Globalization and Conflicts: the Good, the Bad, and the Ugly of Corporations in Africa[*]

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Abstract

Using a novel georeferenced datataset on the affiliates and headquarters of multinational enterprises between 2007 and 2018 together with georeferenced conflict data for the African continent, this work establishes a causal link between the activities of multinational enterprises and violent conflicts: multinationals' activity increases the number of conflicts. This applies particularly to sectors intense in scarce resources, especially land. As farming is the primary source of food and income for Africans, land-intensive activity on the part of the multinationals increases local grievance, escalating to violent actions. These effects are magnified in areas targeted for large-scale land acquisitions.

Keywords: multinational enterprises, civil conflict, land grabbing

JEL Codes: D74, F23, O13, C23

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1 Introduction

This paper examines the impact of multinational enterprises (MNEs) on civil conflict. In the 1980s, with the new wave of globalization, MNEs began to invest massively in developing countries, with their high returns to capital, and this process has never stopped. Since the financial crisis of 2008 the number of multinational subsidiaries in Africa has increased by more than 250%. These multinationals are relatively larger and more profitable firms, engaged in the international trade network. In fact, they account for more than two-thirds of total world trade flows. Their subsidiaries are perceived by the local population as foreign bodies, and their impact on conflict may well differ from that of local businesses.[1] Instability is known to be a key determinant of underdevelopment, but the potential role of multinationals in triggering conflicts has received surprisingly little attention.

I tackle this question by merging geolocalized information on conflict events with novel data on MNE affiliates, and their headquarters, for all African countries since 2007. MNE activity is found to have significant and heterogeneous effects on the probability of conflict. On average, one additional affiliate increases the number of violent conflicts by 4% in areas with some MNE activity and by 34% with respect to the sample mean. This result is driven, in particular, by affiliates active in land-intensive industries. These activities detract form the primary local sources of food and income, increasing violent events, particularly in areas targeted for large-scale land acquisition.

The empirical analysis involves an original ad hoc dataset combining two Bureau van Dijk datasets, *Historical Ownership Dataset* and *Orbis* – on the worldwide location and activities of both MNE affiliates and their headquarters – with the *Armed Conflict Location Events Data*, on the location and type of conflict events and the actors involved. The units of analysis are cells of 0.5×0.5 degree latitude and longitude (approx. 55km $\times$ 55km at the equator) covering the entire African continent. The use of georeferenced information, together with a novel instrumental variables strategy, country$\times$year fixed effects, and cell fixed effects, permits causal identification.

This work proposes a novel algorithm that combines historical information on the ownership of all firms connected through an ownership link, for the entire world. It maps the hierarchical structure of business groups by ascending the ownership structure, constructing the network of business groups for more than 200 countries, from 2007 to 2018, and then geolocates them using zipcodes. Relying on the internal capital market literature and exploiting the headquarter-affiliate credit link, this rich dataset allows a novel way to instrument MNE activity at the local

[1] See, for example, the report by UNCTAD (2011) on the relevance of MNEs worldwide, and the exhaustive analysis on the perception of MNEs and their impact on human rights in developing countries by Ruggie (2013).

level. I use historical financial data at headquarters level and credit availability. More specifically, I interact pre-period headquarters dependence on external credit with the availability of credit to the multinationals, thus obtaining an exogenous variation in MNE activities over time. The intuition is straightforward: some affiliates, in any given cell-year, are part of a relatively healthy and robust multinational, not dependent on external credit, while others have weaker parent corporations. The former are expected to be significantly less affected during periods of credit shrinking and, therefore, to reduce their activities substantially less sharply.[2]

In order to spotlight one important mechanism that underlies the main result, I first provide suggestive evidence for the increase in number of conflicts to be driven by land-intensive sectors. These activities rely on intensive use of land, a precious resource insofar as farming is the primary source of food and income for Africans and accounts for up to 60 percent of all jobs on the continent.[3] Second, the increase in violent events is shown to be amplified in locations of large-scale land acquisition. Data from *LandMatrix*, geolocating land deals larger than 200 hectares, are used to show that the deals are not harmful everywhere, but only where multinationals are active. Third, I show that the type of conflict triggered by multinationals is mainly that outlined by case-studies on land-grabbing, namely localized violent events, likened to insurrections to protect a key resource for survival: land. Fourth, individual-level data from *Afrobarometer* are used to show that MNEs activity significantly increases locals' complains about land management, and that this result is completely driven by land-intensive multinationals' activity.

