo Controls				✓
N	377,384	377,384	377,384	356,232
F	55.69	72.71	95.49	54.10
R_{adj}^2	0.201	0.289	0.471	0.530

Notes: This table shows OLS results with conflict exposure as dependent variable following the specifications from Table B2, but using average lights per grid cell to construct the conflict exposure measure as dependent variable. The unit of observations is the second administrative area (ADM2). The main explanatory variables constitute (a) the natural logarithm of the number of conflict events, denoted “ $Conflict$ ”, and (b) the Gini coefficient of nightlights, denoted “ G_{Light} ”. Standard errors clustered at the ADM2 region in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table B7 – OLS: Economic Activity affected by Conflict, 1992 Lights Exposure

	(1)	(2)	(3)	(4)
	Exposure	Exposure	Exposure	Exposure
G_{Light}	-0.00861** (0.00386)	-0.0176*** (0.00354)	0.00135 (0.00361)	-0.000295 (0.00234)
$Conflict$	0.0549*** (0.00328)	-0.0229* (0.0119)	-0.0217* (0.0113)	-0.0320*** (0.00667)
$G_{Light} \times Conflict$		0.244*** (0.0403)	0.239*** (0.0362)	0.241*** (0.0257)
Country-Year FE	✓	✓	✓	✓
ADM2 FE			✓	✓
Geo Controls				✓
N	410,489	410,336	410,336	388,929
F	77.30	65.05	83.08	67.82
R_{adj}^2	0.158	0.190	0.402	0.401

Notes: This table shows OLS results with conflict exposure as dependent variable following the specifications from Table B2, but using a stable Gini-coefficient based on lights from the year 1992. The unit of observations is the second administrative area (ADM2). The main explanatory variables constitute (a) the natural logarithm of the number of conflict events, denoted “ $Conflict$ ”, and (b) the Gini coefficient of nightlights, denoted “ G_{Light} ”. Standard errors clustered at the ADM2 region in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table B8 – OLS: Economic Activity affected by Conflict, 5km Exposure

	(1)	(2)	(3)	(4)
	Exposure	Exposure	Exposure	Exposure
G_{Light}	-0.00145 (0.00389)	-0.0174*** (0.00356)	-0.0128** (0.00534)	-0.0160*** (0.00437)
$Conflict$	0.103*** (0.00432)	-0.0305** (0.0139)	-0.0327** (0.0132)	-0.0443*** (0.0101)
$G_{Light} \times Conflict$		0.408*** (0.0480)	0.415*** (0.0438)	0.417*** (0.0383)
Country-Year FE	✓	✓	✓	✓
ADM2 FE			✓	✓
N	410,489	410,489	410,489	389,072
F	151.1	125.0	161.2	120.5
R_{adj}^2	0.233	0.283	0.443	0.451

Notes: This table shows OLS results with conflict exposure as dependent variable following the specifications from Table B2, but using 5km Buffers to construct the conflict exposure measure as dependent variable. The unit of observations is the second administrative area (ADM2). The main explanatory variables constitute (a) the natural logarithm of the number of conflict events, denoted by “ $Conflict$ ”, and (b) the Gini coefficient of nightlights, denoted by “ G_{Light} ”. Standard errors clustered at the ADM2 region in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table B9 – OLS: Economic Activity affected by Conflict, 1km Exposure

	(1)	(2)	(3)	(4)
	Exposure	Exposure	Exposure	Exposure
G_{Light}	-0.0111*** (0.00353)	-0.0152*** (0.00320)	0.000677 (0.00319)	-0.00224 (0.00167)
$Conflict$	0.0256*** (0.00243)	-0.00828 (0.00943)	-0.00653 (0.00935)	-0.0183*** (0.00344)
$G_{Light} \times Conflict$		0.104*** (0.0291)	0.0996*** (0.0277)	0.112*** (0.0135)
Country-Year FE	✓	✓	✓	✓
ADM2 FE			✓	✓
N	410,489	410,489	410,489	389,072
F	38.92	33.01	35.40	34.07
R_{adj}^2	0.0901	0.0997	0.329	0.283

