Technical Paper 3. Estimating the Spillover Economic Effects of Foreign Conflict: Evidence from Boko Haram

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4.1 Introduction

Violent conflicts present a formidable threat to regional economies. Throughout the world, border regions in many countries are possibly impacted by the cross-border economic effects of regional insurgencies in neighboring countries or national state failures, i.e. "bad neighbors". This raises two questions. First, what is the magnitude of the spill-over economic effects of foreign conflict and what are the channels through which they operate? Second, what policies can governments adopt in the potentially exposed regions to mitigate such spill-over effects?[276]

In this paper, we adopt a difference-in-difference (DiD) framework leveraging the unexpected rise of the Boko Haram insurgency in Northeastern Nigeria in 2009 to study its economic effects in *neighboring* areas in Cameroon, Chad and Niger that were *not* directly targeted by Boko Haram activities. We find strong cross-border economic effects that are likely driven by reduced trade activities, not the diffusion of conflict. Factors of local economic resilience to this foreign conflict shock then include trade diversification and political and economic securitization. More generally, conflicts, if they have regional economic effects, may necessitate regional responses.

The causal identification of the effects of conflict, and by extension of the mitigation effects of various locational factors, is complicated by a complex endogenous relationship between conflict and socio-economic conditions (Blattman and Miguel, 2010; Djankov and Reynal-Querol, 2010). Conflicts impose large economic tolls (e.g., International Monetary Fund, 2019; Trebbi and Weese, 2019). But poor economies and economic shocks also offer fertile grounds for conflicts (e.g., Miguel et al., 2004; Bazzi and Blattman, 2014; Burke et al., 2015).[277]

While poverty traps and conflict traps can reinforce each other *locally*, spatio-dynamic *spillovers* can also be present (Berman et al., 2017; König et al., 2017; Harari and Ferrara, 2018; Melnikov et al., 2020; Eberle et al., 2020). Conflict in one location can beget conflict in other locations, either via a direct expansion in space of conflict factors (e.g., armies) or because conflict in one location increases poverty, and lowers the opportunity cost of conflict labor, in other locations. Due to spill-overs that reinforce each other across locations, separately identifying local and non-local effects is difficult econometrically (Harari and Ferrara, 2018).

Studies on the impact of policies on conflict then focus on conflict prevention, management, resolution and/or reconciliation in the conflict countries themselves (e.g., Nunn and Qian, 2014; König et al., 2017; Chiovelli et al., 2018; Sviatschi, 2018). Less is known about how non-conflict countries can mitigate, in their border regions, the local economic impact of foreign conflicts.

To address some of these challenges, we exploit the exogenous rise of Boko Haram in Nigeria after 2009 and estimate its local economic effects on neighboring areas within Cameroon, Chad and Niger (CCN), so *outside* Nigeria. Between 2009 and 2014, Boko Haram became the world's deadliest terrorist group ahead of ISIL, the Taliban and Al-Shabaab (Institute for Economics

276 Examples of regional insurgencies plausibly affecting other countries include the Cabo Delgado insurgency in Mozambique (Tanzania), the ISIL insurgency in Iraq and Syria (Turkey but also Jordan and Lebanon), the insurgency in the Maghreb (other countries in West Africa), the Taliban insurgency in Afghanistan (Iran, Pakistan, Tajikistan, Turkmenistan and Uzbekistan), etc. Examples of failed states with possible regional impacts include the Central Africa Republic, the Democratic Republic of the Congo, Somalia, South Sudan, Venezuela, Yemen, Zimbabwe, etc.

277 Other studies on the effects of (absolute or relative) poverty or income shocks on conflict or terrorism include, among many others, Krueger and Malečková (2003); Brückner and Ciccone (2010); Besley and Persson (2011); Ciccone (2011); Miguel and Satyanath (2011); Enders and Hoover (2012); Dube and Vargas (2013); Jia (2014); Couttenier and Soubeyran (2014, 2015); Berman and Couttenier (2015); Crost et al. (2016); Harari and Ferrara (2018); Berman et al. (2019);McGuirk and Nunn (2020); Eberle et al. (2020). Typically, poverty and negative income shocks are associated with individual incentives to engage in conflict as well as weakened state and counterinsurgency capacity.

and Peace, 2012–2020). Until 2014, Boko Haram concentrated its terrorist activities in the Northeastern part of Nigeria close to the border with CCN *but* did not enter these countries, mostly to avoid fighting at least four government armies instead of one. As such, in CCN until 2014, the estimated effects must be due to the spill-over effects described above.

We use a simple DiD framework whereby we compare CCN areas "close to" and areas "farther away from" the Boko Haram region in the years after 2009 versus before 2009. We find a strong negative effect of Boko Haram on regional economic activities (as proxied by changes in night light intensity)—particularly for areas within 200 km from the Boko Haram region. More precisely, we find an average decline of 10 percent for the post-2009 period, and a decline of about 20 percent for places closer to the shock (within 100 km). For all places within 200 km, we find an overall effect of about 20 (50) percent by 2013 (2018), that is, 4 (9) years after the shock began. The effects appear to be driven by declines in per capita incomes rather than population outflows (or refugees inflows since we control for it). We also show that the parallel trends assumption is verified in CCN. Finally, we find no effect on local (i.e. non-Boko Haram) conflict in CCN. Therefore, the estimated spill-over effects are purely economic.

When studying the confidence intervals of the baseline effect, we find that the estimated effects range from about -30 percent to -10 percent in 2013. Thus, while most places within the 200 km region were negatively affected, some were less affected than others, which motivates us to analyze the heterogeneous effects of foreign conflict depending on initial (pre-2009) local conditions. We find stronger effects for initially more developed locations, hence more urban locations, which shows the potential importance of foreign conflict for trade. Indeed, the Boko Haram area historically served as a trade corridor between (relatively wealthier) areas of Nigeria and (relatively poorer) Cameroon-Chad to the East and Niger to the West.[278]

We then use the same econometric framework to identify factors that can help mitigate the effects of foreign conflict shocks. We find stronger mitigation effects in those areas that were initially better connected to other markets either via trade networks or transportation infrastructure (thus benefiting from a more diversified set of potential trade partners), and more politically and/or economically "secured" by government consumption via defense-related facilities (e.g., military headquarters) or public employment (e.g., social services).

This paper makes four important contributions. First of all, various studies show how economic shocks in some locations increase conflict there as well as in neighboring locations (Berman et al., 2017; König et al., 2017; Harari and Ferrara, 2018; Eberle et al., 2020; McGuirk and Nunn, 2020).[279] Two channels explain spatial diffusion. First of all, conflict factors can move (e.g., armies) or be moved (e.g., weapons) spatially. Secondly, due to economic spillovers, poverty can increase in surrounding locations, thus raising the likelihood of conflict there. We do not find any impact of Boko Haram activities in Nigeria on local (non-Boko Haram) conflict activities in CCN, and this despite significant income declines in contexts where most individuals already lived close to the subsistence level.[280] The lack of conflict spillovers does not appear to be due to the increase of government forces in the area. Our interpretation is that poverty disproportionately increased in trade-reliant urban locations. Even if the opportunity cost of conflict labor decreased, other economic factors must have dominated the previous effect and prevented conflict.

278 Likewise, we find weaker effects on "rural" outcomes. Our analysis shows no effects on measures of greenness (proxying for agricultural expansion) or land use. We, however, find effects on agricultural burning, which proxies for agricultural intensification in rural areas (Blankespoor et al., 2021), most likely as a result of reduced urban incomes.

279 There are related literatures on the determinants of the spatial diffusion of conflict (e.g., Bosker and de Ree, 2014; Novta, 2016) and economic shocks (e.g., Amarasinghe et al., 2020). These studies all highlight the role of ethnic networks. Such networks are particularly important for domestic and international trade in Africa (Fafchamps, 2003).

280 Boko Haram also had no incentive to enter CCN, at least until 2014.

Indeed, the causal mechanism of economic shocks leading to conflict is complex, and the type of economic shock and industries should mediate the effects on conflict. Positive shocks to labor-intensive industries, such as agriculture, raise wages and reduce conflict (Dal Bó and Dal Bó, 2011; Berman and Couttenier, 2015; Harari and Ferrara, 2018).[281] But positive shocks to capital-intensive industries raise the likelihood of conflict because the capital intensive industry expands at the expense of the labor intensive one, which lowers the cost of appropriation activities relative to the amount of appropriable resources. Commodity discoveries or price increases then increase violence because there is more to appropriate (Angrist and Kugler, 2008; Dal Bó and Dal Bó, 2011; Dube and Vargas, 2013).[282] In our case, the shock reduced the amount of appropriable resources and disproportionately impacted sectors that were more capital-intensive than agriculture. The trading sector is then particularly sensitive to the impact of conflict on trade costs, and economic agents may internalize that (Martin et al., 2008b, 2012). In our context, urban residents whose incomes decreased due to the shock plausibly internalized that having community members engage in conflict would further reduce incomes. Finally, the shock was for the main period of study (wrongly) seen as temporary, as it was believed that the Nigerian army, helped by international allies, would eventually eradicate Boko Haram. It may have prevented individuals from switching to more conflict-related activities.

Secondly, this paper sheds light on the *heterogeneous*, not just average, effects of conflict on growth at the subnational level. In particular, for a similar conflict "shock", the local impact may differ depending on initial economic conditions. We find stronger effects for more urban locations. Among urban locations, the least developed locations were disproportionately impacted. When studying which locations were more resilient economically to the foreign conflict shock, we find that more connected and more secure locations were better able to "weather" some of the impact of the shock. These results are, we believe, important for policy because it identifies potential factors of resilience to foreign conflict shocks. In contrast, other studies examine countries that are, or were, directly impacted by conflict (instead of indirectly via cross-border effects). In these countries, they focus on policies aimed at conflict prevention, resolution and/or management (de Ree and Nillesen, 2009; Berman et al., 2011; Rohner et al., 2013a; Nunn and Qian, 2014; Crost et al., 2014; König et al., 2017; Chiovelli et al., 2018; Sviatschi, 2018; Hartman et al., 2018; Eberle et al., 2020) or post-conflict reconciliation (Fearon et al., 2009, 2015; Blattman and Annan, 2015; Blattman et al., 2015). The government interventions that our results highlight differ from some of the policies that have been studied in the literature, partly because the affected border regions do not directly suffer deaths and destruction.[283]

Thirdly, there is a large literature on the impact of conflict on local economic development (e.g., Abadie and Gardeazabal, 2003; Nunn and Wantchekon, 2011; Besley and Reynal-Querol, 2014; Burger et al., 2015; Brodeur, 2018; Melnikov et al., 2020).[284] However, conflict often arises endogenously due to socio-economic conditions, making it difficult to measure truly causal local economic effects. Our natural experiment has the merit of being simple and allows us to estimate the effects of a non-local, more exogenous, conflict shock. However, our shock is externally less valid than in some of the other studies since it measures a cross-border effect. Also,

281 As shown by McGuirk and Burke (2020), global food price shocks increase conflict in areas without crop agriculture where most workers are net consumers of food. In food-producing areas, higher food prices may simultaneously reduce conflict due to the higher incomes and increase conflict from workers whose real wages fall.

282 Related studies include Hodler (2006); Lei and Michaels (2014); Caselli et al. (2015); Berman et al. (2017); Chiovelli et al. (2018); Sviatschi (2018); Castillo et al. (2020); de la Sierra (2020); Adhvaryu et al. (2021).

283 The government interventions studied in the literature include, for example, diplomacy, different types and locations of military interventions, weapon embargoes, reforms to property rights, development programs, service provision, community engagement programs, and food aid in conflict-prone or conflict-ridden areas, and demining, development aid, employment programs, cash transfers, and therapy sessions in post-conflict areas.

284 Studies on the more individual-level effects of conflict include, for example, Bellows and Miguel (2009); Blattman and Annan (2010); Annan et al. (2011); Akresh et al. (2012); Bauer et al. (2016); Sviatschi (2018).

in CCN, our shock did not directly lead to deaths and destruction (unlike most conflicts).[285]

Next, one of the mechanisms through which conflict affects economic development is by reducing trade and increasing economic uncertainty. While the linkages between conflict and trade have already been studied, empirical evidence is mostly cross-national (Blomberg and Hess, 2006; Martin et al., 2008b,a, 2012; Glick and Taylor, 2010; Qureshi, 2013; Rohner et al., 2013b; Seitz et al., 2015; De Sousa et al., 2018).[286] Our focus instead lies in understanding how, *within* a country, spatial proximity to a foreign conflict affects local economic development, most likely via trade disruptions as in Chiovelli et al. (2018) who study the effects of post-conflict demining on market access and local economic development. Other within-country studies such as Berman and Couttenier (2015), Berman et al. (2017) or McGuirk and Burke (2020) then exploit trade shocks (from international commodity or food prices) to study the causal effects of income on conflict *rather than* the effects of conflict on income via trade or the role of trade diversification in mitigating the local economic impact of foreign conflict.[287]

Fourthly, this work contributes to a body of literature on the drivers of city growth in poor countries. Other studies on Africa have focused on the impact of transportation investments (e.g. Storeygard, 2016; Jedwab and Moradi, 2016; Jedwab et al., 2017a; Jedwab and Storeygard, 2020), trade more generally (e.g. Glaeser, 2014; Gollin et al., 2016; Haslop et al., 2021a), demographic growth (e.g. Jedwab et al., 2017b; Jedwab and Vollrath, 2019), or climate shocks (Barrios et al., 2006; Henderson et al., 2017; Kocornik-Mina et al., 2020; Haslop et al., 2021b). To our knowledge, the literature on conflict (or terrorism) and city growth is more limited (e.g. Glaeser and Shapiro, 2002; Voigtländer and Voth, 2012; Dincecco and Onorato, 2016).[288]

Lastly, our analysis has limitations. The three countries of study are among the poorest in the world.[289] Understanding the economic effects of foreign conflict in such contexts is particularly important. However, data infrastructure and finances to collect and produce data can be challenging;[290] no consistent panel data on within-country variation in trade and migration flows, production, wages, consumer prices and amenities are available.

The rest of this paper is structured as follows. Section 4.2 provides information on the context while Section 4.3 and Section 4.4 describe the data and the empirical strategy, respectively. Sections 4.5 and 4.6 discuss the estimated average and heterogeneous effects of the Boko Haram shock as well as its effects on local (non-Boko Haram) conflict. Section 4.7 concludes.

285 Other studies of the effects of Boko Haram are mostly qualitative. Exceptions include Adelaja and George (2019); Bertoni et al. (2019). However, they study its effects in Nigeria, which complicates causal identification.