The cases of Mozambique and Liberia help illustrate the magnitude of the phenomenon under investigation here. Mozambique gained its independence from Portugal in 1975, after centuries of resistance, establishing the ideal of "la liberté de l'homme et de la terre" (freedom of man and land). However, in April 2011, an ambitious and highly controversial trilateral cooperation program was signed, the ProSavana project, to promote "sustainable and inclusive agricultural development" together with Japan and Brazil. The project involved well-known multinational agribusiness and logging enterprises, including the Portuguese Espirito Santo Group. The program targets 19 districts in three provinces, covering a total of 10.7M hectares, of which 930K are cultivated annually by 692K rural families.[4] Case studies have found that this project, like

[2] This identification strategy is robust to a large battery of robustness checks, such as (i) controlling for time-varying cell-specific demand and price shocks induced by worldwide credit reduction, and to the heterogeneous impact this channel has on cells for which trade costs are higher, (ii) controlling for cell-specific population and development dynamics, (iii) limiting the analysis to areas where we observe some MNE activity and their surrounding cells, in the spirit of a matching estimation as in Acemoglu et al. (2012), and (iv) the frontier tests concerning potential endogenous shares and non-random exposure to exogenous shock in shift-share research designs as in Borusyak et al. (2022) and Borusyak and Hull (2020).

[3] See, for example, the reports by Sy (2016) and Coulibaly (2020).

[4] The population of the target area was estimated at 4.3M in 2011, most in rural areas and depending on agri-

many others, violated local people's rights (e.g. expropriation of villages, threats to food security, intensive use of water depriving people in the surrounding areas) with little if any compensation, and often produced conflict situations.[5] There is a growing literature on the behaviour of private logging firms as a cause of violence. See the exhaustive analysis of the Liberian case in the report *Holding the Line* by Global Witness (2017), which documents in detail all the links between local government, multinationals and large logging contracts, with the emblematic case of the multinational Samling Global. Sonno and Zufacchi (2020) use the Ebola outbreak as an exogenous variation to multinationals' land acquisition to show that the jump in the trading value of Liberian palm oil (+1428% with respect to the pre-Ebola period) is due to the activity of palm oil multinationals, such as Golden Veroleum Liberia, which increased their land deals by almost 50% during the peak of the epidemic (Global Witness, 2015).

This paper is related to different strands of literature. An influential body of work in recent decades has debated the complex link between trade and conflict. Examining both international and domestic conflicts, a first set of papers use *country-level* aggregate trade data (imports plus exports) as the measure of trade.[6] However, global value chains now represent the main mechanism of international trade, in which multinationals are the main players. Despite this predominant role, much less attention has been paid to the relation between multinational enterprises and conflict. Importantly, country-level foreign direct investment (FDI) sales was mainly used in these works as a proxy for MNE activities, owing to the lack of data on the actual location of MNE affiliates.[7] The main constraint of any analysis studying the trade-off between exports and opening an in-country affiliate has been the "dearth of internationally comparable measures of the extent

culture for subsistence. More specifically, the average rural household in the region has 5 members, so almost 3.5M people in the area (more than 80% of the total) live in the countryside and are engaged in agriculture. Note that smallholder farming is practiced by 99% of all rural households in the region, the typical farm averaging 1.34 hectares in size (MASA, 2015).

[5] Arslan et al. (2011); Von Braun and Meinzen-Dick (2011); Meinzen-Dick and Markelova (2009); Oakland Institute (2013); Thaler (2013).