Notes: This table shows OLS results with conflict exposure as dependent variable following the specifications from Table B2, but using 1km Buffers to construct the conflict exposure measure as dependent variable. The unit of observations is the second administrative area (ADM2). The main explanatory variables constitute (a) the natural logarithm of the number of conflict events, denoted by “ $Conflict$ ”, and (b) the Gini coefficient of nightlights, denoted by “ G_{Light} ”. Standard errors clustered at the ADM2 region in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table B10 – OLS: Economic Activity affected by Conflict, dropping outliers

	(1)	(2)	(3)	(4)
	Exposure	Exposure	Exposure	Exposure
G_{Light}	0.00823*** (0.000950)	-0.00374*** (0.000542)	-0.00639*** (0.00228)	-0.00674*** (0.00232)
$Conflict$	0.0511*** (0.00384)	-0.0871*** (0.00711)	-0.0853*** (0.00695)	-0.0703*** (0.00633)
$G_{Light} \times Conflict$		0.398*** (0.0257)	0.392*** (0.0242)	0.334*** (0.0220)
Country-Year FE	✓	✓	✓	✓
ADM2 FE			✓	✓
Geo Controls				✓
N	327,379	327,379	327,208	317,543
F	47.52	99.94	110.0	60.25
R_{adj}^2	0.274	0.484	0.602	0.613

Notes: This table shows OLS results with conflict exposure as dependent variable. For this table, I exclude all districts within the bottom ten percent and the top ten percent of the lights distribution from the sample. The unit of observations is the second administrative area (ADM2) for the sample of 70 countries. The main explanatory variables constitute (a) the natural logarithm of the number of conflict events, denoted by “Conflict”, and (b) the Gini coefficient of nightlights, denoted by “ G_{Light} ”. Controls are the sum of lights, population, (squared) precipitation and (squared) temperature.

Standard errors clustered at the ADM2 region in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table B11 – OLS: Conflict Exposure and Economic Activity

	(1)	(2)	(3)	(4)	(5)
	ln(light)	ln(light)	ln(light)	ln(light)	ln(light)
<i>Exposure</i>	-0.0322 (0.0216)	-0.0351* (0.0200)	-0.0418** (0.0200)	-0.0298 (0.0198)	-0.0306 (0.0205)
<i>Exposure</i> _{<i>t</i>-1}		-0.0236 (0.0178)	-0.0381** (0.0168)	-0.0409** (0.0178)	-0.0325** (0.0165)
<i>Exposure</i> _{<i>t</i>-2}			-0.0205 (0.0163)	-0.0346** (0.0154)	-0.0415** (0.0167)
<i>Exposure</i> _{<i>t</i>-3}				0.00401 (0.0157)	-0.00785 (0.0153)
<i>Exposure</i> _{<i>t</i>-4}					0.0257 (0.0162)
ADM2 FE	✓	✓	✓	✓	✓
Country-Year FE	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓
<i>N</i>	387,407	369,250	351,092	332,931	314,716
<i>R</i> _{<i>adj</i>} ²	0.996	0.996	0.997	0.997	0.997

Notes: This table shows OLS results with the natural logarithm of the sum of nightlights as dependent variable. The unit of observations is the second administrative area (ADM2) for the sample of 33 countries in Sub-Saharan Africa. The main explanatory variable constitutes conflict exposure, measured as the share of economic activity in close proximity to a conflict event. As controls variables, I include the number of conflict events, the spatial Gini of lights, population density, (squared) precipitation and (squared) temperature.

Standard errors clustered at the ADM2 region in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table B12 – 2SLS: Varying the Oil-Price Lag

	(1)	(2)	(3)	(4)	(5)	(6)
	ln(light)	ln(light)	ln(light)	ln(light)	ln(light)	ln(light)
<i>Exposure</i>	-3.808 (2.393)	-7.395* (4.444)	-8.089** (3.441)	-6.825** (2.692)	-5.864** (2.908)	-4.248** (2.112)
Oil Price	$t - 3$	$t - 2$	$t - 1$	t	$t + 1$	$t + 2$
ADM2 FE	✓	✓	✓	✓	✓	✓
Ctry-Year FE	✓	✓	✓	✓	✓	✓
<i>N</i>	171,178	180,902	190,624	190,624	181,112	171,600
<i>F</i> _{1st}	5.583	3.947	15.82	10.37	8.243	8.488