286 Martin et al. (2008b,a); Seitz et al. (2015) study the role of trade in conflict. Other studies examine the reverse relationship. Fenske and Kala (2017) study the relationship between historical African conflict and the slave trade. Emran et al. (2019) examine the long-lasting effects from temporary trade restrictions on the spatial distribution of employment and resource allocation exploiting the disrupted change in routes to the international market for two neighboring landlocked countries as the result of the the civil war in Côte d'Ivoire.

287 Berman and Couttenier (2015) find strong effects of negative income shocks (from lower international demand for a location's crops) on conflict. They find a weaker effect for more remote locations. Because remote locations are more disconnected from international markets, their shock is smaller, hence their effect is smaller. Our analysis differs because we study how trade diversification is a factor of resilience for a *given* (conflict-driven) economic shock.

288 There is, however, a literature on the economic impact of refugees on cities (e.g., Lewis and Peri, 2015; Alix-Garcia et al., 2018; Fallah et al., 2019; Rozo and Sviatschi, 2021). In our analysis, the number of refugees received by each location is a control, not the main outcome of study. Indeed, we aim to capture the economic spill-over effects of conflict via trade disruptions mostly, instead of the direct reallocation of populations from Nigeria to CCN.

289 According to the *World Economic Outlook* database of the International Monetary Fund, Niger, Chad and Cameroon are in 2021 the 8th, 10th and 38th poorest countries in the world, respectively.

290 For household survey data collection, Kilic et al. (2017) find significantly higher survey implementation cost per household in Africa compared to other regions of the world.

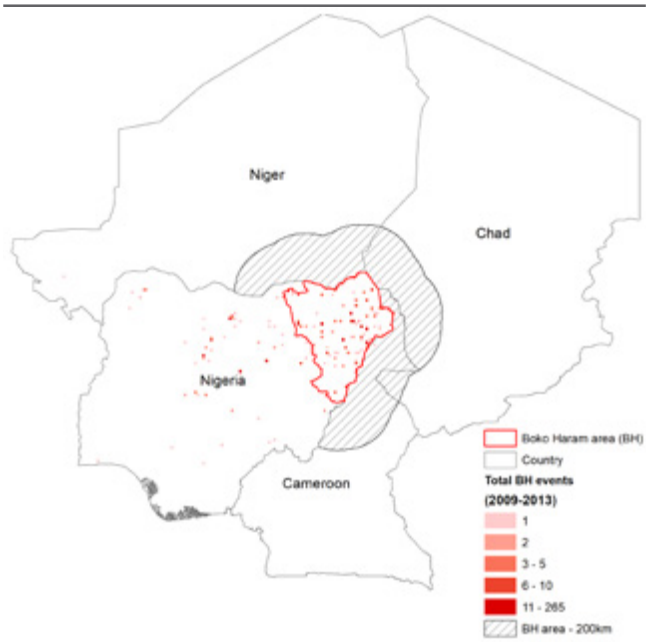
4.2 Background: Studying Boko Haram as a *Foreign* Conflict

In Nigeria. A decade-long insurgency posed by Boko Haram in Northeastern Nigeria (2009–present) is a case in point where its devastating economic and humanitarian impact has spilled over to its neighboring countries of Cameroon, Chad and Niger, killing tens of thousands of people and displacing 2.6 million globally (Tayimlong, 2020). According to the *Global Terrorism Index* of the Institute for Economics and Peace (2012–2020), Boko Haram became during our main period of study—2009–2013—the world's deadliest terrorist group, ahead of ISIL, the Taliban and Al-Shabaab. It is still the second deadliest terrorist group as of 2020.

The group was founded in 2002. Boko Haram's radicalization dates back to 2009 when state security forces killed 800 of its members, including its founder M. Yusuf (Kimenyi et al., 2014). At its peak (2015), the group seized a large swath of territories in Northeastern Nigeria, including major cities. 15 million people have been severally affected by the insurgency and the counterinsurgency efforts (Vanda Felbab-Brown, 2018). Boko Haram has continued to engage in killing and abducting civilians, forcibly marrying off women and girls to its fighters, and conducting terrorist attacks against government property, markets, refugee camps, and mosques (Omenma et al., 2020). Anecdotal evidence abounds to suggest that regional trade has been severely disrupted by the insurgency, which has resulted in repeated temporary border and road closures hampering the mobility of people, goods and services in the whole Lake Chad region (World Food Program, 2016; Opoku et al., 2017; Foyou et al., 2018; OECD/SWAC, 2020).

As seen in Map 4.1, most of the attacks between 2009 and 2013—our main period of study—were geographically concentrated in a few states in the Northeastern corner of Nigeria, essentially Borno (60 percent of all Boko Haram conflict events), but also Yobe and Adamawa. However, within Yobe, most conflict events took place south of the Yobe river. Within Adamawa, most conflict events occurred north of the Benue river. In this figure and in the rest of the paper, we thus define the core *Boko Haram area* as the area of Borno, Yobe and Adamawa that is between the Yobe river in the North (in Yobe) and the Benue river in the South (Adamawa).

Map 4.1: Boko Haram Area and the Three Countries of Study



Notes: This figure shows the main Boko Haram area (defined as the area corresponding to the states of Adamawa, Borno and Yobe that is between the Komadugu Yobe river in the Yobe and the Benue river in Adamawa, and where most Boko Haram conflict events in 2009–2013 were located). It also shows the three countries of study (Cameroon, Chad and Niger) as well as the area within these three countries that is within 200 km from the Boko Haram area.

Seen from space, the rise of Boko Haram after 2009 is strongly associated with a rapid (relative) decline in the level of economic activity in Northeastern Nigeria, as measured based on changes in night-time light intensity (NTL). As explained in the next section, this data comes from the U.S. Air Force Defense Meteorological Satellite Program (OLS-DMSP, 1992–2013). Using data for 7,761 0.1×0.1 degree grid cells (≈ 11x11km at the equator) in Nigeria for the years 2000–2013 (N = 108,654), and relying on a simple

panel difference-in-difference (panel-DiD) framework to account for cell and year effects, we find that the level of NTL decreased by 6 percent on average between 2000–2008 (pre) and 2009–2013 (post) (not shown).[291] By 2013, the correlation was -7.5 percent (Figure A4.1 shows the coefficient of the Boko Haram area dummy in each year with 2000 being the omitted year). If we restrict the panel-DiD to 3,717 cells that were lit at any point between 2000 and 2013, we get -8.5 percent and -10 percent economic decline respectively (not shown).[292] We focus on the period 2000–2013 because Boko Haram had not yet entered Cameroon, Chad and Niger. In addition, night lights data from DMSP is only available until 2013. However, Li et al. (2020) combine night light data from two satellite series—OLS-DMSP (1992–2013) and SNPP-VIIRS (2012–2018)—to generate global DMSP NTL time-series data for the whole period 1992–2018 (DMSP is used as the baseline until 2013). As seen in Figure A4.2, Boko Haram areas have experienced an even bigger relative decline in night light intensity between 2014 and 2018. Note that we use the same model as just described (N = 7,761 cells) but for the full period 2000–2018. While there are still apparent comparability issues between DMSP and VIIRS, the figure suggests that night light intensity might have decreased by as much as 60 percent by 2018.[293]

As expected, the negative correlation between the Boko Haram area dummy and economic development decreased in 2015 and 2016 when a coalition of West African forces managed to regain part of the territory that Boko Haram had captured. However, attacks by Boko Haram have since escalated and Boko Haram remains in control of large swaths of Northeastern Nigeria.

Exogeneity. *Within-Nigeria* effects are not necessarily causal given that the rise of Boko Haram might have not been independent of local socio-economic conditions. That said, the *timing* of the insurgency—2009—could be pointed as exogenous. Boko Haram was founded in 2002 and existed more or less peacefully as a sect for seven years (Cook, 2011). When in 2009 the government started investigating Boko Haram's activities and members were arrested, deadly clashes took place and the insurrection broke out. For many observers, it was surprising that the Nigerian government waited so long before cracking down on the movement. For others, it was surprising that the government finally decided to act in 2009. Thus, the government's investigation could have started anytime prior to, or after, 2009. Likewise, such investigation could have been successful without resulting in an insurrection, or the insurrection might have been swiftly contained instead of dragging on for years.[294] Finally, "control" locations outside the Boko Haram area were also affected by Nigeria losing control of almost one fifth of its territory.

Focusing on Cameroon, Chad, and Niger (henceforth "CCN"). To bypass these identification issues as well as focus on the spill-over effects of foreign conflict, we restrict our analysis to grid cells in CCN. Indeed, it was not until 2014 that Boko Haram expanded its terrorist activities outside the territory of Nigeria and into the territory of CCN (Figure 4.1 shows the trends in the number of conflict events by country for the period 2009–2018). Indeed, Boko Haram did not want to have to face four government armies. It is only when Boko Haram had no choice that it did, in particular after the Nigeria government dramatically intensified its military campaign against Boko Haram, forcing the movement to

291 The dependent variable is the log of mean light intensity (sum of lights divided by area + 1) in cell *c* in year *t*. We include cell *c* fixed effects, year *t* fixed effects, and interact the *Boko Haram area* dummy *c* (equal to one if the cell is within the Boko Haram area or if its centroid is within 10 km from the area's border) with a post-2009 (incl.) dummy *t*. The coefficient of interest is the coefficient of the interacted dummy. To account for spatial autocorrelation, standard errors are clustered at the Local Government Area (LGA; N = 721). With 7,761 cells, there are 11 cells per LGA.

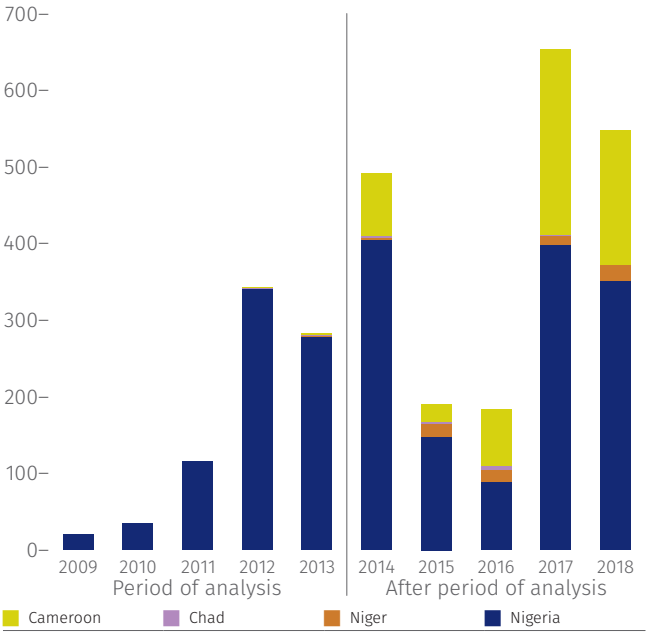
292 Also excluding 89 cells with top-coded pixels (whose maximum value is 63), we get -8.5 percent and -10.5 percent, respectively.

293 The harmonized night light data 1992–2018 is comparable by design, but harmonizing two disparate night light data sets from two different satellite series does rely on model estimates subject to error/assumptions.

294 Using the full sample and the same panel as before and interacting the Boko Haram dummy with a dummy for each year 2001–2013, we find that the negative effect of Boko Haram appears *after* 2009 (see Figure A4.1). Interestingly, we observe a slight positive effect in 2009, most likely due to the increased military presence in the area.

move some of its activities to neighboring countries. The population of the broader Lake Chad region has since been subject to an increasing number of attacks by Boko Haram, which is now linked to al-Qaeda in the Islamic Maghreb as well as the Islamic State (Enobi and Johnson-Rokosu, 2016; Daouda, 2020).

Figure 4.1: Number of Boko Haram Events, 2009–2018



Notes: This figure shows for Nigeria and each of the countries of study the number of Boko Haram conflict events in each year. As can be seen, the Boko Haram conflict was restricted to Nigeria until 2013 (incl.).

The Boko Haram insurrection represented a major economic shock at the "doorstep" of the affected regions in CCN. While the Boko Haram area of Nigeria was about twice poorer (based on mean night light intensity) than the rest of Nigeria in 2008, it was on average almost 10 percent wealthier than the whole sample of CCN (ibid.). In the region—defined as the Boko Haram area plus CCN's areas within 200 km from the Boko Haram area (see Map 4.1)—the Boko Haram area contributed more than 50 percent of the total sum of night lights in 2008. The economic shock caused by the insurrection was then amplified by the fact that the Boko Haram area offered a major trade corridor between the other three countries. The state capital of Maiduguri is the principal trade hub in Northeastern Nigeria and also between Niger and Cameroon-Chad. Anecdotal evidence suggests that trade volumes severely diminished as borders were intermittently closed and major trade routes became less accessible or even inaccessible (UNHCR and World Bank, 2016; World Food Program, 2016) as well as local markets (Blankespoor, 2021).

4.3 Sample and Main Data for Cameroon, Chad and Niger

We focus on estimating the spill-over effects of the Boko Haram-driven economic shock on the Boko Haram area's neighboring areas in CCN. Our full sample consists of 25,491 0.1*0.1 degree grid cells in CCN for the period 2000–2013 (N = 356,874). Our baseline analysis relies on a subsample of cells that were lit (NTL>0) at any point between 2000–2013, which yields a sample of 1,546 cells and a total of 21,644 observations (1,546 cells x 14 years).

Conflict Data and Boko Haram (BH) Area. We define the (core) *BH area* as the area of Borno, Yobe and Adamawa that is between the Yobe river in the North (in Yobe) and the Benue river in the South (Adamawa) (see Map 4.1). For each CCN cell, we obtain their centroid's Euclidean distance to the BH area. Our main conflict data is from the Armed Conflict Location & Event Data Project (ACLED) (Raleigh et al., 2010). We will also use data from the Uppsala Conflict Database (UCD) (University, 2020) and the Social Conflict Analysis Database (SCAD) (CCAPS, 2020).