[6] Two opposing views of international conflict have characterized the debate: the "liberal" view, in which economic ties are seen as opportunity costs of conflict (Oneal and Russet, 1997, 1999, 2001), and the "realist" view, according to which trade dependence implies future insecurity, increasing the incentive to avoid dependence by force (Barbieri, 1996, 2002). Martin et al. (2008b) analyse the impact of international trade on conflict probability at country level, and then at the intra-state level, Martin et al. (2008a).

[7] Polachek et al. (2012) develop and empirically test a two-country, one-period model, with homogeneous multinationals, showing that FDI can improve international relations. This result is confirmed empirically by Bussmann (2010). Morelli and Sonno (2017) show how country-level asymmetries in foreign value added can be relevant in conflict analysis. A different strand of literature focuses on the effects of international aid in developing countries. Although this field is quite distant from the topic of multinationals' activity and conflict, recent geocoded data on Chinese aid and non-concessional official financing allowed study of the impact of country-specific aid-flows on protests, finding mixed evidence (Iacoella et al., 2021; Gehring et al., 2019).

of FDI across both industries and countries" (Helpman et al., 2004, pp. 306). The dataset produced for this work contributes to the literature by filling this gap. Systematizing ownership links from the *Historical Ownership Database*, (i) I elaborate a novel algorithm that provides the network of business groups for more than 6.3 million business groups, with 12.8 million affiliates in more than 200 countries, from 2007 to 2018, and then (ii) I geolocate them using zipcodes. To my knowledge, this is the first global, firm-level dataset documenting multinationals' hierarchies and activities in a panel setting.[8] Moreover, capitalizing on this dataset, this work proposes a novel way to instrument multinationals' activity through a direct credit link between affiliates and headquarters.

A separate body of literature uses disaggregated data to study the determinants of conflict in African countries (Guidolin and La Ferrara, 2007; Brückner and Ciccone, 2011; Nunn and Wantchekon, 2011; Besley et al., 2011; Dube and Vargas, 2013; König et al., 2017; Berman et al., 2017; Harari and Ferrara, 2018; Manacorda and Tesei, 2020; Berman et al., 2021). Two works study the role of firms, one on protest and one on conflict, both focusing exclusively on mining. Christensen (2018) finds that the probability of protest is twice as great in the case of foreign mining investment. Berman et al. (2017) analyse the impact of mining on conflict using exogenous variations in world prices to document a sizeable and significant positive impact of mining on conflict at the local level.[9] I contribute to this literature in three ways. First, being the first examining the impact of multinational enterprises on conflict. These are significantly different entities with respect to from local firms (larger, more productive, linked to the international trade network) and, in particular, are perceived as strangers by the local communities. Therefore, their impact on conflict in developing countries might differ from local firms. Second, the analysis covers granular and geolocated multinationals' activity in *all* industries. This is a key improvement in the literature, which has been focusing exclusively on mining, considering MNE activity in different industries might have heterogeneous effects on conflict, depending on specific characteristics such as their land-intensive nature. Third, this study covers an entire continent over more than a decade. This cross-country panel framework ensures the external validity of the results, overcoming country-specific and/or period-specific settings.[10]

[8] For the scope of this paper, I focus on African affiliates of multinational enterprises, but the MNE dataset is suitable for a number of different projects involving the effect and/or the evolution of business groups' structure worldwide. See the subsequent works using the data produced with this algorithm, e.g. Altomonte et al. (2021a); Altomonte et al. (2021b); Mendola et al. (2021); Noack et al. (2022).

[9] Some recent works contribute to the literature on the effects and spillovers of FDI in developing countries. These works are not directly related to conflicts, but can help to frame the analysis. In particular, Dhingra et al. (2021) study the role of agribusinesses in Kenya in shaping the gains from trade. Méndez-Chacón and Van Patten (ming) provide micro-level evidence of the benefits of large-scale FDI in Costa Rica.

[10] This work contributes also to the very lively policy debate about the phenomenon known in the literature,

The paper is organized as follows. Section 2 describes the data. Section 3 presents the empirical analysis. In section 4 one potential mechanism is examined. Section 5 concludes.