Controls: (Lagged) Conflict & Gini, Population, Climate

Robust standard errors in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table B13 – 2SLS: Conflict Exposure and Economic Activity

	(1)	(2)	(3)	(4)	(5)
	ln(light)	ln(light)	ln(light)	ln(light)	ln(light)
<i>Exposure</i>	-3.792*** (1.114)	0.116 (0.119)	-0.238** (0.121)	-0.115 (0.120)	-0.262** (0.125)
<i>Exposure</i> _{<i>t</i>-1}		-3.571*** (1.125)	0.0438 (0.0757)	-0.386** (0.184)	-0.144 (0.110)
<i>Exposure</i> _{<i>t</i>-2}			-2.239** (0.979)	-0.0101 (0.0975)	-0.464** (0.233)
<i>Exposure</i> _{<i>t</i>-3}				-3.047*** (1.118)	-0.0841 (0.108)
<i>Exposure</i> _{<i>t</i>-4}					-3.102*** (1.204)
ADM2 FE	✓	✓	✓	✓	✓
Country-Year FE	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓
<i>N</i>	190,514	180,822	171,128	161,438	151,748
<i>F</i> _{1st}	20.07	25.03	28.62	30.33	27.92

Notes: This table provides the second stage results for the 2SLS estimates. The unit of observations is the second administrative area (ADM2) for countries with active on-shore oil production. The endogenous variable is the share of lights at night within 3km to a conflict event and is instrumented by a triple-interaction of *i*) the regional average of conflict events *ii*) the regional average of the Gini of lights and *iii*) the yearly world price for crude oil. All regressions include a control variables population density, precipitation, precipitation squared, temperature, temperature squared, as well as ADM2 and Country-Year Fixed Effects.

Standard errors clustered at the ADM2 region in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table B14 – 2SLS: Conflict Exposure and Economic Activity

	(1)	(2)	(3)	(4)	(5)
	ln(light)	ln(light)	ln(light)	ln(light)	ln(light)
<i>Exposure</i>	-5.771** (2.646)	0.444 (0.331)	-0.437* (0.242)	-0.148 (0.188)	-0.704* (0.417)
<i>Exposure</i> _{<i>t</i>-1}		-6.118** (2.485)	0.360 (0.324)	-0.556* (0.321)	-0.263 (0.237)
<i>Exposure</i> _{<i>t</i>-2}			-5.605** (2.642)	0.281 (0.311)	-0.956 (0.664)
<i>Exposure</i> _{<i>t</i>-3}				-5.691* (3.000)	0.253 (0.426)
<i>Exposure</i> _{<i>t</i>-4}					-8.308 (5.272)
ADM2 FE	✓	✓	✓	✓	✓
Country-Year FE	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓
<i>N</i>	216,385	205,881	195,377	184,870	174,369
<i>F</i> _{1st}	4.218	5.655	4.510	4.228	2.373

Notes: This table provides the second stage results for the 2SLS estimates. The unit of observations is the second administrative area (ADM2) for countries with active on-shore oil production. The endogenous variable is the share of the 1990 population within 3km to a conflict event and is instrumented by a double-interaction of the local conflict propensity and the global world price for crude oil. All regressions include a control variables population density, precipitation, precipitation squared, temperature, temperature squared, as well as ADM2 and Country-Year Fixed Effects. All regressions also control for the endogenous exposure variable in year *t* (column 1 aside) as well as for the yearly number of conflict events and the yearly Gini of lights in year *t* – *s*, where *s* indicates the lag of the endogenous variable.