Nighttime Lights (NTL). Since there is no reliable data that measures income or economic activities at a fine spatial level, we rely on satellite data on light emitted into space at night.[295] Satellites from the U.S. Air Force Defense Meteorological Satellite Program (DMSP) have been recording data on lights at night using their Operational Linescan System (OLS) sensor since the mid-1960s, with a global digital archive beginning in 1992. Since two satellites are recording in most years, 30 satellite-years worth of data are available for the 22-year period 1992–2013. Each 30-arcsecond pixel (≈ 1x1km) in each satellite-year contains a digital number (DN), an integer between 0 and 63, inclusive, that represents an average of lights in all nights after sunlight, moonlight, aurorae, forest fires, and clouds have been removed algorithmically, leaving mostly human settlements. This data is typically subject to the issue of top-coding. In our case, however, this is not an issue. In fact, among the 1,546 cells of our main analysis, only 11 have some top-coding. Indeed, the three countries of interest are among the poorest countries in the world. Among these 11 cells, the mean share of top-coded pixels is then only 0.05.[296] Finally, to study long-term effects we rely on the harmonized NTL data (1992–2018) from Li et al. (2020).[297]

Rural Outcomes. NTL may not perform well in capturing economic activities in rural areas which remain largely dark at night. We thus turn to other measures proxying for agricultural economic development in rural areas. The first indicator of such activities is the *Normalized Difference Vegetation Index* (NDVI)—or Greenness Index—from NASA (2020b) and we calculate its monthly mean at the grid level from 2001 to 2018. Higher values indicate denser vegetation. From European Space Agency (2017, 2019), we then obtain the share of land that can be classified as "cropland", "mosaic", "other" or "urban" (available in 2000–2018).[298]

A common agricultural practice in the region is the burning of fields (Kull and Laris, 2009; Nwaga et al., 2010). Thick layers of biomass burning aerosols, generated

295 Henderson et al. (2011) and Bruederle and Hodler (2018) demonstrate the utility of it as a local measure of GDP and human development, respectively. See Michalopoulos and Papaioannou (2013, 2014) for studies on Africa.

296 We could have used instead the radiance calibrated data from NOAA 2015 which has the advantage of not being top coded. However, this data stops in 2011 whereas DMSP-OLS stops in 2013 and we need to study 2009–2013.

297 Li et al. (2020) combine night light data from OLS-DMSP (1992–2013) and SNPP-VIIRS (2012–2018). The nighttime lights from the SNPP satellite, carrying VIIRS, series brings unprecedented information compared to the previous OLS series, including improvements such as spatial resolution (15 arc seconds or 500m) and measurement (14 bit quantization) with a wider dynamic range and lower detection limits (Elvidge et al., 2017).

298 Cropland corresponds to rain-fed, irrigated or post-flooding. Mosaic corresponds to mosaic cropland (>50 percent) or natural vegetation (tree, shrub, herbaceous cover) (<50 percent). Other corresponds to all remaining land cover.

mainly by agricultural burning during the dry season, can be detected across the Sahel region of Africa (Johnson et al., 2008). Aside from the threat to the atmospheric environment such aerosols pose, agricultural burning also causes the loss of forest system carbon, biomass and nutrient stocks due to deforestation, leading to long-term soil infertility despite achieving short-term soil fertility (Kotto-Same et al., 1997; Kanmegne, 2004). Despite the long-term harm to agricultural outcomes, impoverished farmers resort to agricultural burning to secure food and income.[299]

Following Blankespoor et al. (2021) who examine the effect of conflict on agricultural activity in the Central African Republic, we sum at the grid level the MODIS Burned Area data product (v6), which provides a burned-area estimate per 500m pixel by month (NASA, 2020a). Then, according to the main food crops for each country-crop calendar (FAO, 2020) we define each month into three seasons: (i) land preparation; (ii) sowing and growing; and (iii) harvest.

Finally, the controls and other outcomes considered in our analysis are described below.

299 70 percent of deforestation in Africa is attributed to agricultural burning, compared to 50 percent in Asia and 30 percent in Latin America (Nwaga et al., 2010). In Cameroon, about half of the annual rate of deforestation, at 0.6 percent overall, is for agricultural purposes, while the other half is attributed to logging (Gockowski et al., 2005).

4.4 Econometric Specification and Issues

We examine in a panel-DiD framework the average effect of the Boko Haram (BH) shock in CCN areas neighboring the BH area. To do so, we first investigate the geographical scope of the BH effect, i.e. how "far" into CCC a significant BH effect is observed. Second, we verify that this effect only appears in 2009, thus confirming parallel trends and the local exogeneity of the *foreign* BH shock, and also investigating how the effect varied over time during the 2009–2013 period.

Model 1. The model examines the *geographical scope* of the effect and can be formalized as follows:

$$\text{NTL}_{s,c,t} = \alpha + \sum_{d=25}^{250} \beta_d \, \text{BH}_{s,c,d} * \text{Post 2009 Dummy}_t + \lambda_s + K_{c,t} + \mathbf{X}_{s,c} B_{X,t} + \varepsilon_{s,c,t} \quad (1)$$

where s denotes the cell, c the cell's country, and t the year. NTL is the log of mean night light intensity (sum of lights divided by cell area). Since NTL can be zero in some years, we use log (mean night light intensity + 1). As discussed earlier, for our main regressions we focus on 1,546 cells with some night lights at one point in 2000–2013, thus yielding 21,644 observations in total. λ_s and $K_{c,t}$ correspond to cell fixed effects and country-year fixed effects, respectively. The main variables of interest are the interactions of the dummies $BH_{s,c,d}$ equal to one if the cell is d kilometers (in terms of simple Euclidean distance) away from the BH area in Nigeria (with d ranging from 25 km through 250 km at an increment of 25 km) multiplied by a dummy $Post\ 2009\ Dummy_t$ equal to one if the Boko Haram conflict has started, hence post-2009.

Controls. We include various important time-invariant controls $X_{s,c}$ which we interact with year fixed effects to allow their effects to vary flexibly over time. First, we control for the log of the Euclidean distances to the largest city and the capital city in the cell's country.[300] We do so because spatial patterns of economic development over time could be affected by proximity to the main economic and political centers of the country. We also control for the log of the Euclidean distance to N'Djamena, the capital and largest city of Chad. In Map 4.1, N'Djamena is located in the North-West of Chad, close to the border with Cameroon. Since N'Djamena has been growing rapidly over time, for reasons unrelated to Boko Haram, we need to avoid conflating the economic impact of Boko Haram with the rapid expansion of N'Djamena *per se*.

Due to attacks close to the border areas, Chad and Niger increased border controls as well as military presence at their borders with the North-East of Nigeria. Cameroon also increased controls at the border with Chad that is close to the BH area. This may have resulted in public expenditure—and thus night lights—in these areas, which would cause an upward bias of the effect. In other words, this would make us under-estimate how *negative* the effect is. We thus consider a dummy if the cell is a border cell and is within 50 km from the BH area.

Resource-rich areas may have also seen their NTL change over time, for example due to commodity price fluctuations. For example, there is oil production and oil refining in the three countries and Niger is also a major exporter of uranium. We create a dummy equal to one if the cell intersects with oil- or uranium-producing areas or contains an oil refinery.[301]

300 These two are different in Cameroon where the largest city is Douala, followed closely by the capital city Yaoundé.

301 We use the Petroleum Dataset version 1.0 (Lujala et al., 2007) to identify onshore oil producing areas and we digitize locations of oil refineries from national sources (e.g. Nigeria Department of Petroleum Resources, 2020). Even though both Chad and Niger have a long history with the oil industry, the only refinery in Chad, Djarmaya, opened in 2011. In Niger, the Agadem oilfield and the Soraz refinery near Zinder opened in 2011. Niger exports oil via Chad or Cameroon. U.S. Geological Survey (2006) then capture the locations of uranium producing areas near Arlit, Niger.

Finally, due to heightened insecurity in Northeastern Nigeria, areas close to the border in the three countries received Nigerian refugees but also Cameroonese, Chadian or Nigerien returnees. Some of them were accommodated by the governments and international organizations in formal refugee camps. Others moved to localities in these areas. As such, this may have induced population increases and public investments, and thus amplified night lights, in these areas. This would cause an upward bias and thus make us under-estimate the negative local effect of Boko Haram. We thus add two dummies for whether there is a refugee camp in the cell (ca. 2015) and the estimated log number of (refugees + returnees) in each cell (ca. 2015). However, the influx of refugees + returnees could also have negative economic effects, for example if social tensions are increased as a result. One could then argue that there is overcontrolling. We will thus show that results are little sensitive to the omission of these controls.[302]

Spatial Autocorrelation. To account for spatial autocorrelation, standard errors are clustered at the 3rd level administrative unit, which corresponds to *arrondissements* in Cameroon (N = 343), *sous-prefectures* in Chad (N = 336) and *communes* in Niger (N = 265).[303] For our full sample, this corresponds to 12, 33 and 40 cells per unit on average in each country respectively (areas of 1,452, 3,993 and 4,840 sq km, respectively). We use standard errors clustered using administrative units instead of Conley standard errors because, as discussed in Section 4.7, the latter are computationally intensive with many spatial units. However, we will show in the same section that results hold when clustering at a higher level or using Conley standard errors.

Model 2. The second model examines the *temporal scope* of the effect. In particular, we will find that Boko Haram only has a significant effect within 200 km from the BH area. We then slightly modify Equation (1) so as to let the effect of proximity to the Boko Haram area (within 200 km) vary each year (relative to the omitted year 2000) instead of only comparing the 2009–2013 period to the pre-2009 period. More formally, we estimate the following panel model:

$$\mathrm{NTL}_{s,c,t} = \alpha + \sum_{i=2001}^{2013} \Upsilon_i \times \mathrm{BH\ 200km}_{s,c,d} + \lambda_s + K_{c,t} + \mathbf{X}_{s,c} B_{X,t} \quad (2)$$

where the dummy variable $BH\,200km_{s,c,d}$ coded as 1 if the cell is within 200km from the BH area is interacted with year dummies Υ_i generated for each year between 2001 and 2013. Our expectation is that the effect becomes negative and statistically significant *only after* 2009.

302 Refugee camp locations come from UNHCR (2020). The estimated local numbers of refugees and internally displaced people come from Direction Régionale de l'État Civil et des Réfugiés (2016); IOM (2016); UN OCHA (2015).

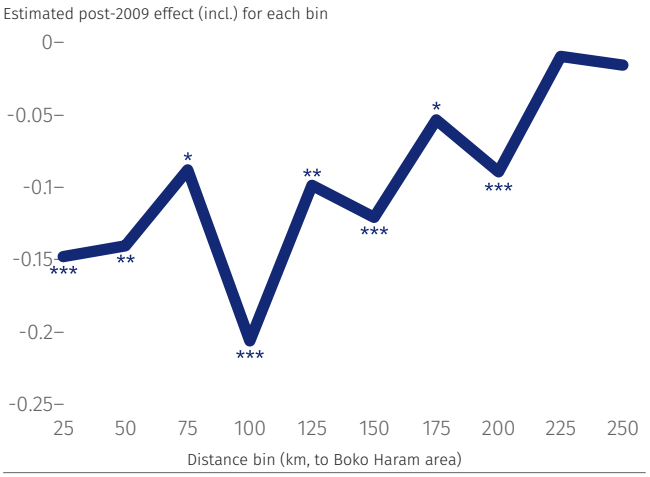
303 Administrative country boundaries come from GADM version 3.6.

4.5 Average Effects in Cameroon, Chad and Niger

4.5.1. Baseline Results

Results from the panel-DiD model (1) are shown in Figure 4.2. There is a significant effect of Boko Haram in the range between 25 (0–25) and 200 (175–200) km. The average effect within 50 km (across the 25 and 50 bins) is -0.15 (p < 0:01), implying that the rise of Boko Haram reduces NTL by 15 percent. The average effect for 50-100 km (across the 75 and 100 bins), 100-150 km (across the 100 and 125 bins) and 150–200 km (across the 175 and 200 bins) is -15, -11 and -7 percent (p < 0:01), respectively. The average effect within 200 km is then -0.12 (p < 0:01), implying an average decrease of 12 percent. For the sake of simplicity, in the rest of the analysis we focus on a simple 0–200 km dummy, thus estimating an average effects across all affected bins.

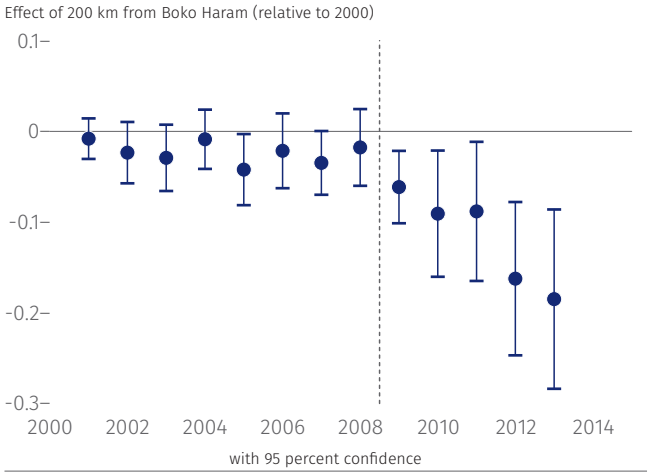
Figure 4.2: Post-2009 (Incl.) Boko Haram Effect by Distance to the Boko Haram Area



Notes: The figure shows the post-2009 (incl.) Boko Haram effect for each distance (to the Boko Haram area) bin. 25 corresponds to 0–25 km, 50 corresponds to 25–50 km, ..., and 250 corresponds to 225–250 km. See Equation (1) for details on the specification. See Appendix for data sources. * p<0.10, ** p<0.05, *** p<0.01.

We find evidence that the assumptions of parallel trends and local exogeneity of the BH shock hold. As seen in Figure 4.3, when using the model of Eq. (2) no effect is observed before 2009, a small effect is observed in 2009, and the effect decreases after that. This is expected given the rapid intensification of the Boko Haram insurgency after 2009. By 2013, the effect is about -0.20, so cells "close" to the BH area have lost 20 percent of their level of economic activity on average.

Figure 4.3: Yearly Effect of Proximity to the Boko Haram Area (0–200 km)



Notes: The figure shows the yearly effect (relative to the year 2000) of a dummy equal to one if the cell is within 200 km from the Boko Haram area. See Equation 2 for details on the specification. * p<0.10, ** p<0.05, *** p<0.01.

If we use same model but further separate the BH 0-200 km dummy into 0–50, 50–100, 100–150 and 150–200 km dummies, we find that Boko Haram has no effect before 2009 in the four groups of cells. The effect by 2013 is then about -15, -20, -20 and -30 percent (p < 0:01), respectively (see Figure A4.3). Aggregating some of these effects, cells within 100 km have lost almost 25 percent while the cells farther away (but still within the 200 km window) have lost about 15 percent. In the rest of the analysis, we will also sometimes distinguish 0–100 and 100–200 km.