2 Data

The dataset is structured as a full grid of Africa divided into sub-national units of 0.5×0.5 degrees latitude and longitude. This level of aggregation is used instead of administrative boundaries in order to ensure that the unit of observation itself is not endogenous to conflict events.[11]

Multinational enterprise data. For this work, the ownership data are obtained from the *Historical Ownership Database* of Bureau Van Djik, which provides, for each company, information on all shareholders. Starting from these data, I elaborate an algorithm that retrieves the network of ownership for each business group, relying on the definition of direct or indirect majority ($\geqslant 50.01\%$) of the voting rights provided by Bureau Van Djik. This definition of control follows the international standards for multinational corporations (OECD, 2005; Eurostat, 2007; UNCTAD, 2009b). I elaborate a novel algorithm, based on the ownership links, that provides the hierarchical structure of business groups, by ascending the ownership structure. With this approach, this paper constructs the network of business groups for more than 6.3 million business groups, with 12.8 million affiliates in more than 200 countries, from 2007 to 2018, and then geolocate them using zipcodes. To my knowledge, this is the first global, firm-level dataset documenting multinationals' hierarchies and activities in a panel setting. I validate the panel dataset obtained for this paper with the rare datasets available in the literature for specific years or sub-groups of countries. See Appendix A for a detailed description of the MNE data and its validation, both in terms of coverage and precise affiliates' location.[12] I focus on the subset of af-

and by activists, as "land grabbing". This is far more widespread in Africa than in any other continent (Nolte et al., 2016), and several reasons link it to conflict, chief among them food security (GRAIN, 2012) and intense use of water (Rulli et al., 2013; Woodhouse and Ganho, 2011; Woodhouse, 2012). Although there have been case-by-case analyses of these deals and the conflicts they have brought about (Hall, 2011), no systematic study of the impact of large-scale land acquisition on conflicts, in particular in areas where large multinationals are active, has yet been done. This paper contributes to this literature by starting to fill this gap with novel panel and cross-country evidence.

[11] See, among others, Harari and Ferrara (2018), Berman et al. (2017), Michalopoulos and Papaioannou (2016), or Besley and Reynal-Querol (2014) for recent papers using similar grid-cell level data and combined with the same conflict data. As in Manacorda and Tesei (2020), I drop small island nations of Comoros, Mauritious, Sao Tome, and Principe, Seychelles, as these are likely outliers. In order to keep the dataset balanced, I also do not account for the creation of South Sudan in 2011, treating Sudan as a single country through the entire sample period.

[12] The validity of this data is extensively tested in Appendix A where, among other exercises, (i) the data are compared with official statistics such as the Outwards FATS from OECD Countries, showing that both the representativeness and the coverage are particularly high, and (ii) the locations obtained from the *Bureau van Dijk* data are compared with locations directly obtained from Google Maps for each MNE, with a correlation of the locations higher than 99% (both in terms of latitude and longitude).

filiates located in Africa and their relative headquarters around the world. The final sample covers the full continent and the MNE affiliates operating within it, with information on location and sector of activity. Knowing the geolocation of each affiliate, I aggregate them at the cell-year level.

Conflict data. I use the *Armed Conflict Location and Event Dataset* (Raleigh et al., 2014), whose main characteristic is information on geo-located conflicts with and without fatalities for all African countries. In other words, it records all political violence, whether part of a civil conflict or not, and with no threshold of battle-related deaths. These data have been widely used in recent conflict literature (among others, Harari and Ferrara, 2018; Manacorda and Tesei, 2020; Berman et al., 2021). The sample period is 2007-2018, which overlaps with the available data on multinationals. The data comprise the latitude, longitude and the date of conflict events, the actors involved, and their intensity, e.g. the number of fatalities. As standard in the literature, the only events considered are those that are geolocalized with the finer precision level. I also follow the literature in dropping duplicated events, that is, events for which all of the ACLED variable's content (precise date, location, actors, description, etc.) is the same for several observations. In these cases we retain only one observation for the event. ACLED uses several sources, including press accounts from regional and local news, humanitarian agencies and research publications. I aggregate the data by year. A variable is constructed which counts the number of *violent* events (battles, explosion/remote violence, violence against civilians, riots) in the cell during the year. This is my main dependent variable throughout the paper. In the robustness section, I show that results are completely robust if I include all ACLED events. I focus on violent actions to avoid minor events such as protests, defined as non-violent and potentially linked to strikes, which would mechanically increase due to multinationals' activity. In the same section I also show that results are confirmed if we use different conflict data, i.e. GDELT (Leetaru and Schrodt, 2013).[13] ACLED is not immune to potential bias and measurement errors. For example, we cannot rule out the possibility that the reporting of conflicts is biased towards certain countries, regions or type of events; in particular, some areas might have better media coverage. However, the empirical methodology makes it unlikely that the results are affected, since structural differences in media coverage or more generally in the reporting of events are captured by cell and country-year (or, alternatively, region-year) fixed effects.