Standard errors clustered at the ADM2 region in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table B15 – 2SLS: Conflict Exposure and Economic Activity

	(1)	(2)	(3)	(4)	(5)
	ln(light)	ln(light)	ln(light)	ln(light)	ln(light)
<i>Exposure</i>	185.1 (149.3)	-9.442 (8.877)	10.05 (7.047)	5.707 (8.897)	79.73 (383.2)
<i>Exposure</i> _{<i>t</i>-1}		158.8 (116.4)	-6.424 (6.279)	21.17 (19.44)	32.56 (153.9)
<i>Exposure</i> _{<i>t</i>-2}			127.1 (89.98)	-6.215 (9.482)	110.7 (528.6)
<i>Exposure</i> _{<i>t</i>-3}				210.2 (192.5)	-5.570 (44.32)
<i>Exposure</i> _{<i>t</i>-4}					899.6 (4289.2)
ADM2 FE	✓	✓	✓	✓	✓
Country-Year FE	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓
<i>N</i>	200,346	190,624	180,902	171,178	161,458
<i>F</i> _{1st}	1.537	1.867	2.007	1.196	0.0440

Notes: This table provides the second stage results for the 2SLS estimates. The unit of observations is the second administrative area (ADM2) for countries with active on-shore oil production. The endogenous variable is the share of the 1990 population within 3km to a conflict event and is instrumented by a double-interaction of the average local Gini coefficient and the global world price for crude oil. All regressions include a control variables population density, precipitation, precipitation squared, temperature, temperature squared, as well as ADM2 and Country-Year Fixed Effects. All regressions also control for the endogenous exposure variable in year *t* (column 1 aside) as well as for the yearly number of conflict events and the yearly Gini of lights in year *t* – *s*, where *s* indicates the lag of the endogenous variable.

Standard errors clustered at the ADM2 region in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table B16 – 2SLS: Conflict Exposure based on 1km Buffers

	(1)	(2)	(3)	(4)	(5)
	ln(light)	ln(light)	ln(light)	ln(light)	ln(light)
<i>Exposure</i>	-4.491** (1.811)	0.104 (0.211)	-0.608** (0.253)	0.103 (0.164)	-0.317 (0.195)
<i>Exposure</i> _{<i>t</i>-1}		-4.678*** (1.733)	0.0144 (0.178)	-0.826*** (0.316)	0.0592 (0.156)
<i>Exposure</i> _{<i>t</i>-2}			-3.328*** (1.290)	-0.0199 (0.201)	-1.006*** (0.390)
<i>Exposure</i> _{<i>t</i>-3}				-3.781*** (1.237)	-0.102 (0.252)
<i>Exposure</i> _{<i>t</i>-4}					-4.118*** (1.291)
ADM2 FE	✓	✓	✓	✓	✓
Country-Year FE	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓
<i>N</i>	190,624	180,902	171,178	161,458	151,738
<i>F</i> _{1st}	29.57	39.78	38.82	42.76	36.79

Notes: This table provides the second stage results for the 2SLS estimates. The unit of observations is the second administrative area (ADM2) for countries with active on-shore oil production. The endogenous variable is the share of the 1990 population within 3km to a conflict event and is instrumented by a double-interaction of the average local Gini coefficient and the global world price for crude oil. All regressions include a control variables population density, precipitation, precipitation squared, temperature, temperature squared, as well as ADM2 and Country-Year Fixed Effects. All regressions also control for the endogenous exposure variable in year *t* (column 1 aside) as well as for the yearly number of conflict events and the yearly Gini of lights in year *t* – *s*, where *s* indicates the lag of the endogenous variable.

Standard errors clustered at the ADM2 region in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table B17 – 2SLS: Conflict Exposure based on 5km Buffers

	(1)	(2)	(3)	(4)	(5)
	ln(light)	ln(light)	ln(light)	ln(light)	ln(light)
<i>Exposure</i>	-2.905** (1.342)	0.238* (0.136)	-0.114** (0.0546)	-0.110* (0.0561)	-0.195*** (0.0667)
<i>Exposure</i> _{<i>t</i>-1}		-3.150*** (1.197)	0.107 (0.0691)	-0.171** (0.0691)	-0.132** (0.0597)
<i>Exposure</i> _{<i>t</i>-2}			-1.975*** (0.582)	0.0665 (0.0626)	-0.205** (0.0939)
<i>Exposure</i> _{<i>t</i>-3}				-2.048*** (0.512)	0.0437 (0.0725)
<i>Exposure</i> _{<i>t</i>-4}					-2.298*** (0.645)
ADM2 FE	✓	✓	✓	✓	✓
Country-Year FE	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓
<i>N</i>	190,624	180,902	171,178	161,458	151,738
<i>F</i> _{1st}	13.89	23.11	60.52	54.49	50.73