Finally, we use the panel-DiD model of eq. (1) and the harmonized NTL data from Li et al. (2020) to study the long-term effects of the shock. There are several caveats with this analysis. First of all, there may still be comparability issues between DMSP (used for the 2000–2013 period) and VIIRS (2014–2018) in the data of Li et

al. (2020). Second, Boko Haram had attacked Cameroon by 2014 and Chad and Niger by 2015 and there may have been local and spill-over effects of these attacks. However, only 60 cells were ever affected in CCN. To attempt to study the long-term effects of foreign conflict, we exclude the 60 cells as well as 166 cells within 50 km of these 60 cells. We also control for the log of the Euclidean distance to a CCN Boko Haram event in year *t*.

As seen in Figure A4.4, the negative effect of Boko Haram increased in magnitude over time, reaching -35 percent by 2015 and -50 percent by 2018. We see some recovery effects in 2016 when West African troops managed in 2015 to regain some of the territory captured by Boko Haram in Nigeria, another implicit test of our identification strategy. We thus see positive spill-over effects of a successful foreign counter-insurgency campaign. Next, the high standard errors for the VIIRS observations likely reflect the fact that the assumptions made by Li et al. (2020) to recreate consistent NTL for the whole period also introduced a significant amount of noise. Lastly, we may not be capturing a long-term effect *per se* as the conflict never ended.[304]

Overall, we find very strong negative local effects of foreign conflict. The question now is which sectors, and thus locations, foreign conflict disproportionately impacts and why.

4.5.2 Foreign Conflict as a Trade Shock Disproportionately Impacting Cities?

In this section, we examine whether the foreign conflict shock disproportionately impacted trade-reliant cities, mostly due to trade disruptions. To do so, we first show using the night lights data and other data on rural economic development that urban areas were far more impacted than rural areas. Next, we argue that curfews, the in-migration of refugees and/or the outmigration of residents were not driving the results. Finally, we do not find evidence for spill-over effects on conflict. Thus, incomes did not decrease in the border regions because conflict factors (e.g., armies and weapons) moved from the BH area to these regions. Ultimately, we believe that conflict in the BH reduced CCN's trade with Nigeria but also trade between the regions of Cameroon-Chad and Niger that historically used the BH area as a trade corridor.

4.5.2.1 Other Results on Night Lights and Rural Economic Outcomes

Night lights. Our analysis thus far focused on the sample of cells that were ever lit at some point between 2000 and 2013. We now consider other samples of cells.

Table 4.1: Post-2009 Effect of Proximity to the Boko Haram Area (0–200 km), Night Lights

Dependent Variable:	*Col. (1)–(3) and (5): Log (Mean Night Light Intensity + 1) in Year t* *Col. (4): Dummy if Mean Night Light Intensity in Year t > 0*				
Sample:	*Intensive (1)*	*All (2)*	*Extensive (3)*	*Extensive (4)*	*Pure Intensive (5)*
BH 200 Km * Post-2009	-0.097***	-0.007**	-0.001	-0.004	-0.143***
	[0.027]	[0.003]	[0.001]	[0.003]	[0.046]
Cell FE, Country-Year FE	Y	Y	Y	Y	Y
Year FE*Controls	Y	Y	Y	Y	Y
Observations	21,644	356,874	348,470	373,227	7,835
Adjusted R-squared	0.89	0.89	0.21	0.27	0.93

Notes: SEs clustered at the 3rd-level administrative unit. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

304 The data from Li et al. (2020) generate more consistent results between the pre- and post-2013 periods for CCN than for Nigeria. Indeed, Li et al. (2020) explain that the harmonization of the DMSP and VIIRS series might work differently for locations with a level of night lights below vs. above 30. Nigeria has locations both below and above 30 whereas there are fewer such values in CCN. As such, harmonization should be less problematical there.

Table 4.1 shows the results for: i) the "intensive" margin sample, i.e. only the cells that were ever lit between 2000 and 2013 (Col. 1); ii) all observations (Col. 2); iii) the "extensive" margin sample, which excludes cell-years with night light intensity > 0 in t-1 (Col. 3); iv) the "extensive" margin sample but with a simple dummy coded 1 if light intensity is higher than 0 in year t (Col. 4); and v) the "pure intensive" margin sample that consist of cell-years for which light intensity > 0 in both t-1 and t (Col. 5).

The negative effects of foreign conflict are particularly pronounced in urban areas (as reflected in cells that are lit between 2000 and 2013). In the "intensive" and "pure intensive" samples (Cols. 1 and 5), the average effects are -10 percent and -14 percent both significant at the 0.01 level, respectively, whereas these effects are smaller in the full sample (Col. 2) and insignificant at the extensive margin (Cols. 3 and 4).[305] More generally, the intensive margin effect of -0.097*** in Col. 1 represents about 47 percent of the mean in the sample (which is 0.47) whereas the extensive margin effect of -0.004 in Col. 4 represents only 5 percent of the mean in the sample (0.07).

We thus do not find any effect of foreign conflict on the likelihood that non-lit cells become lit, a proxy for rural economic development. Villages and small towns close to the BH area are thus not less likely to generate enough luminosity picked up by the satellites. These results could suggest that the geographical scope of the spill-over effects is limited to more urban areas, likely because these urban settlements rely more extensively on regional trade with, or through, the BH area than their rural counterparts (more on this later).

However, one caveat is that NTL may not measure well rural growth or decline, even when focusing on the extensive margin only. Thus, to better examine rural effects, we study other reasonable proxies for rural economic activities: greenness, land use, and agricultural burning.

The effects of foreign conflicts on rural economic development are theoretically ambiguous. Rural areas are possibly isolated from such shocks if they do not trade with foreign areas. However, if they sell their agricultural products to the foreign area, the level of demand decreases. Furthermore, if urban areas are negatively impacted by reduced trade with the foreign area, this could in turn impact the demand for agricultural products in rural areas. In a context of high population growth, the latter mechanisms would lead to slower rates of land expansion.

Alternatively, if urban areas import rural products from the foreign area, insecurity may lead urban areas to demand local rural products instead. Reduced economic opportunities in urban areas trading with the foreign area could also lead urban residents to seek economic opportunities in the rural sector (in the region, it is common for urban residents to have farming relatives in surrounding rural areas). In such cases, we might observe faster land expansion.

Greenness. The measures of greenness, land use and burned area are available at the grid cell level for 23,945 cells *without* night lights at any point between 2000 and 2013, which correspond to more rural areas.[306] In terms of the Greenness index, data is available on the monthly basis. When studying monthly patterns, we find that greenness peaks in August in Niger and Chad—at the height of the rainy season—and is high in Cameroon around May (the light rainy season) and September (the heavy rainy season). Once one accounts for country-month effects, greenness could capture land expansion or land abandonment and thus proxy for rural growth.

For greenness (available in 2001–2013), the model is the same panel-DiD model as before except the dependent variable is the log of (mean greenness + 1) in the cell s in

305 We find similar non-effects at the extensive margin when separating 0–100 km and 100–200 km (not shown).
306 Results are similar if we keep all cells including those cells that are ever lit between 2000 and 2013 (not shown).

Table 4.2: Post-2009 Effect of Proximity to the Boko Haram Area (0–200 km), Rural Outcomes

Dep. Var.:	*LogMean Green. t*	*Share Crop+ Mos*	*Col. (3)–(4) and (6)–(9): Log (Agricultural Burning + 1) in t Col. (5): Dummy if Agricultural Burning > 0 in t*						
Sample:	*All (1)*	*All (2)*	*All (3)*	*Extensive (4)*	*Intensive (5)*	*Pure Prep. (6)*	*Land Growing (7)*	*Sowing (8)*	*Harvest (9)*
BH 200 km * Post-09	-0.000	-0.001	0.042**	0.007*	0.007	0.047	0.001	0.005*	0.070**
	[0.001]	[0.001]	[0.017]	[0.004]	[0.006]	[0.035]	[0.016]	[0.003]	[0.027]
Cell FE, Cntry-Yr FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year FE*Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	311,285	311,285	232,040	232,040	61,496	311,285	311,285	311,285	311,285
Adjusted R-squared	1.00	1.00	0.85	0.40	0.38	0.71	0.77	0.31	0.79

Notes: SEs clustered at the 3rd-level administrative unit. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

year *t* (mean = 0.31).[307] As can be seen in Col. (1) of Table 4.2, we find no effect of Boko Haram on greenness (the point estimate only represents 5 percent of the mean in the sample that is 0.31).[308]

Land Use. We know the share of land that can be classified as either "cropland" or "mosaic cropland" (at least 50 percent cropland) for the full period 2000–2013 (mean = 0.09). As seen in Col. (2), we also find no effect of Boko Haram on land intensification or de-intensification (the point estimate only represents 1 percent of the mean in the sample that is 0.09).[309]

Agricultural Burning. When studying monthly patterns in agricultural burning, we find that it peaks in November-December when the harvest season ends. This type of agricultural burning corresponds to the practice of stubble burning, where farmers set fire to the straw stubble that remains after crops have been harvested. Agricultural burning is then observed until April–May, at the end of the land preparation season. For land preparation (which includes the preparation of new land that was not agricultural before), slash-and-burn is common there. We thus investigate how agricultural burning (available in 2001–2013) varies with the rise of Boko Haram, depending on the season: "harvest", "land preparation" and "sowing-growing".[310] Since agricultural burning area can be equal to 0, we use log(burning + 1) as the dependent variable. As we did for NTL, we explore different margins (intensive, extensive, etc.) in Table 4.2 Col. 3–9.

In Col. 3, which includes all cell-years, we find a positive and significant effect of 0.042*.** It is however smaller than what was found for night lights. In particular, the point estimate represents 20 percent of the mean in the sample (20.4) against 47 percent for night lights.

The burning effect is driven by both extensive margin (Col. 4) and pure intensive margin (Col. 6) effects. More precisely, in Cols. 4 and 5, we restrict the sample to cell-years whose burning in *t*-1 is zero. In Col. 4, the outcome is log(burning + 1) in *t* whereas in Col. 5 it is a dummy equal to one if burning > zero. The effect on the

307 Greenness has negative values. To use logs, we first shift all observations by the absolute value of the minimum value in the data (so that the new minimum value is 0) and then add +1. Also, since greenness is not bottom-coded we do not need to distinguish the intensive and extensive margins as we did for NTL.

308 For the sake of simplicity, we use mean greenness averaged across the 12 months of a given year. We obtain the same non-results if we regress for each cell-year-month greenness on country-month dummies and use as our measure the log of the average of the residuals (not shown). There also no effects for 0–100 vs. 100–200 km (ibid.).

309 The coefficients are not significantly different between 0–100 km and 100–200 km (not shown).

310 We rely on crop calendars from FAO GIEWS. "Harvest": October–November in Cameroon; September–November in Niger; September–December in Chad. "Land preparation": December–April in Cameroon; December–May in Niger; January–April in Chad. "Sowing-growing": May–September in Cameroon; June–August in Niger and Chad.

dummy is small and not significant (Col. 5). However, the effect on log(burning + 1) is positive and significant (0.007*). Thus, BH resulted in more burning amongst those cells without any burning in the previous year. In Col. 6, we focus on the pure intensive margin effect for cell-years with burning > 0 in both *t*-1 and *t*. The effect is not significant but seven times higher than for the extensive margin (0.047, or about 5 percent).

Burning, while traditionally used, is not a sustainable farming practice as it depletes the nutrients in the soil. Results suggest that agriculture is little mechanized (i.e., more traditional) in these areas, and that farmers are willing to increase short-term incomes at the expense of future incomes. Thus, farming households (and their possibly more urban-based members) may have become more present-biased in the face of the shock. Note that these results hold if we exclude border cells within 50 km from the Boko Haram area in case the measures of agricultural burning pick up fires related to destruction caused by Boko Haram itself (not shown).

Finally, in Cols. 7–9 which disaggregate the results by different seasons, we show the effects are driven mainly by the end of the harvest period. This finding implies that burning was not a result of preparing new land that had not been exploited before (Col. 7) but came from increasing income as soon as the harvest season was over (Col. 9). This practice is particularly damaging in the long run since soils cannot recover at all. Also, the fact that it is at the end of the harvest season indicates that the observed effects are for parcels that were already exploited the year before, not new parcels (in line with the non-results for greenness and land use).[311]

Overall, we find no effect on rural lights or land expansion. Thus, the positive effects of the shock on rural growth must have somewhat compensated its negative effects. For example, even if the export of rural products to Nigeria decreased, there was also less competition from rural products coming from Nigeria. However, even if land use did not change overall, it could still be that the shock very negatively impacted some farming communities. As their members likely live close to the subsistence level, they found ways to increase short-run incomes even if it meant borrowing against the future. Overall, while some rural areas were negatively impacted, the rural sector does not appear to have been driving the economic crisis observed in the region, hence our characterization of the Boko Haram-led economic shock as an "urban" shock.

4.5.2.2 Income Shocks, Migration, and Urban Land Expansion

Curfews. First of all, the reduction in night lights was not due to curfews. While curfews were indeed imposed in some parts of Northeastern Nigeria, especially around the city of Maiduguri, there were no curfews occurring in CCN before Boko Haram actually entered these countries.

Refugees and Returnees. Second, we could imagine that the inflows of refugees and returnees had negative economic effects on host communities in the border regions. Such inflows could also have had positive effects if they generated economic activity and/or led to local increases in public expenditure. The results reported so far are conditional on various controls for the location of refugee camps and the (log) number of returnees in each cell c. 2015 (all interacted with year fixed effects to allow their effects to vary over time). Our baseline intensive margin effect is -0.097*** (Col. 1 of Table 4.1). If we omit the refugees/returnees controls, we obtain a slightly more negative effect of -0.103***. If anything, this suggests that the inflows of refugees/returnees had, on net, slightly positive, not negative, local economic effects.[312]

311 Throughout (Cols. (3)–(9)), the effects are stronger for 0–100 km than for 100–200 km (not shown).

312 Results are similar whether we omit the "refugees" controls only or the "returnees" controls only (not shown). As expected, cross-sectional regressions for the 1,546 cells confirm that the border regions had more refugee camps c. 2015 (Ibid.). However, conditional on the baseline controls, they did not receive more returnees c. 2015 (Ibid.).

Population Outflows due to Heightened Insecurity. We could also imagine that populations afraid of the rise of Boko Haram in Nigeria left the border regions, thus causing reductions in luminosity. Indeed, changes in night light intensity (sum of night lights divided by area) may reflect both changes in nighttime lights *per capita* (in other words, per capita incomes) and population changes (net migration). Of course, the two subcomponents are mechanically correlated. If incomes decrease, local residents will more likely out migrate to other areas and non-local residents will less likely migrate in. We now discuss the respective contributions of each channel, which allows us to discuss the potential role of outmigration.