Land deals data. I use data from *LandMatrix*.[14] This initiative provides information about

[13] This is an open-source database that collects information on the occurrence and location of political events through an automated coding of news wires worldwide. Events come from both digitalized newspapers and news agencies and web-based news aggregators (e.g. Google News, which collects more than 4 thousands media outlets).

[14] International Land Coalition (ILC), Centre de Coopération Internationale en Recherche Agronomique pour le Developpement (CIRAD), Centre for Development and Environment (CDE), German Institute of Global and

large-scale land acquisitions in different years.[15] In order to be recorded by *LandMatrix*, a deal must satisfy several requirements. Of particular interest to the scope of this work is the fact that land deals must (i) cover a significant area of land (200 hectares or more), and (ii) imply the potential conversion of land from smallholder production, local community use, or important ecosystem service provision to commercial use. This information is collected through several strategies. First, decentralized teams of experts, NGOs, coordinators, and research assistants provide information to *Land Matrix* about deals. Second, through contacts with public, private, and civil society stakeholders. Then finally, using publicly available reports, research papers, official government records, company websites, and policy reports. Using latitude and longitude, I geolocate the information contained in the dataset. Then, assuming that all deals are circular, using their size I transform data points into circular polygons. This is clearly an approximation, but considering that precise shapefiles about the land deals are not available for the whole continent, it is the most conservative approach. Finally, using an intersection algorithm, I compute the number of deals for each cell and the proportion of the area of the cell subject to a land deal. As a result, I have a panel dataset with information about the number of deals and the percentage of area occupied from the deals for each cell-year.

Individual level data. Rounds from 4 to 7 of *Afrobarometer* are used for the individual level analysis. It is a public attitude survey on governance and economic conditions in Africa (Afrobarometer, 2017). In addition to a large array of socioeconomic variables, it provides individual-level information on the main problems the government should solve, according to respondents (e.g. land management). The version of Afrobarometer data made available for this work also contains information on individuals' locality of residence, which allow to match respondents with cells.[16]

Other data. For population data I use data from *LandScan*.[17] This dataset has information about the population living in 30-arc second cells (that is approximately 1km $\times$ 1km near the equator). The number of individuals is provided per cell. In particular, *LandScan* aims to "de-

Area Studies (GIGA) and Deutsche Gesellschaft fur Internationale Zusammenarbeit (GIZ). Web, May 2021.

[15] LandMatrix defines land deals in the following way: "any intended, concluded, or failed attempt to acquire land through purchase, lease, or concession (...) in low- and middle-income countries". For our analysis, we only consider concluded land deals.

[16] These data, also merged with PRIO-GRID cells, have been widely used for research in economics and political science (see, for example, Manacorda and Tesei, 2020; Michalopoulos and Papaioannou, 2014; Rohner et al., 2013; Nunn and Wantchekon, 2011).

[17] This product was made utilizing the LandScan (2006-2018)™ High Resolution global Population Data Set copyrighted by UT-Battelle, LLC, operator of Oak Ridge National Laboratory under Contract No. DE-AC05-00OR22725 with the United States Department of Energy. The United States Government has certain rights in this Data Set.

velop a population distribution surface in totality, not just the locations of where people sleep". For this reason, it integrates diurnal movements and travel habits in one measure called ambient population.[18] Finally, as standard in this literature, a number of cell-specific data are added, including climate (rainfall, temperature, and water balance, i.e. the difference between evapotranspiration and precipitation), night lights, distance from the border, and whether the cell is in a capital city. Additional details on these variables can be found in Appendix B.