Notes: This table provides the second stage results for the 2SLS estimates. The unit of observations is the second administrative area (ADM2) for countries with active on-shore oil production. The endogenous variable is the share of the 1990 population within 3km to a conflict event and is instrumented by a double-interaction of the average local Gini coefficient and the global world price for crude oil. All regressions include a control variables population density, precipitation, precipitation squared, temperature, temperature squared, as well as ADM2 and Country-Year Fixed Effects. All regressions also control for the endogenous exposure variable in year *t* (column 1 aside) as well as for the yearly number of conflict events and the yearly Gini of lights in year *t* – *s*, where *s* indicates the lag of the endogenous variable.

Standard errors clustered at the ADM2 region in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table B18 – 2SLS: Conflict Exposure based on Gridded Light

	(1)	(2)	(3)	(4)	(5)
	ln(light)	ln(light)	ln(light)	ln(light)	ln(light)
<i>Exposure</i>	-2.573** (1.011)	0.0777 (0.0968)	-0.150*** (0.0472)	-0.110** (0.0549)	-0.255*** (0.0693)
<i>Exposure</i> _{<i>t</i>-1}		-2.584*** (0.931)	-0.00136 (0.0574)	-0.204*** (0.0571)	-0.128** (0.0567)
<i>Exposure</i> _{<i>t</i>-2}			-1.765*** (0.584)	-0.0184 (0.0515)	-0.225*** (0.0750)
<i>Exposure</i> _{<i>t</i>-3}				-1.839*** (0.501)	-0.0641 (0.0527)
<i>Exposure</i> _{<i>t</i>-4}					-1.987*** (0.555)
ADM2 FE	✓	✓	✓	✓	✓
Country-Year FE	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓
<i>N</i>	190,642	180,919	171,194	161,473	151,752
<i>F</i> _{1st}	31.15	46.67	134.4	125.5	82.86

Notes: This table provides the second stage results for the 2SLS estimates. The unit of observations is the second administrative area (ADM2) for countries with active on-shore oil production. The endogenous variable is the share of the 1990 population within 3km to a conflict event and is instrumented by a double-interaction of the average local Gini coefficient and the global world price for crude oil. All regressions include a control variables population density, precipitation, precipitation squared, temperature, temperature squared, as well as ADM2 and Country-Year Fixed Effects. All regressions also control for the endogenous exposure variable in year *t* (column 1 aside) as well as for the yearly number of conflict events and the yearly Gini of lights in year *t* – *s*, where *s* indicates the lag of the endogenous variable.

Standard errors clustered at the ADM2 region in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table B19 – 2SLS: Conflict Exposure based on Gridded Light

	(1)	(2)	(3)	(4)	(5)
	ln(light)	ln(light)	ln(light)	ln(light)	ln(light)
<i>Exposure</i>	-1.172*** (0.424)	-0.0278 (0.0647)	-0.105** (0.0451)	-0.160*** (0.0527)	-0.205*** (0.0572)
<i>Exposure</i> _{<i>t</i>-1}		-1.283*** (0.474)	-0.0563 (0.0624)	-0.133** (0.0539)	-0.190*** (0.0558)
<i>Exposure</i> _{<i>t</i>-2}			-1.261** (0.579)	-0.0612 (0.0639)	-0.137*** (0.0502)
<i>Exposure</i> _{<i>t</i>-3}				-1.718** (0.698)	-0.0911 (0.0581)
<i>Exposure</i> _{<i>t</i>-4}					-1.842** (0.801)
ADM2 FE	✓	✓	✓	✓	✓
Country-Year FE	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓
<i>N</i>	190,622	180,899	171,174	161,453	151,732
<i>F</i> _{1st}	51.32	82.02	92.48	34.85	21.43

Notes: This table provides the second stage results for the 2SLS estimates. The unit of observations is the second administrative area (ADM2) for countries with active on-shore oil production. The endogenous variable is the share of the 1990 population within 3km to a conflict event and is instrumented by a double-interaction of the average local Gini coefficient and the global world price for crude oil. All regressions include a control variables population density, precipitation, precipitation squared, temperature, temperature squared, as well as ADM2 and Country-Year Fixed Effects. All regressions also control for the endogenous exposure variable in year *t* (column 1 aside) as well as for the yearly number of conflict events and the yearly Gini of lights in year *t* – *s*, where *s* indicates the lag of the endogenous variable.