Suppose that income (NTL) per capita increases in a cell relative to other cells. Under this hypothetical situation, people migrate in and population density in settled areas initially increase (built-up area is fixed in the short-run as construction takes time). As a result, housing prices increase. Housing supply eventually responds. In areas where land is relatively cheap and construction technology not so advanced, housing supply is likely to respond by using more land, not building taller structures. Hence, the cell's built-up share should eventually increase. As urban land expands, the population density in settled areas that initially increased redecreases. As population increases, NTL per capita may also decrease after initially increasing if increased labor supply reduces wages. However, the levels of income per capita and population density are likely to remain higher than they were before the initial per capita income increase. In this case, cell growth may be captured by a combination of NTL per capita, population density (population divided by built-up areas) and land expansion (built-up area divided by total area).

Now, when income (NTL) per capita decreases in a given location to another location, people out-migrate (or migrate-in less). As a result, population density in settled areas decreases. However, housing is durable (Glaeser and Gyourko, 2005). Thus, if people outmigrate, housing prices decrease, incentivizing them to stay. Individuals more sensitive to lower housing prices are more likely to stay, thereby resulting in a greater proportion of poorer individuals. As housing supply is now relatively higher (compared to demand), there is less construction. Since construction takes the form of land expansion in poor countries (Jedwab et al., 2020, 2021), one prediction could be that there is less land expansion in these areas as a result of the shock. However, the effect should not be instantaneous since the construction sector often reacts with some temporal lag. In addition, people may wait for a few years before deciding whether to outmigrate and thus just "weather" the shock. In particular, observers initially did not expect the BH insurrection to last long as Nigeria was the most developed country in West Africa. The residents of Cameroon, Chad and Niger also probably expected the BH shock to be temporary.

To conclude, with the negative BH-led economic shock, we may expect a strong effect on NTL per capita that is only weakly associated with an effect on population density and land expansion. In that case, most of the effect on NTL should come from changes in NTL per capita.

To better assess the plausibility of the previous hypothesis, in Table 4.3 we focus on urban population outcomes by leveraging data from the *Global Human Settlements (GHS)* database. GHS use satellite data to obtain for each cell built-up land area over time, more precisely c. 1975, 1990, 2000 and 2013/14, which nicely coincides with the end of our period of study.[313] Furthermore, GHS reconstructs city populations c. 1975, 1990, 2000 and 2015, using urban population levels at a relatively low administrative level circa these years and then allocating the population within these administrative areas depending on the distribution of built-up area.[314] However, the population levels reported by GHS may

313 Built-up area is from GHS Builtup (Corbane et al., 2019). See https://ghsl.jrc.ec.europa.eu/ for details.
314 Note that the GHS database focuses on urban agglomerations with more than 50,000 inhabitants c. 2015.

Table 4.3: Post-2009 Effect of Proximity to the Boko Haram Area (0–200 km), Urban Outcomes

Dependent Variable:	***Log (Mean Light Intensity + 1) t***				***LogUrb. Pop. t***	***(6), (8)–(9): Log (Built-Up Area + 1) t (7): Dummy if Built-Up Area t > 0***			
Sample:	***All (1)***	***All (2)***	***Niger (3)***	***Niger (4)***	***Niger (5)***	***All (6)***	***Extensive (7)***	***Extensive (8)***	***Intensive (9)***
BH 200 km * Post-2009	-0.18***	-0.17***	-0.24***	-0.24***	0.07	0.17	-0.05	-0.49	0.11
	[0.06]	[0.06]	[0.07]	[0.07]	[0.19]	[0.46]	[0.10]	[0.86]	[0.19]
Log(BuiltUp Area/ Area+1)*t*		9.13***							
		[1.85]							
Log(Urb. Pop./Area+1)*t*				0.023					
				[0.015]					
Cell FE, Country-Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year FE*Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	4,638	4,638	1,689	1,689	1,165	4,638	2,237	2,237	2,401

Notes: SEs clustered at the 3rd-level administrative unit. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

not be reliable in our context because of the lack of census data. In Niger, there were censuses in 2001 and 2012, so their population level c. 2015 actually reflects 2012. For Chad, the last two censuses were 1993 and 2009. For Cameroon, these were 1988 and 2005. As such, the reported population levels for 2015 likely measure populations *pre*-Boko Haram. Thus, in this analysis, we report the results based on built-up land area or the results based on urban population sizes but for Niger only.

In Table 4.3 Cols. 1–4, we use log(NTL + 1) for the years 1992—which we call "1990"—2000 and 2013. This is the same panel-DiD regression (eq. (1)) as before but we exclude the years in between. Note that we use data from 1990, 2000, and 2013 to mimic the structure of the GHS data. First, in Cols. 1–3, we focus on the 1,546 cells with NTL > 0 at any point in 2000–2013 × 3 years, hence N = 4,638. The sample of 1,546 cells is the sample where we showed strong negative effects on NTL. More precisely, according to Figure 4.2, we had an effect of almost -0.20 (hence -20 percent) by 2013. In Col. 1, we use the same BH 200 Km dummy × post-2009 (in this case, the year "2013", hence 2013/14) and obtain -0.18 (p < 0:01), hence the same result.

In Col. 2, we control for the log of built-up density (or urban built-up area divided by total area) since it is available for all cells in 1990–2013. The effect is only slightly lower, at -0.17 (p < 0:01), hence -17 percent. Thus, assuming built-up density captures the effects of both built-up density and population density in settled areas—thus, population—almost all of the effect of the shock on night light intensity must be due to the income shock (i.e., NTL per capita).[315]

In Cols. 3–4, we focus on Niger, the only country with city population data post-2009. In Col. 3, we run the same regression as in Col. 1 for Niger only. The estimated effect is -0.24 (p < 0:01). Thus, the negative effect on NTL appears to have been stronger in Niger than in Cameroon/Chad. However, if we control for log urban population density (total city population divided by area) in the cell, we observe the same effect. Thus, almost all of the effect of the shock on night light intensity must be due to reductions in income per capita (i.e., NTL per capita).[316] Relatedly, if we use log(total city population) as the dependent variable, thus comparing the population size of existing urban agglomerations over time, we also find no effect of Boko Haram post-2009 (Col. 5).

315 Note that we use the log of (urban built-up area divided by total area +1). Indeed, some cells with NTL > 0 have an urban built-up area of 0 according to GHS. We thus verify that these cells also have very low levels of NTL.

316 Since some cells have no urban population according to GHS, we use log(total city population area + 1).

Alternatively, we study if built-up area changed due to the shock. Since structures are durable, built-up areas did not shrink. However, the shock may slowed down urban land expansion. We thus study log(built-up area + 1) for the years 1990, 2000 and 2013.[317] In Col. 4, we focus on the same 1,546 cells but study how log built-up area grew slower with the shock. Given that structures are durable, we control for log (built-up area +1) in *t*-1 interacted with year fixed effects.[318]

As seen in Col. 6, the coefficient is positive and not significant. Thus, the main negative effect on night light intensity is not due to urban land expansion slowing down. Next, in Cols. 7 and 8, we study the extensive margin and focus on cell-years whose built-up area in *t*-1 is zero (we no longer need to control for past built-up area). In Col. 7, the dependent variable is a dummy if the cell has some built-up area in *t*. In Col. 8, it is the log of (built-up area +1). The effect is negative but insignificant, which leads us to conclude that while urban land expansion could have slowed down, reductions in income (NTL) per capita drove the results.

Finally, in Col. 9, we focus on the pure intensive margin, keeping cell-years whose built-up area in *t*-1 is higher than 0 (we control for past built-up area). The positive effect suggests accelerated urban land expansion in cells where there were already built-up areas. Since the overall effect (Col. 6) is positive, the intensive margin effects must have been stronger than the extensive margin effects. This may be counter-intuitive since the coefficient in Col. 9 is lower in absolute value than the coefficient in Col. 8. However, the coefficient captures percentage changes, so the absolute effects depend on the initial levels of built-up area in cells with built-up areas in *t*-1.

Overall, we find that the negative effects of foreign conflict on local economic development are driven by per capita incomes falling, not migration. If anything, affected individuals appeared to have stayed in these areas despite the massive income shock, one plausible explanation being the fact that the shock was seen as temporary (even it was not in the end).

4.5.2.3 Foreign Conflict, Local Conflict, and Local Economic Development

Foreign conflict should have direct economic effects. However, foreign conflict can also have a direct impact on local conflict, for example by increasing the supply of weapons and trained mercenaries in the region. Alternatively, foreign conflict, by reducing local incomes, increases the likelihood of local conflict. In that case, we still capture a direct economic effect of foreign conflict but the effect is magnified by a local conflict effect. While possible, we show below that the Boko Haram shock did not increase the likelihood of local conflict in CCN. Consequently, the effect estimated so far are the pure direct economic effects of foreign conflict.

For the years 2000–2013, we employ the same panel-DiD model as before, but we now use measures of conflict as the dependent variable. In Panel A of Table 4.4, the dependent variable is a dummy equal to one if a conflict event unrelated to Boko Haram occurred in the cell in year *t*. In Panel B, it is the number of non-Boko Haram conflict events in the cell in year *t* (unlogged because there are few events in a same cell in each year). Next, for each conflict database, we study the effect for all cells first and then for the intensive sample (where NTL > 0 at any point in 2000–2013) and the extensive sample separately. Finally, ACLED and UCD focus on armed

317 Since most cells have the same area, log built-up area is similar to the log of the share of built-up areas.

318 This allows for the durability effect to vary over time, for example due to changing construction technologies. Adding a lag of the dependent variable in a panel model introduces a dynamic panel bias (Nickell, 1981) so these results should be taken with caution. However, we do not need these controls when studying the extensive margin.

Table 4.4: Effects of Boko Haram on Domestic Conflict, Various Databases, 2000–2013

Conflict Database:	*ACLED (Armed Conflict)*			*Uppsala (Armed Conflict)*			*SCAD (Social Conflict)*		
Sample:	*All (1)*	*Intensive (2)*	*Extensive (3)*	*All (4)*	*Intensive (5)*	*Extensive (6)*	*All (7)*	*Intensive (8)*	*Extensive (9)*
Panel A:	*Dep. Var.: Dummy if Non-Boko Haram Conflict Event in the Cell in Year t*								
BH 200Km * Post-09	0.0002	0.0047	-0.0002	0.0003	0.0035	0.0000	0.0005	0.0028	0.0002
	[0.0004]	[0.0042]	[0.0003]	[0.0002]	[0.0025]	[0.0001]	[0.0005]	[0.0046]	[0.0002]
Mean	0.0011	0.0106	0.0004	0.0004	0.0028	0.0002	0.0005	0.0047	0.0002
Panel B:	*Dep. Var.: Number of Non-Boko Haram Conflict Events in the Cell in Year t*								
BH 200Km * Post-09	0.0024	0.0219	0.0000	0.0009	0.0092	-0.0000	0.0010	0.0055	0.0003
	[0.0022]	[0.0223]	[0.0006]	[0.0007]	[0.0072]	[0.0001]	[0.0007]	[0.0070]	[0.0002]
Mean	0.0011	0.0106	0.0004	0.0004	0.0028	0.0002	0.0005	0.0047	0.0002
Cell FE, Cntry-Yr FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Yr FE*Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	356,874	21,644	335,230	356,874	21,644	335,230	356,874	21,644	335,230

Notes: SEs clustered at the 3rd-level admin. unit. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

conflict (Cols. (1)–(6)) whereas SCAD focuses on (not necessarily armed) social conflict ((7)–(9)).[319]

As seen, none of our variables is significant. Therefore, the likelihood of domestic conflict did not increase significantly, which suggests that any economic impact of BH on neighboring areas in CCN must have been due to reduced trade, not a direct effect of BH on conflict supply factors. Likewise, the effect of the BH-led economic shock was not reinforced by an indirect feedback effect in which poverty led to conflict, which in turn further caused poverty.[320]

In addition, the effect of BH on conflict appears stronger (but is still not significant) in the more urban intensive sample than in the more rural extensive sample. Indeed, more urban areas have been disproportionately hit by the BH-led economic shock.

We then obtain similar non-results if, for the full (intensive + extensive) sample, we: (i) study a composite index based on the number of conflict events plus 0.5 × the number of fatalities, thus giving more weight to more lethal conflict events (note that 0.5 is arbitrary); and (ii) examine specific types of conflict. The results when using conflict data from ACLED, UCD and SCAD can be seen in Tables A4.1, A4.2 and A4.3, respectively.[321] We then find similar non-results if we focus on the intensive sample only (not shown, but available upon request).

Next, CCN's governments increased military presence in the region. As such, domestic conflict might have been prevented in areas close to BH. Yet, if increased military presence came from redeployment, which is plausible given the time it takes to expand an army, it might have increased conflict in areas farther away from BH. However, we do not observe negative effects. In addition, we find similar non-results as in Table 4.4

319 The total number of conflict events that took place in 2000–2013 is 900 in ACLED, 221 in UCD, and 276 in SCAD. The discrepancy between ACLED, UCD and SCAD could be due to them capturing distinct aspects of conflict or the way they assign the events to specific locations. However, results hold if we combine the three databases (not shown).

320 We also do not find stronger effects for 0–100 km than for 100–200 km (not shown, but available upon request).

321 For ACLED, we consider battles, violence against civilians, protests/riots, non-violent strategic developments, and explosions/remote violence. For UCD, we consider state violence (government forces are involved), non-state violence (none of the warring parties is a government), and one-sided violence (armed force is used against civilians). For SCAD, we consider demonstrations, riots, strikes, and violence. Note that the significant effect for UCD and one-sided violence (A2) is due to conflict ending in Eastern Chad in 2008, so not Boko Haram in Western Chad.

if we drop cells located within 50 km from a military or gendarmerie headquarter c. 2020 (Table A4.4). In francophone countries the gendarmerie is a paramilitary organization with law enforcement duties among the civilian population and gendarmes often intervene where there is a national emergency crisis.[322]

Lastly, one way to interpret these non-results is that reduced urban incomes (especially related to a trade shock) does not automatically lead to more conflict. Otherwise, the average effects would have been significant. Thus, foreign conflict does not always beget domestic conflict.