Descriptive statistics. Table 1 reports some descriptive statistics. Figure 1 and Figure 2 show maps with averages over the period of the two key variables. We observe more than 10,400 cells in 12 years. A few elements are worth mentioning. First, the unconditional number of violent events in a given cell and a given year is low, around 0.47. In most cells no conflict event occurs during the entire period. In fact, the unconditional probability of observing at least one violent event is around 10%. The probability of observing at least one MNE affiliate is also very low, at 2%, with an average number of affiliates of 0.39 over the full sample. Second, affiliates tend to be spatially clustered: conditional to observing at least one affiliate in a cell, the average number of affiliates is 16.42. Finally, conflict probability is much higher in cells with at least one MNE affiliate, around 49%. Of course, these descriptive statistics do not take into account key variables at the cell-year level, such as population and local economic development, something which is dealt with in detail in the empirical analysis.

Appendix B presents additional statistics for the conflict and the MNE data, and for all additional data used in the analysis and not included here. In the sample period the ACLED dataset records 128,310 conflict events, as Table A2 shows in Appendix B, together with additional descriptive statistics. When conditioning on observing a violent conflict event (12,418 cell-year observations), the median number of conflicts is 2, while at the 25^{th} and 75^{th} percentiles the number of conflict events are 1 and 4 respectively. Among all cell-years (125,076 observations), the percentage of cells with consistent peace is around 67%. Figure A7 in Appendix B shows annual aggregates of the number of MNE affiliates and headquarters in the African sample. The rate of growth of the number of affiliates drops sharply owing to the crisis. Before 2009, the average growth rate of African affiliates was 26%, but it drastically dropped to 4% in the first couple of years after 2009, and stabilizes to an average of 9% in the years post crisis (2010-2018).[19] In terms

[18] To construct the data it uses a "smart interpolation" technique taking together information from Census, primary geospatial input, ancillary datasets and high resolution imaginery analysis. I have imported these data, for each year, in Qgis as rasters and computed population statistics in each PRIO-GRID cell through an algorithm in Qgis. This algorithm is called Zonal statistics, and it calculates some statistical values of rasters inside specific zones, defined as polygon layers, in this case, PRIO-GRID cells.

[19] Due to data limitations, this statistic is computed only from 2007 onward, but other data sources (in flows, not stocks) confirm this growth also before 2007 (UNCTAD, 2009a; UNCTAD, 2009b).

Table 1: Descriptive statistics

		Obs.	Mean	S.D.	Median
Conflict					
	# conflict, all cells	125,076	0.47	2.97	0
	# conflict, if affiliates $= 0$	122,114	0.37	2.52	0
	# conflict, if affiliates > 0	2,962	4.27	9.79	0
	Prob. conflict > 0, all cells	125,076	0.10	0.30	0
	Prob. conflict > 0, if affiliates $= 0$	122,114	0.09	0.29	0
	Prob. conflict > 0, if affiliates > 0	2,962	0.49	0.50	0
MNE					
	# affiliates, all cells	125,076	0.39	8.16	0
	# affiliates, if affiliate > 0	2,962	16.42	50.47	2
	Prob. affiliates > 0, all cells	125,076	0.02	0.15	0

Notes: Author's computation from ACLED and the multinational enterprises (MNE) datasets. The final dataset is composed of a panel of 10,423 cells from 2007 to 2018. Additional descriptive statistics on the variables not included here can be found in Appendix B.

of nationality, the most frequent non-African headquarters are British (10% of affiliate-year observations), American and French (both around 8%), and German (5%).