Standard errors clustered at the ADM2 region in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table B20 – 2SLS with Conflict Events as Endogenous Variable

	(1)	(2)	(3)	(4)	(5)
	ln(light)	ln(light)	ln(light)	ln(light)	ln(light)
$\ln(\text{conflict})$	-0.581*** (0.147)	0.239*** (0.0786)	0.0753 (0.0559)	22.26 (3143.0)	-0.615 (2.949)
$\ln(\text{conflict})_{t-1}$		-1.060*** (0.329)	0.490* (0.290)	-12.13 (1710.0)	-0.686 (3.316)
$\ln(\text{conflict})_{t-2}$			-2.519* (1.431)	-102.4 (14453.0)	0.154 (0.855)
$\ln(\text{conflict})_{t-3}$				595.5 (84052.7)	3.204 (15.74)
$\ln(\text{conflict})_{t-4}$					-19.25 (94.02)
ADM2 FE	✓	✓	✓	✓	✓
Country-Year FE	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓
N	205,899	195,394	184,886	174,384	163,882
F_{1st}	38.33	18.65	3.643	0.0000502	0.0419

Notes: This table reproduces the main results from Table 2 with the number of conflict events as the endogenous variable. Only African countries are used due to a weak IV problem with the worldwide sample – results for the complete sample are reported in the Appendix for comparability. The instrument is constructed by interacting a time-invariant indicator variable for positive conflict propensity with the international crude oil price. The controls include the Gini of light, population, climate indicators, and climate squared.

Standard errors clustered at the ADM2 level in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table B21 – 2SLS: Subset of SSA Countries

	(1)	(2)	(3)	(4)	(5)
	ln(light)	ln(light)	ln(light)	ln(light)	ln(light)
<i>Exposure</i>	-5.354*** (1.421)	0.445 (0.382)	-0.241* (0.136)	-0.296 (0.192)	-0.665*** (0.139)
<i>Exposure</i> _{<i>t</i>-1}		-5.988*** (2.076)	0.241 (0.229)	-0.372* (0.198)	-0.321 (0.199)
<i>Exposure</i> _{<i>t</i>-2}			-4.028*** (1.424)	0.260 (0.252)	-0.419* (0.235)
<i>Exposure</i> _{<i>t</i>-3}				-4.882*** (1.517)	0.130 (0.271)
<i>Exposure</i> _{<i>t</i>-4}					-5.354*** (1.029)
ADM2 FE	✓	✓	✓	✓	✓
Country-Year FE	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓
<i>N</i>	24,826	23,516	22,204	20,896	19,588
<i>F</i> _{1st}	26.53	10.79	12.12	16.90	57.64

Notes: This table provides the second stage results for the 2SLS estimates. The unit of observations is the second administrative area (ADM2) for countries with active on-shore oil production. The endogenous variable is the share of the 1990 population within 3km to a conflict event and is instrumented by a double-interaction of the average local Gini coefficient and the global world price for crude oil. All regressions include a control variables population density, precipitation, precipitation squared, temperature, temperature squared, as well as ADM2 and Country-Year Fixed Effects. All regressions also control for the endogenous exposure variable in year t (column 1 aside) as well as for the yearly number of conflict events and the yearly Gini of lights in year $t - s$, where s indicates the lag of the endogenous variable.