A body of literature has shown that negative income shocks, most often related to weather related shocks, lead to increased instances of conflicts (Berman and Couttenier, 2015; Harari and Ferrara, 2018). Hegre and Sambanis (2006) also show that conflict begets more conflict. Lower incomes are often one of the main channels explaining spillover effects. Indeed, with lower incomes, the cost of hiring soldiers is lower (i.e. the opportunity cost of conflict labor is lower) (Harari and Ferrara, 2018). The existing literature relies on shocks that disproportionately affect the agricultural sector and thus rural areas. However, our shock disproportionately impacts urban areas, and urban areas might be more negatively impacted by conflict than agriculture. Indeed, urban production relies more on trade and thus security whereas rural production relies more on fixed factors of production such as land. Subsequently, rural production should be less affected by conflict than urban production. As such, there could be reduced economic incentives to engage in conflict when the income shock originates in urban areas.

To summarize, while it is possible that the shock led to increased conflict in some areas of CCN, *on average* we do not find significant effects of Boko Haram activities in Nigeria on domestic conflict. We interpret this non-result as confirming that the very negative economic impact of Boko Haram on neighboring areas in CCN was driven by reduced trade in the region.

322 Military headquarters include the headquarters of military regions (5–8 depending on the country). Gendarmerie headquarters include the headquarters of "compagnies" or "legions de gendarmerie" (15–23). Sources used include administrative sources, security reports, newspaper articles, and Wikipedia. There is no data for the pre-2009 period.

4.6 Heterogeneous Effects for Cameroon, Chad and Niger

Now that we have identified the "nature" of the Boko Haram shock for neighboring areas in CCN, we can investigate the factors that accentuated or mitigated these spillovers of foreign conflict.

As seen in Figure 4.3, the 95 percent confidence interval values of the estimated effects vary significantly, from -0.10 to -0.30 percent in 2013. For the year 2018, the effects varied by between -30 and -80 percent (Figure A4.4). However, given issues when harmonizing the DMSP and VIIRS series, these values respectively represent upper- and lower-bound values of the 95 percent confidence intervals.

Likewise, the effect varies across the three countries. In particular, we use the same panel-DiD model as before but interact the "200 km Boko Haram x post-2009" dummy with three dummies for whether the cell's country is Cameroon, Chad or Niger. For the year 2013 and relative to the year 2008, we find an effect of about -5 percent (n.s.), -20 percent (***) and -25 percent (**), respectively (not shown, but available upon request). Thus, in Cameroon, no significant effect is found on average. In the three countries, we then observe marked heterogeneity in the effects, as suggested by the wide confidence intervals (-0.13/0.03, -0.36/-0.10 and -0.47/-0.04, respectively).[323]

Thus, the disruption effects of Boko Haram were very heterogeneous. However, for a given shock and country, it does not answer the question of which locations "suffered" more vis-á-vis others. Conversely, which locations were ultimately more resilient to the negative effects of the shock? To answer these questions, we use the same panel-DiD model as before but add the interaction between the 200 km Boko Haram dummy and cell-specific characteristics defined c. 2009 or before. Lastly, given the country-year fixed effects we compare cells *within* the same country.

4.6.1 Heterogeneity with Respect to Initial Economic Conditions

We first explore how the effects vary depending on initial economic conditions, i.e. night light intensity in 2008 (Boko Haram rose in 2009). For each cell, we create a dummy equal to one if the cell's night light value in 2008 is below the 10th or 25th percentile (i.e., the cell is "less" developed) or above the 75th or 90th percentile (i.e., the cell is "more" developed) in the cell's country. In a triple-difference framework, we then interact the "200 km Boko Haram x post-2009" dummy with the dummy to see if the effect is stronger, or weaker, for less, or more, developed areas.

Our analysis reveals that those places that were initially more developed than other areas were relatively less affected by the rise of Boko Haram. As seen in Cols. (1)–(2) of Table 4.5, places that were relatively less developed are the places where the effect was most negative, with the overall effect about -0.14 (***). The overall effect in the third row corresponds to the combined effect of the effect of the BH 200 km x Post-09 dummy and its interaction with the chosen pre-2009 characteristic. When we examine the effect for places that were initially more developed (Cols. (3)–(4)), then we find that the interaction is strongly positive, enough to make the observed negative effect of BH—about -14 percent—

323 The stronger effects in Chad and Niger might be explained by the heterogeneous effects shown below or the fact that Chad's and Niger's regions close to Boko Haram historically disproportionately relied on their trade links with Northeastern Nigeria. In contrast, Cameroon's North was also trading with Southern Nigeria via Southern Cameroon (see Map 4.1). In particular, Niger's Southeast is poorly connected to the more developed Western areas of Niger and its Northeast correspond to the Sahara, hence its Southeastern areas' over-reliance on Northeastern Nigeria.

disappear (Col. (3)) or even turn positive (Col. (4); 0.11**).

Overall, while we found stronger negative effects for the more urban intensive sample than for the more rural extensive sample, within the intensive sample we actually find stronger negative effects for less developed areas (which may for example include small towns). If anything, the most developed areas relatively gained from (or lost relatively less) from the presence of BH. The relative gain in the most developed areas suggests that their sectors were more resilient to the BH shock, for example because they trade more with other places within their respective country, with other regions of Nigeria, or with neighboring countries. Likewise, these places may have attracted more economic outmigrants coming from negatively impacted areas.

To improve our understanding of the factors of resilience in the face of an economic shock brought about by foreign conflict, we next study heterogeneous effects related to trade diversification, agricultural development, infrastructure, human capital, and institutions.

4.6.2 Factors of Resilience to Foreign Conflict Shocks

We now examine the heterogeneous effects of other categories of initial (pre-2009) conditions. However, due to lack of data, we sometimes use post-2009 cell data. Next, in order to capture an interacted effect that is *different* from the interacted effect with initial development (or "explain" some of the interacted effect with initial development), we simultaneously control for the interaction of the BH 200 km x Post-09 dummy and the dummy equal to one if the cell's night light intensity is above the 75th percentile value in 2008. When doing so, we found that the average *residual* decline due to Boko Haram was 14 percent (see Col. (3) of Table 4.5). Finally, we study the interacted effect of each characteristic one at a time, mostly due to power issues.

Note that using the 10th and 90th percentile values captures a more local, possibly stronger, effect, that could be better identified as a result. At the same time, if the studied characteristic has an effect above the 10th percentile value of distance or below the 90th percentile value of distance, the effect may be mis-estimated because places above the 10th percentile or places below the 90th percentile are also directly affected by the characteristic.

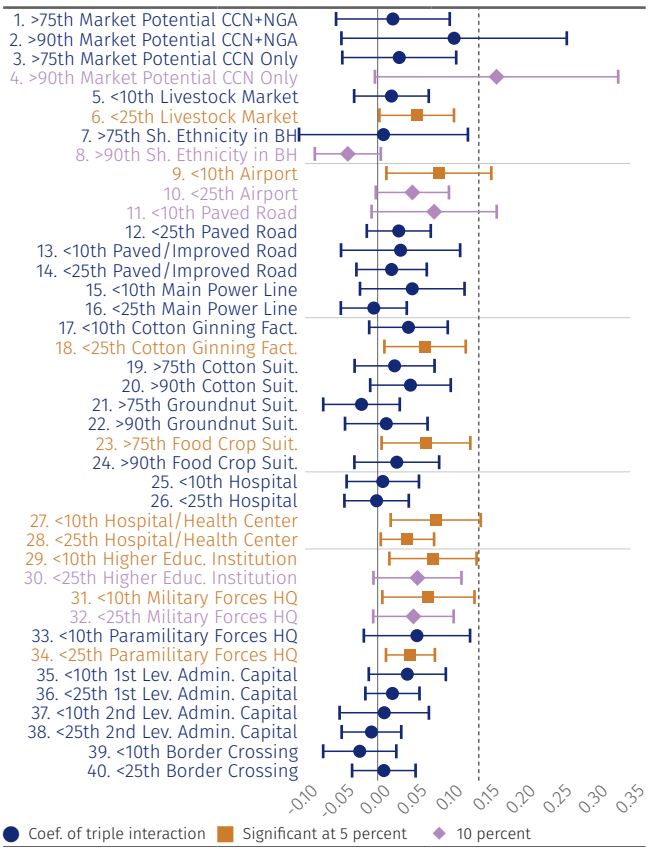
Table 4.5: Baseline Heterogeneous Effects of Boko Haram

Dep. Var.:	***Log (Mean Night Light Intensity + 1) in Year t***			
Interaction:	***Interaction of BH 200km * Post-09 with Dummy if Night Light Intensity in 2008 is ...***			
Percentile:	***Below 10th (1)***	***Below 25th (2)***	***Above 75th (3)***	***Above 90th (4)***
BH 200 km * Post-09	-0.001	-0.001	-0.135***	-0.110***
	[0.030]	[0.030]	[0.026]	[0.026]
Interaction	-0.135***	-0.135***	0.166***	0.216***
	[0.026]	[0.026]	[0.026]	[0.039]
Overall Effect	-0.14***	-0.14***	0.03	0.11**
	[0.03]	[0.03]	[0.03]	[0.04]
Cell FE, Cntry-Yr FE	Y	Y	Y	Y
Yr FE*Controls	Y	Y	Y	Y
Observations	21,644	21,644	21,644	21,644

Notes: The dummy used for the interaction withBH200km * Post-09 is constructed using the 10th, 25th, 75th and 90th percentile values of night light intensity in the cell's country in 2008. SEs clustered at the 3rd-level admin. unit. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

In that case, using the 25th or 75th percentile could help better estimate the effect. With the 25th or 75th percentile, more cells are included in the "relatively more treated" group, which may also improve precision. There is thus a trade-off. As a result, we report the effects for the 10th and 25th percentiles as well as the 75th and 90th percentiles. Figure 4.4 shows the interacted effects and their confidence intervals. Two vertical lines are added, one at 0 and one at 0.14. Indeed, a resilience effect of 0.14 is needed to offset the average residual decline due to Boko Haram (14 percent).[324]

Figure 4.4: Heterogeneous Resilience Effects Depending on Initial Local Conditions



Notes: The figure shows the interacted effect of the 200 km BH*Post-2009 dummy with the variable shown at left. Each row represents a separate regression. The 2nd vertical line is for x = 0.14 because 14 percent is the average residual decline due to Boko Haram (= the independent effect of the 200 km BH dummy). * p<0.10, ** p<0.05, *** p<0.01.

Trade Diversification. We first present our findings on heterogeneity based on market potential (MP). For each cell i and other cells j, MP of cell i is the weighted sum of the sum of night lights of other cells j, using as weights the driving time (in hours) circa 2008 between cell i and cell j to the power α. To begin, we assign to a cell the maximum speed between the speed(s) based on road categories applied in Jedwab and Storeygard (2020) and the speed of travel across off-road cells from a hiking function (Tobler, 1993) that incorporates slopes from Verdin et al. (2007). Then, we use the least-cost path algorithm to calculate the minimum travel time between each cell and each other cell.[325] Next, we assume $\alpha = 3$ in our baseline specification.[326] Finally, when crossing borders, we impose that drivers have to go through border crossings (whose locations we know for the year 2008). The cost to cross the border is then assumed to be 4 hours.

MP can first be defined using the cells of CCN and Nigeria but excluding the BH area itself since we aim to capture how the cell can trade with other areas than the BH area. As seen in rows 1–2 of Figure 4.4, we find a positive (but not significant) resilience effect if the cell is in the top 10th percentile in market potential in 2008 (no effect is observed for the top 25th percentile). The point estimate is relatively high, at 0.11, enough to almost offset the negative independent effect of the BH shock. Standard errors are high, with the 95 percent confidence interval values ranging from -0.05 to 0.26. We thus observe heterogeneous effects of the heterogeneous effect itself.

Nigeria's economy dramatically suffered as a result of Boko Haram and a cleaner test of the trade diversification hypothesis could be to define MP using only the cells of CCN, thus excluding Nigeria (rows 3–4). The effect with the 10th percentile value is now even

324 In the 40 specifications described below, the effect of BH 200 km x Post-09 is almost always equal to 0.14.

325 The road data come from Jedwab and Storeygard (2020). The data include information on the surface of each road in 2008, i.e. whether the road is a highway, a paved road, an improved (gravel or laterite) road, or a dirt road.

326 Results are generally not sensitive to the alpha used (not shown). A high α implies a high trade cost of distance, making cells farther away from cell i matter less. α is not known in our context. Jedwab and Storeygard (2020) use 3.8 but they study the effect of market potential for the whole continent, thus focusing on long-distance trade.

stronger (and significant). The point estimate—0.16—is enough to fully offset the Boko Haram shock and the 95 percent confidence interval values now range from 0.00 to 0.33. Therefore, some locations among the most connected locations might have even (relatively) gained with the BH shock.

While such locations perhaps trade more—which means that they could have been affected *relatively more* by the income shocks experienced in the BH areas—the positive effects may indicate that their economy is more diversified (i.e. they trade more in general, not just with Northeastern Nigeria). As a result, they may be *on net* less susceptible to foreign conflict shocks. More generally, taking the simple average across rows 3 and 4, we obtain +10 percent.

Next, we use the location of major livestock markets as a proxy for general markets. In the region, markets are used for agricultural products, cattle that is eventually exported to urban markets in Southern Nigeria or Southern Cameroon, and manufactured products bought with income from the sale of agricultural products and cattle. Given the lower demand from Nigeria, we could expect a negative interacted effect for the cells closest to the markets. At the same time, as livestock markets proxy for markets more generally, the negative effects could be (more than) compensated by positive effects for locations trading more in general. In addition, cattle can travel to Nigeria through other routes not impacted by the "closure" of the BH region.[327] We find positive effects of livestock markets (rows 5–6 of Figure 4.4). However, the effect is weaker for the 10th percentile value than for the 25th percentile value, possibly due to a more negative impact for locations specialized in cattle export. The positive and significant effect for the 25th percentile (+5 percent) may then capture a more general resilience effect for trade-oriented regions.

Rohner et al. (2013b) discuss how a lack of inter-ethnic trust hampers trade. Therefore, ethnically connected areas should trade more. Amarasinghe et al. (2020) then find that ethnic connectivity, among other factors, is particularly important for the diffusion of economic spillovers. We use the Murdock (1959) map to obtain for each cell the main ethnic group in terms of area in the cell. For each cell/group, we then obtain the share of the group's total homeland area that is within the BH area. By interacting this share with the BH 200 km x Post-09 dummy, this allows us to test if cells that were historically more "connected" to other cells in the BH area are more directly affected, likely because of stronger trade links with the BH area (via ethnicity-based trade networks). More precisely, we use dummies if the share is above the 75th or 90th percentile value in the country. As seen in row 8 of Figure 4.4, we find a negative significant effect of about -4 percent for the most connected cells (i.e., when using the 90th percentile). Thus, ethnic connectivity plausibly helped the diffusion of the economic shock caused by Boko Haram.