3 Impact of multinationals on conflict

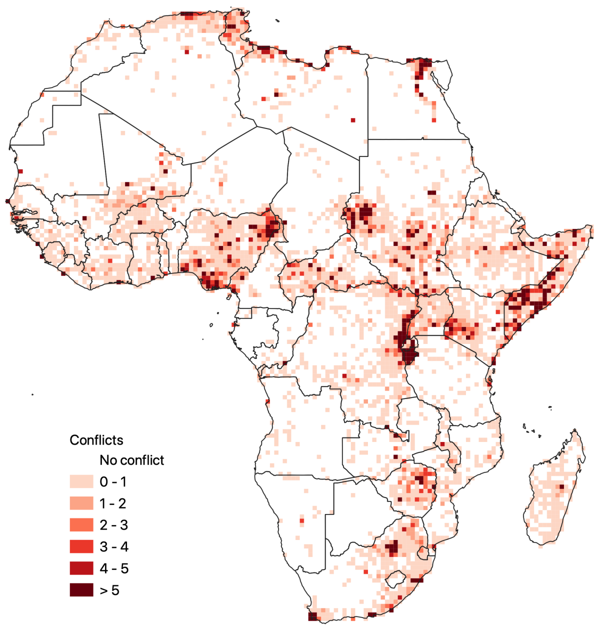
Assessing the impact of MNE activities on violence poses a series of methodological difficulties, chief among them being the potential reverse causality of local violence on MNE activity. The direction of this bias is most likely negative; that is, the existence of conflict incidence might decrease the likelihood of an affiliate being active. However, we cannot completely rule out the possibility that conflicts may affect MNE affiliate presence in a non-trivial way. Accordingly, in order to demonstrate causality, I present a regression model that expresses conflict occurrences as a function of multinationals' activity, where the latter is instrumented in each cell-year.

3.1 Econometric model

In this section, I model the occurrence of conflict events in a cell as a function of MNE activity. If we denote a generic cell k, with $k \in c$, where c denotes a country and t denotes a generic year, and ignoring controls, our regression model is:

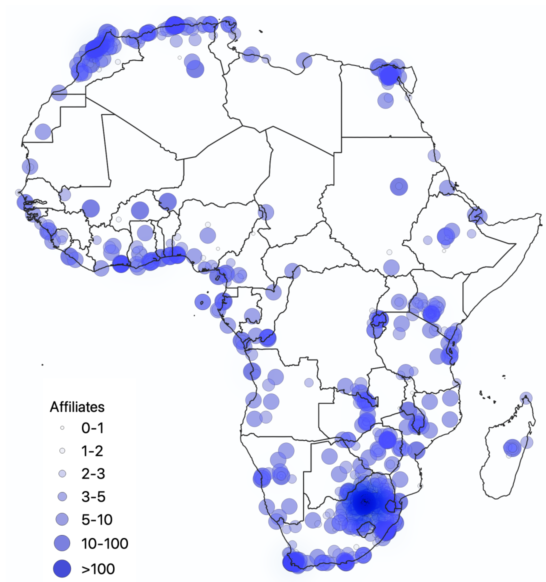
$$conflicts_{k,c,t} = \alpha + \beta \ affiliates_{k,c,t} + f_k + f_{c,t} + u_{k,c,t} \tag{1}$$

Figure 1: Conflict events



Notes: The map shows the average number of violent conflicts (ACLED) over the years 2007-2018.

Figure 2: MNE affiliates



Notes: The map shows the average number of MNE affiliates over the years 2007-2018.

where $conflicts_{k,c,t}$ denotes the number of violent events in cell k in country c in year t, and $affiliates_{k,c,t}$ is the number of MNE affiliates.[20] f_k and $f_{c,t}$ are cell and country × year fixed effects, implying that β is estimated from changes in the number of affiliates within the same cell over time, compared to other cells in the same country in a given year.[21]