Standard errors clustered at the ADM2 region in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table B22 – 2SLS: Controlling for Province-times-Year Fixed Effects

	(1)	(2)	(3)	(4)	(5)
	ln(light)	ln(light)	ln(light)	ln(light)	ln(light)
<i>Exposure</i>	-5.252*** (2.017)	0.139 (0.137)	-0.290 (0.180)	-0.120 (0.115)	-0.375** (0.189)
<i>Exposure_{t-1}</i>		-4.264*** (1.547)	0.0525 (0.0887)	-0.401 (0.249)	-0.208 (0.136)
<i>Exposure_{t-2}</i>			-2.735** (1.380)	-0.0116 (0.101)	-0.673* (0.400)
<i>Exposure_{t-3}</i>				-3.154** (1.555)	-0.122 (0.164)
<i>Exposure_{t-4}</i>					-4.514** (1.994)
ADM2 FE	✓	✓	✓	✓	✓
Province-Year FE	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓
<i>N</i>	190,113	180,421	170,727	161,037	151,347
<i>F_{1st}</i>	8.685	11.43	8.862	9.132	8.605

Notes: This table provides the second stage results for the 2SLS estimates. The unit of observations is the second administrative area (ADM2) for countries with active on-shore oil production. The endogenous variable is the share of the 1990 population within 3km to a conflict event and is instrumented by a double-interaction of the average local Gini coefficient and the global world price for crude oil. All regressions include a control variables population density, precipitation, precipitation squared, temperature, temperature squared, as well as ADM2 and Province(ADM1)-Year Fixed Effects. All regressions also control for the endogenous exposure variable in year t (column 1 aside) as well as for the yearly number of conflict events and the yearly Gini of lights in year $t - s$, where s indicates the lag of the endogenous variable.

Standard errors clustered at the ADM2 region in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table B23 – 2SLS: Constant Sample Across Specifications

	(1)	(2)	(3)	(4)	(5)
	ln(light)	ln(light)	ln(light)	ln(light)	ln(light)
<i>Exposure</i>	-8.773 (5.756)	0.223 (0.349)	-0.445** (0.195)	-0.127 (0.200)	-0.442*** (0.166)
<i>Exposure_{t-1}</i>		-8.420** (4.087)	0.0337 (0.159)	-0.641** (0.257)	-0.246 (0.163)
<i>Exposure_{t-2}</i>			-4.371*** (1.266)	-0.0749 (0.194)	-0.762** (0.330)
<i>Exposure_{t-3}</i>				-4.880*** (1.205)	-0.116 (0.180)
<i>Exposure_{t-4}</i>					-5.155*** (1.191)
ADM2 FE	✓	✓	✓	✓	✓
Country-Year FE	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓
<i>N</i>	151,738	151,738	151,738	151,738	151,738
<i>F_{1st}</i>	3.963	8.742	19.76	20.57	36.20

Notes: This table provides the second stage results for the 2SLS estimates. The unit of observations is the second administrative area (ADM2) for countries with active on-shore oil production. The endogenous variable is the share of the 1990 population within 3km to a conflict event and is instrumented by a double-interaction of the average local Gini coefficient and the global world price for crude oil. All regressions include a control variables population density, precipitation, precipitation squared, temperature, temperature squared, as well as ADM2 and Country-Year Fixed Effects. All regressions also control for the endogenous exposure variable in year t (column 1 aside) as well as for the yearly number of conflict events and the yearly Gini of lights in year $t - s$, where s indicates the lag of the endogenous variable.

Standard errors clustered at the ADM2 region in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table B24 – 2SLS: 1992 Gini Coefficient in Local Share

	(1)	(2)	(3)	(4)	(5)
	ln(light)	ln(light)	ln(light)	ln(light)	ln(light)
<i>Exposure</i>	-8.722** (3.910)	0.336 (0.335)	-0.512** (0.247)	-0.189 (0.193)	-0.496** (0.195)
<i>Exposure</i> _{<i>t</i>-1}		-8.885*** (3.167)	0.117 (0.177)	-0.668** (0.303)	-0.274 (0.186)
<i>Exposure</i> _{<i>t</i>-2}			-5.084*** (1.457)	0.0102 (0.178)	-0.857** (0.390)
<i>Exposure</i> _{<i>t</i>-3}				-5.317*** (1.389)	-0.128 (0.203)
<i>Exposure</i> _{<i>t</i>-4}					-5.813*** (1.568)
ADM2 FE	✓	✓	✓	✓	✓
Country-Year FE	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓
<i>N</i>	190,624	180,902	171,178	161,458	151,738
<i>F</i> _{1st}	14.91	18.64	18.64	16.99	30.73

Notes: This table provides the second stage results for the 2SLS estimates. The unit of observations is the second administrative area (ADM2) for countries with active on-shore oil production. The endogenous variable is the share of the 1990 population within 3km to a conflict event and is instrumented by a double-interaction of the average local Gini coefficient and the global world price for crude oil. All regressions include a control variables population density, precipitation, precipitation squared, temperature, temperature squared, as well as ADM2 and Country-Year Fixed Effects. All regressions also control for the endogenous exposure variable in year *t* (column 1 aside) as well as for the yearly number of conflict events and the yearly Gini of lights in year *t* – *s*, where *s* indicates the lag of the endogenous variable.