Infrastructure. We now investigate how infrastructure factors related to trade or not may have mattered for the diffusion of the economic shock as well as local economic resilience. We examine how proximity to airports mediates the impact of Boko Haram. We calculate the distance of each locality to all airports in the same country.[328] We find a positive and significant effect for the 10th and 25th percentiles (rows 9–10; +7 percent on average) but the effect is, as expected, higher for the 10th percentile. It could be that cities close to airports have specific sectors that are more resilient to land-based economic shocks (i.e. overland trade with Northeastern Nigeria).

Amarasinghe et al. (2020) show that road connectivity, along with ethnic connectivity, is a critical factor in the diffusion of economic spillovers. We use the road network database of Jedwab and Storeygard (2020)

327 The location of 81 livestock markets in Chad and 10 livestock markets in Cameroon (c. 2004–2005) is obtained from République du Tchad (2010). The location of 66 livestock markets in Niger (in the 2010s) is obtained from USGS FEWS.NET (2017). There are fewer markets in Cameroon as most of the cattle is produced in Chad or Niger.

328 The locations of airports (circa 2003) come from U. S. Geological Survey (2003).

to obtain for each cell and the year 2008 the minimal distance to a paved road (incl. highways), the minimal distance to a paved or improved road, and the minimal Euclidean distance to *all* roads (i.e., paved, improved, and dirt roads). We then create dummies based on whether the cell's distance to a paved road, a paved/improved road or any road is below the 10th or 25th percentile value in the country. As seen in rows 11–14, we find stronger effects for paved roads (+5 percent) than for other roads. The only significant effect is for the *most connected* cells, i.e. cells whose distance to a paved road is below the 10th percentile value in the country (+8 percent).

Other types of infrastructure that are not related to trade but possibly important include access to electricity and mobile networks. A reliable access to electricity is particularly important in countries where power failures are frequent. We thus investigate heterogeneity with respect to proximity to a major electricity transmission line, assuming that such locations are more protected against regional power outages. In rows 15–16 of Figure 4.4, we interact the BH 200 km x Post-09 dummy with a dummy if the cell's distance to a power line (c. 2008) is below the 10th or 25th percentile value in the country. We find a positive but not significant effect of +5 percent for the 10th percentile and no effect for the 25th percentile. The average effect is +2 percent.[329]

Next, we examine heterogeneity with respect to GSM coverage. More precisely, for each cell we obtain the area share that is covered by 2G mobile phone coverage c. 2009.[330] We then create dummies if coverage is above the 75th or 90th percentile value in the country. However, we do not find any effect (not shown, but available upon request). Therefore, infrastructure factors not related to trade do not appear as important as the ones related to trade in our context.

Agricultural Development. We turn to heterogeneity with regard to agricultural development. Two main cash crops are grown in the area, cotton and groundnut. With the shock, the demand from Nigeria likely decreased. At the same time, the supply of cotton and groundnut from Nigeria was also reduced, which may have increased prices for local producers. The effect of the shock on producing areas is thus ambiguous. In addition, if cash crop production is "fixed" in space, because of land suitability being an unsubstitutable factor of production or because of past sunk investments in transformation factories, then these locations remain valuable even in times of crisis. In that case, we might expect these areas to be affected relatively less.

We estimate mean cotton and groundnut production within 50 km from the cell's centroid. We then create dummies based on whether cotton suitability is higher than the 75th or 90th percentile value in the country.[331] Next, for cotton ginning factories, we use proximity to a factory, and thus create dummies if the cell's distance to a factory is below the 25th or 10th percentile value in the country. Finally, note that there was no formal groundnut oil extraction plant in the area during the period. Groundnut oil was instead extracted artisanally by local producers.[332]

As can be seen in Figure 4.4, we see positive interacted effects for cotton (rows 17–20; average affect of +4 percent), which are only significant in two out of the four cases. No effect is observed for groundnut (rows 21–22), possibly because it is considered a less profitable cash crop in the area.

329 Data is obtained from the Africa Infrastructure Country Diagnostic (AICD) database of the World Bank.

330 The source of the data on 2G mobile phone geographic coverage is the Global System for Mobile Communications (GSMA) c. 2009, who summarizes submissions of mobile operators data that provide representation of network coverage with roaming detail based on strong and variable signal strength.

331 The distance threshold of 50 km is arbitrary. Results hold with 100 km (not shown, but available upon request).

332 Cotton and groundnut suitability-based measures of production c. 2010 are from SPAM 2010 (IFPRI, 2019). According to their website: "SPAM relies on a collection of relevant spatially explicit input data, including crop production statistics, cropland data, biophysical crop 'suitability' assessments, population density, as well as any prior knowledge about the spatial distribution of specific crops or crop systems." The locations of cotton ginning factories are digitized from a map on *Cotton Zones, Ginning Factories and Exports of West Africa* in OECD (2006).

The interacted effect with overall food crop suitability then merits particular attention. Access to food crops is important because, in time of (urban) crisis, urban areas surrounded by land that is relatively more suitable for food production may be more resilient to the shock. People are more likely to stay in these locations to weather an economic shock. We interact the BH 200 km x Post-09 dummy with dummies based on food crop suitability (averaged across 12 major food crops in Sub-Saharan Africa).[333] We see positive interacted effects (rows 23–24; average effect of +5 percent, close to what we found for cotton). These are only significant for the 75th percentile.

Overall, the resilience effects appear weaker for agricultural development. However, if we focus on the cotton industry or food suitability, we find resilience effects that are about 5 percent on average.

Human Capital. Health infrastructure proxies for both human capital and government social expenditure as the health sector is mostly public in CCN. We construct measures of the distance to hospitals or health centers (2013–17) and create dummies based on whether it is below the 10th or 25th percentile value in the country.[334] We do not see any effect for hospitals (rows 25–26). When considering hospitals and health centers simultaneously, we then see positive significant effects (rows 27–28; average effect of +3 percent). The non-effects for hospitals suggests that these effects are not driven by health supply per se. Instead, locations with health centers might have higher levels of social services and offer higher levels of social protection in times of crisis.

We then examine heterogeneity with respect to higher education institutions (c. 2020), which are for the most part public universities in CCN. For each cell we obtain the Euclidean distance to a higher education institution and create dummies based on the 10th and 25th percentile values in the country.[335] As seen in rows 29–30, we find significant positive effects for both percentile values. The effects are on average twice higher than the effects found for health (+6 percent vs. +3 percent).

Government Expenditure. We examine more broadly if the effect of Boko Haram depends on government expenditure. Indeed, locations supported by the presence of government services may be more resilient due to the fact a larger share of their economy does not depend on local economic conditions but government budget allocations most often made at the national level. In addition, the presence of government services may also positively, or negatively, impact the ability of local economies to bounce back in the face of a massive economic shock.

We first examine heterogeneity with respect to major military and paramilitary headquarters (c. 2020 as information is not available for earlier years). For each cell we obtain the minimal Euclidean distance to a major military headquarter or a major paramilitary headquarter and create dummies based on the 10th and 25th percentile values in the country.[336] As seen in rows 31–34, the interaction effects are strong and significant in three out of the four cases (average of about +5 percent). The effect is larger for military headquarters than for paramilitary headquarters.

We then study if the effect of Boko Haram depends on proximity to "regional" capitals (for 1st level administrative units) or "district" capitals (2nd-level

333 FAO (2013) provides for the period 1981–2010 a measure of food crop suitability that is based on both soils and the climate and the following 12 crops: manioc (cassava), maize, rice paddy (Japonica), rice paddy (Indica), common wheat, sorghum (low alt.), common millet, potato, potato yam, sugar beet, cowpea and common bean.

334 We rely on Maina et al. (2019). Cameroon (2014–17), Chad (2013–16) and Niger (2013–17) have 183 (2,836), 41 (824) and 78 (1,151) hospitals (health centers), respectively. Data does not exist for the pre-2019 period.

335 The location of higher education institutions comes from Wikipedia, reports, and newspaper articles. Cameroon, Chad and Niger have 31, 21 and 11 such institutions, respectively. Data does not exist for the pre-2019 period.

336 Cameroon, Chad and Niger have 5 (15), 8 (23) and 10 (23) military (paramilitary) headquarters, respectively.

administrative units).[337] For each cell we obtain the Euclidean distance to a regional capital or a district capital and create dummies based on the 10th and 25th percentile values in the country. The effects are not significant (rows 35–38; +2 percent on average). The effect is larger for regional capitals than for district ones.

More broadly, one can see that the interacted effect is higher for military headquarters (about +6 percent) than for paramilitary headquarters (+5 percent), regional capitals (+3 percent) or district capitals (0 percent).[338] Thus, security might have been a more important concern than government employment. Given that Boko Haram had not entered CCN then, one interpretation could be that firms reduced investments as a result of increased uncertainty in the region, especially in potentially more unsafe areas located farther away from military and paramilitary headquarters.

Finally, we examine heterogeneity with respect to border crossings/posts. A negative effect could be expected in such areas due to reduced trade. However, such areas likely received more public investments and saw an increase in military and police presence. For each cell we compute the minimal Euclidean distance to a border crossing circa 2008 and then create dummies based on the 10th and 25th percentile values in the country.[339] As seen in rows 3–40, we find a negative, but insignificant, effect for the 10th percentile and no effect for the 25th percentile. As such, any negative effect due to reduced trade must have been offset by government expenditure.

To summarize, factors of resilience in the face of an economic shock brought about by foreign conflict include trade diversification and infrastructure related to trade (resilience effect of about +5–10 percent), agricultural development (+5 percent), human capital (+3–6 percent), and government expenditure (especially when related to security for which the resilience effect is about +5/+6 percent). We do not find significant effects for access to electricity or mobile networks, technologies that might only produce resilience if more resilient sectors are already present in the local economy.

While our results could have straightforward policy implications, one important caveat is that we only measure population, not real wages or welfare more generally. Some "better endowed" locations may have experienced a slower relative decline in their population possibly because they were also attracting economic refugees from equally affected neighboring locations. Our analysis only captures *relative* population growth patterns and suggests that initially (pre-shock) better endowed locations, by being more resilient, grow faster than less well endowed locations. As such, economic shocks due to foreign conflict may accentuate spatial inequality.

In addition, mostly due to power issues, we estimate each interacted effect one by one rather than simultaneously. Some of the heterogeneity variables are also correlated with each other and may as such capture similar dimensions.

337 For each country, we obtain a list of 1st-administrative level capitals—regional capitals (9 in Cameroon c. 2005, 22 in Chad c. 2020 and 7 in Niger c. 2014, respectively)—and a list of 2nd-administrative level capitals—departments capitals (48, 68 and 57, respectively). Sources used include the Humanitarian Data Exchange. While for Chad and Niger we use capitals defined post-2009, the total number of capitals barely changed there in the 2010s.

338 The coefficient of correlation between the 10th percentile dummies for these four types of government expenditure is between 0.16 and 0.65 (mean = 0.43). The dummies thus do not necessarily capture the same locations.

339 The locations of border crossings are obtained from Jedwab and Storeygard (2020).

4.7 Robustness and Other Considerations

Spatial autocorrelation. To account for spatial autocorrelation, we cluster standard errors at the 3rd level administrative unit (N = 343, 336, and 265 in Cameroon, Chad and Niger, respectively). We verify that the baseline negative effect of Col. (1) in Table 4.1 remains strongly significant when (Table A4.5): (i) clustering standard errors at the 2nd (36; 58; 53) or even 1st (8; 10; 23) administrative level; and (ii) using Conley standard errors using a distance cut-off of 100, 200 or even 300 km. However, given how computationally intensive computing Conley standard errors are when the number of spatial units is high, we first residualize the data, thus removing any variation due to the fixed effects and the controls. Using Conley standard errors is not feasible for regressions involving the full/extensive sample of cells, which we use for our analysis on the extensive margin of night lights, rural outcomes, and conflict. We also verify that these regressions and other regressions return similar results if we cluster standard errors at the 2nd or 1st administrative level (not shown, but available upon request). More generally, for the analysis on the extensive margin of night lights, greenness, land use and local conflict, we already find no effects. Thus, more conservative standard errors would not change our conclusions.

Other Definitions of the Treatment. For the sake of simplicity, proximity to BH is constructed using Euclidean distance to the BH area, which we define as the area of the states of Borno, Yobe and Adamawa that is between the Yobe river in the North (in Yobe) and the Benue river in the South (Adamawa). Table A4.6 shows that the results hold if we: (i) define the BH area as the state of Borno (where 60 percent of conflict events took place) or the full area of the Borno, Yobe and Adamawa; (ii) use a dummy for whether the cell is within 300 km from Maiduguri, Northeastern Nigeria's main city, which was particularly impacted by Boko Haram activities. We use 300 km instead of 200 km because Maiduguri is about 100 km from the border. The effects are stronger for Borno or Maiduguri, likely because these were more affected; (iii) use a dummy for whether the cell is within a 6.5 hours driving distance from the BH area. 6.5 hours corresponds to the 20th percentile in driving time to the BH area. We use the 20th percentile because 200 km corresponds to the 20th percentile in Euclidean distance to the BH area; and (iv) use the negative of the log distance to the BH area. The last two regressions are less comparable to our baseline regression. The coefficients, while different, remain strongly negative.

4.8 Conclusion

What are the spillover effects of foreign terrorism and conflict on regional economies? Adopting a difference-in-difference framework leveraging the unexpected rise of the Boko Haram insurgency in Northeastern Nigeria in 2009, we studied its effects in neighboring areas in Cameroon, Chad and Niger. We found strong negative effects on regional economic activities—proxied by reductions in nighttime lights—particularly amongst areas within 200 km from the Boko Haram area. Our findings suggested that this negative impact was concentrated in urban areas and was particularly pronounced among those areas that were initially less developed and connected, which highlights the role of trade diversification and infrastructure in mitigating the effects of economic shocks brought about by foreign conflict. We also found that the rise of Boko Haram resulted in more agricultural burning—an agricultural practice that is profitable in the short-term but typically leads to long-term environmental and economic losses.

Overall, these findings attest to both the short-term and long-term negative impacts of foreign conflicts on regional economies. More generally, we believe our findings might have important policy implications. First, conflicts have spillover effects that significantly impact regional economies as a whole, not only in the short run but also in the long run as well. For example, foreign conflicts push individuals in the urban sector to seek opportunities in the rural sector and engage in agricultural practices—namely, agricultural burning—that potentially jeopardizes long-run economic gains. Peace interventions can have positive effects "beyond" the country or countries in which they take place. Second, certain types of mitigation measures are perhaps more effective than others at alleviating the negative spillover economic effects of foreign conflict. In our context, initially more developed, connected, infrastructure-endowed, and government-protected areas were better able to "weather" the impact of the shock.