Standard errors clustered at the ADM2 region in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table B25 – 2SLS: Conflict Exposure based on Events with more than 5BD

	(1)	(2)	(3)	(4)	(5)
	ln(light)	ln(light)	ln(light)	ln(light)	ln(light)
<i>Exposure</i>	-2.320** (1.138)	0.0422 (0.0973)	-0.128** (0.0548)	-0.0994 (0.0631)	-0.182** (0.0837)
<i>Exposure</i> _{<i>t</i>-1}		-2.449** (1.132)	-0.0127 (0.0781)	-0.173** (0.0692)	-0.134** (0.0665)
<i>Exposure</i> _{<i>t</i>-2}			-1.877** (0.851)	-0.0126 (0.0858)	-0.162* (0.0824)
<i>Exposure</i> _{<i>t</i>-3}				-2.116** (0.980)	-0.0880 (0.0904)
<i>Exposure</i> _{<i>t</i>-4}					-2.182** (0.997)
ADM2 FE	✓	✓	✓	✓	✓
Country-Year FE	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓
<i>N</i>	187,064	177,520	167,974	158,432	148,890
<i>F</i> _{1st}	12.23	15.02	23.23	13.07	11.92

Notes: This table provides the second stage results for the 2SLS estimates. The unit of observations is the second administrative area (ADM2) for countries with active on-shore oil production. The endogenous variable is the share of the 1990 population within 5km to a conflict event that was associated with at least 5 battle deaths, and is instrumented by a double-interaction of the average local Gini coefficient and the global world price for crude oil. All regressions include a control variables population density, precipitation, precipitation squared, temperature, temperature squared, as well as ADM2 and Country-Year Fixed Effects. All regressions also control for the endogenous exposure variable in year *t* (column 1 aside) as well as for the yearly number of conflict events and the yearly Gini of lights in year *t* – *s*, where *s* indicates the lag of the endogenous variable. Standard errors clustered at the ADM2 region in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table B26 – Spatial Spillovers of Conflict Exposure

	(1)	(2)	(3)
	ln(light)	ln(light)	ln(light)
Pct. Affected	-0.212*** (0.0288)	-0.251*** (0.0695)	-0.0940** (0.0375)
Conflict	-0.00261 (0.00224)	0.00972* (0.00524)	-0.00859*** (0.00285)
W × Pct. Affected		37.43*** (2.113)	20.25*** (1.639)
Country-Year FE	✓	✓	✓
ADM2 FE	✓	✓	✓
W × ϵ			✓
<i>N</i>	191,163	191,163	191,163

SE clustered at ADM2 reg in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

C Spatial Gini of Lights at Night

To construct the Spatial Gini on lights, I aggregate the raster-level nightlights data, which are measured at a spatial resolution of 30 arc-seconds (ca. 1.8 km^2 at the equator), to $3 \times 3 \text{ km}$ grid cells and then calculate the spatial Gini over all such grid cells within an ADM2 area. Similar to the common Gini coefficient of wealth or income, the spatial Gini coefficient is a widely used concept to measure the concentration of various outcomes in space (Clark et al., 2018). Just as a regular Gini coefficient, the spatial Gini coefficient takes on values between 0 and 1, where a value of 0 would indicate a perfectly equal distribution of light and a value of 1 would indicate a perfectly concentrated distribution in only one point or pixel of a region. Other than as an indicator for the concentration of economic activity, the spatial Gini has already been used to measure the spatial concentration of, e.g., access to public transport (Jang et al., 2017) or CO_2 emissions (Zhou et al., 2020).