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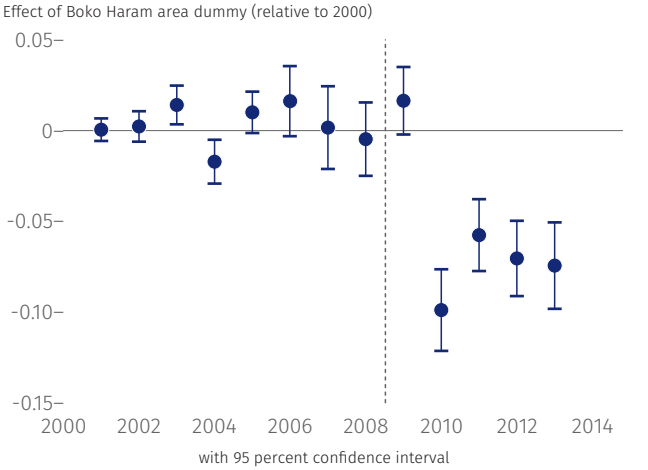
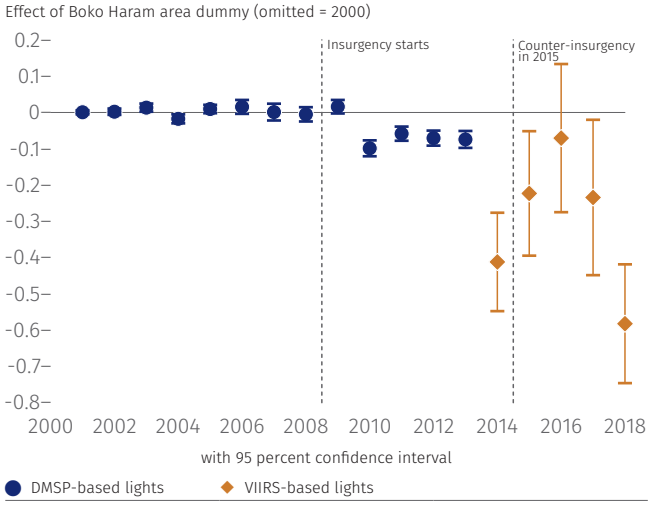
Appendix

Figure A4.1: Boko Haram Area Effect in Nigeria, 2000–2013



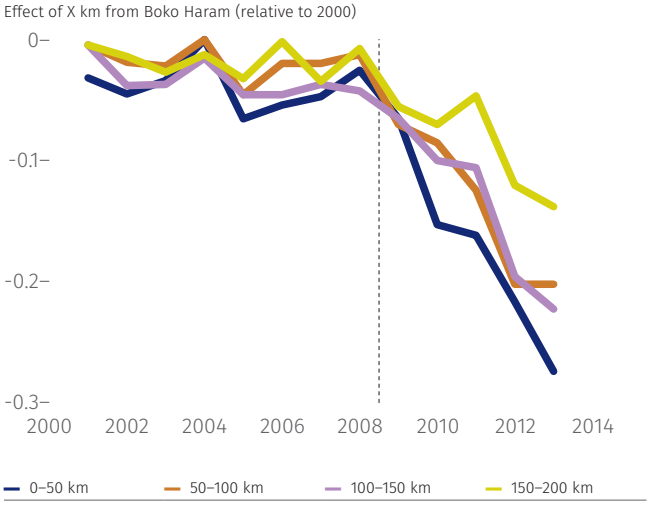
Notes: The figure shows for Nigeria the yearly effect (relative to the year 2000) of a dummy equal to one if the cell is within the Boko Haram area (the area of Borno, Yobe and Adamawa that is between the Yobe river in the North (in Yobe) and the Benue river in the South (Adamawa)). More precisely, we use data for 7,761 0.1×0.1 degree grid cells (≈ 11x11km at the equator) in Nigeria for the years 2000–2013 (hence N = 108,654). The dependent variable is the log of mean light intensity (sum of lights divided by area + 1) in cell *c* in year *t*. We include cell c fixed effects, year t fixed effects, and interact the *Boko Haram area* dummy *c* (equal to one if the cell is within the Boko Haram area or if its centroid is within 10 km from the area's border) with a dummy for each year *t* in 2001–2013. Standard errors are clustered at the Local Government Area (LGA; N = 721). With 7,761 cells, there are 11 cells per LGA.

Figure A4.2: Boko Haram Area Effect in Nigeria, 2000–2018



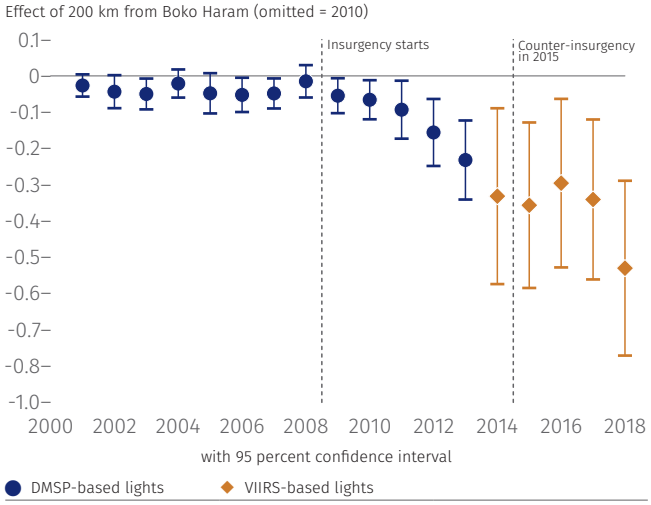
Notes: We use the same panel-DiD model as for Fig. A4.1 except that we now consider the full period 2000–2018. For this analysis we rely on the harmonized NTL data (1992–2018) from Li et al. (2020) who combine night light data from OLS-DMSP (used until 2013) and SNPP-VIIRS (use for the period 2014–2018). Note that the high standard errors for the VIIRS observations in 2014–2018 likely reflect the fact that the assumptions made by Li et al. (2020) to recreate harmonized NTL for the whole period 2000–2018 also introduced a significant amount of noise.

Figure A4.3: Boko Haram Area Effect in Cameroon, Chad and Tchad, 50 Km Bins, 2000–2013



Notes: For 1,546 cells in Cameroon, Chad and Niger, we use the same panel-DiD model as eq. (1) except that we now separate the 0–200 km Boko Haram Area Dummy into four dummies for whether the cell is within 0–50 km, 50–100 km, 100–150 km or 150–200 km from the Boko Haram area (1,546 cells x 14 years = 21,644 obs.). To avoid the figure being too cluttered, we do not report confidence intervals. See text for details on the specification.

Figure A4.4: Boko Haram Area Effect in Cameroon, Chad and Niger, 2000–2018



Notes: For 1,320 cells in Cameroon, Chad and Niger (CCN), we use the same panel-DiD model as eq. (1) except that we now consider the full period 2000–2018 (1,320 cells x 19 years = 25,080 obs.). We start with the sample of 1,546 cells but exclude cells having ever experienced a Boko Haram event during the period of study as well as cells within 50 km from these cells. We also control for the log of the Euclidean distance to any CCN cell with a Boko Haram event in the same year *t*. For this analysis we rely on the harmonized NTL data (1992–2018) from Li et al. (2020) who combine night light data from OLS-DMSP (used until 2013) and SNPP-VIIRS (use for the period 2014–2018). Note that the high standard errors for the VIIRS observations in 2014–2018 likely reflect the fact that the assumptions made by Li et al. (2020) to recreate harmonized NTL for the whole period 2000–2018 also introduced a significant amount of noise.

Table A4.1: Effects of Boko Haram on Domestic Conflict, ACLED Database, 2000–2013

Conflict Measure:	***All Events***	***Combined (Including Fatalities)***	***Battles***	***Violence Against Civilians***	***Protests or Riots***	***Non-Violent Strategic Dev.***	***Explosions & Remote Violence***
Panel A. *Dep. Var.: Dummy if Non-Boko Haram Conflict Event in the Cell in Year t*							
BH 200Km* Post-09	0.0002	–	-0.0003	0.0004	0.0002	0.0000	0.0002
	[0.0004]	–	[0.0003]	[0.0003]	[0.0003]	[0.0001]	[0.0002]
Panel B. *Dep. Var.: Number of Non-Boko Haram Conflict Events in the Cell in Year t*							
BH 200Km* Post-09	0.0024	0.0212	0.0016	0.0005	0.0001	-0.0001	0.0002
	[0.0022]	[0.0129]	[0.0018]	[0.0004]	[0.0004]	[0.0002]	[0.0002]
Cell FE, Cntry-Yr FE	Y	Y	Y	Y	Y	Y	Y
Yr FE*Controls	Y	Y	Y	Y	Y	Y	Y
Observations	356,874	356,874	356,874	356,874	356,874	356,874	356,874

Notes: SEs clustered at the 3rd-level admin. unit. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Table A4.2: Effects of Boko Haram on Domestic Conflict, UCD Database, 2000–2013

Conflict Measure:	***All Events***	***Combined (Incl. Fatalities)***	***Type of Organized Violence***		
			State	***Non-State***	***One-Sided***
Panel A. *Dummy if Non-Boko Haram Conflict Event in the Cell in Year t*					
BH 200Km * Post-09	0.0003	–	0.0000	0.0000	0.0003**
	[0.0002]	–	[0.0001]	[0.0000]	[0.0002]
Panel B. *Dep. Var.: Number of Non-Boko Haram Conflict Events in the Cell in Year t*					
BH 200Km * Post-09	0.0009	0.0299	0.0004	0.0000	0.0005*
	[0.0007]	[0.0236]	[0.0004]	[0.0000]	[0.0003]
Cell FE, Cntry-Yr FE	Y	Y	Y	Y	Y
Yr FE*Controls	Y	Y	Y	Y	Y
Observations	356,874	356,874	356,874	356,874	356,874

Notes: SEs clustered at the 3rd-level admin. unit. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Table A4.3: Effects of Boko Haram on Domestic Conflict, SCAD Database, 2000–2013

Conflict Measure:	***All Events***	***Combined (Incl. Fatalities)***	***Type of Social Conflict***			
			Demonstration	***Riot***	***Strike***	***Violence***
Panel A. *Dummy if Non-Boko Haram Conflict Event in the Cell in Year t*						
BH 200Km * Post-09	0.0005	–	0.0003	0.0003	0.0002	-0.0001
	[0.0005]	–	[0.0003]	[0.0002]	[0.0002]	[0.0003]
Panel B. *Dep. Var.: Number of Non-Boko Haram Conflict Events in the Cell in Year t*						
BH 200Km * Post-09	0.0010	0.0024	0.0007	0.0003	0.0001	-0.0001
	[0.0007]	[0.0020]	[0.0004]	[0.0002]	[0.0003]	[0.0003]
Cell FE, Cntry-Yr FE	Y	Y	Y	Y	Y	Y
Yr FE*Controls	Y	Y	Y	Y	Y	Y
Observations	356,874	356,874	356,874	356,874	356,874	356,874

Notes: SEs clustered at the 3rd-level admin. unit. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Table A4.4: Effects on Domestic Conflict, 2000–2013, Excluding Military Headquarters Cells

Conflict Database:	***ACLED (Armed Conflict)***			***Uppsala (Armed Conflict)***			***SCAD (Social Conflict)***		
Sample:	***All (1)***	***Intensive (2)***	***Extensive (3)***	***All (4)***	***Intensive (5)***	***Extensive (6)***	***All (7)***	***Intensive (8)***	***Extensive (9)***
Panel A. *Dep. Var.: Dummy if Non-Boko Haram Conflict Event in the Cell in Year t*									
BH 200Km * Post-09	-0.0005	-0.0056*	-0.0004	0.0001	0.0011	0.0001	-0.0004	-0.0052	0.0001
	[0.0004]	[0.0031]	[0.0003]	[0.0001]	[0.0020]	[0.0001]	[0.0004]	[0.0032]	[0.0002]
Panel B. *Dep. Var.: Number of Non-Boko Haram Conflict Events in the Cell in Year t*									
BH 200Km * Post-09	-0.0016*	-0.0337**	-0.0004	0.0000	0.0014	0.0000	-0.0004	-0.0063*	0.0002
	[0.0009]	[0.0162]	[0.0006]	[0.0002]	[0.0034]	[0.0001]	[0.0004]	[0.0036]	[0.0002]
Cell FE, Cntry-Yr FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Yr FE*Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	302,344	12,796	289,548	302,344	12,796	289,548	302,344	12,796	289,548

Notes: SEs clustered at the 3rd-level admin. unit. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Table A4.5: Post-2009 Effect of Proximity to the Boko Haram Area, Lights, Alternative SEs

Dependent Variable:	***Log (Mean Night Light Intensity + 1) in Year t***					
Standard errors:	***SEs Clustered using Admin. units***			***Conley SEs - Distance Cut-Off =***		
	Level 3 (1)	***Level 2 (2)***	***Level 1 (3)***	***50 km (4)***	***100 km (5)***	***200 km (6)***
BH 200Km * Post-09	-0.097***	-0.097***	-0.097**	-0.097***	-0.097***	-0.097***
	[0.027]	[0.031]	[0.038]	[0.029]	[0.034]	[0.036]
Cell FE, Cntry-Year FE	Y	Y	Y	Y	Y	Y
Year FE*Controls	Y	Y	Y	Y	Y	Y

Notes: Obs.: 21,644. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Table A4.6: Post-2009 Effect of Proximity to Boko Haram, Alternative Measures of the Shock

Dependent Variable:	***Log (Mean Night Light Intensity + 1) in Year t***					
Measure:	***Baseline (1)***	***Borno Only (2)***	***Borno + Yobe + Adamawa (3)***	***City of Maiduguri (4)***	***Driving Time (5)***	***Log Dist. to BH Area (6)***
BH 200 Km * Post-09	-0.097***	-0.123***	-0.057**			
	[0.027]	[0.038]	[0.026]			
Maiduguri 300Km * Post-09				-0.119***		
				[0.039]		
BH 6.5 Hrs * Post-09					-0.044**	
					[0.018]	
(-) Log Dist. BH * Post-09						-0.033***
						[0.012]
Cell FE, Cntry-Year FE	Y	Y	Y	Y	Y	Y
Year FE*Controls	Y	Y	Y	Y	Y	Y

Notes: Obs.: 21,644. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.