A potential concern with the estimates of model (1) is that MNE activity might be impacted by conflict events, potentially generating a bias in the estimates of model parameters. In order to deal with this concern, I use an instrumental variable strategy. Multinational activities can work their effects through several channels, both at the extensive margin (e.g. opening/closing of affiliates) and at the intensive margin (e.g. number of employees). The data available allows work mainly on the number of affiliates; the coverage of size variables, like sales or number of employees, is particularly poor. So we instrument multinational activities with only one dimension of its realizations, i.e. number of affiliates. Appendix C shows that results are confirmed, both qualitatively and quantitatively, when accounting for the intensive margin of multinationals' activity (affiliates' size).[22] The basic empirical strategy exploits the fact that some affiliates within a cell-year were part of relatively healthy and robust multinationals, whereas others belonged to less healthy groups, which were affected more severely by the crisis. More specifically, pre-period data on the parent corporation's exposure to external credit is used, together with the amount of credit given in the international market, where multinational enterprises usually finance themselves (Desai et al., 2003; Huizinga et al., 2008). I use this within-cell-year variation to identify how the number of conflicts changes with the exogenous change in multinational activity. The idea is that when a shock hits the parent company (especially a credit shock like that of 2008-2009), if some constraint on the amount of borrowing or any general financial help is imposed on affiliates by the parent, there will be an impact on the affiliates' activities. This thesis has found extensive support in the internal capital market literature (see, for example, Boutin et al., 2013).

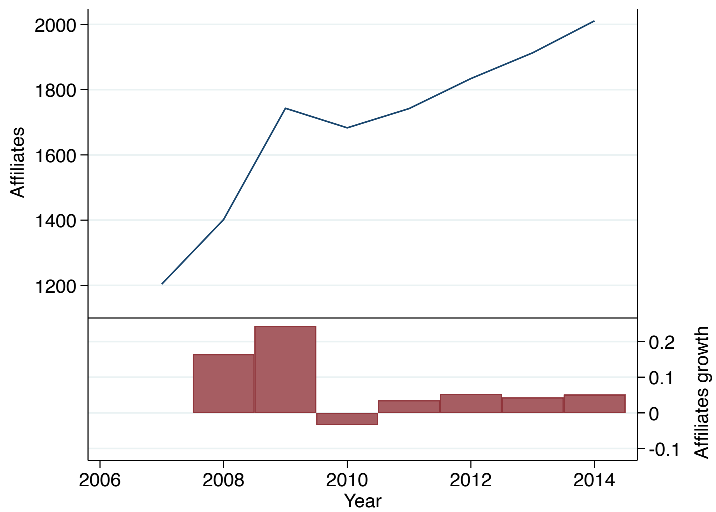
[20] One important feature of the conflict and MNE data is that their distribution is highly skewed to the right, with a very few cells displaying a very high number of violent conflicts and affiliates. For this reason, both the dependent and independent variables are winsorized at the top percentile. In section 3.3, I present estimates without winzorizing and with alternative functional forms, showing that this make no substantial difference to the results.

[21] Border cells are assigned to the country that represents the largest share of their territory. As a robustness check, in the sensitivity analysis (section 3.3), all cells belonging to multiple countries are dropped from the analysis.

[22] In Appendix C, the whole analysis is repeated (i) using the sub-sample of affiliates with size information (approximately 55% of affiliate-year observations), and (ii) incorporating the size dimension in the analysis (both in the OLS and 2SLS estimations, augmenting the IV approach with this intensive margin dimension). Results are confirmed, also quantitatively. This underlines that the extensive margin used in the main analysis (opening/closing of affiliates) is an accurate proxy of multinationals' activity. Indeed, 83% of affiliates are large or very large firms, see details in Appendix C. Despite the results are robust to this perturbation, this exercise forces the analysis to be limited to a sub-sample of affiliates. Therefore, in the main analysis, I prefer to focus on the extensive margin of multinational activity to safeguard the generality of results.

Indeed, the years of credit shortage had a clear impact on multinational activities in Africa, as already discussed in the descriptive statistics part of section 2. As an illustrative example, Figure 3 shows the aggregate number of affiliates in South Africa, the country with the highest number of observations in our sample, around the crisis. Note the sharp drop in the number of affiliates following the crisis, with their growth rate decreasing from 20% to an average of 3% in the first few years after 2009 (2010-2014). The same trend is confirmed in the overall sample, with an average of 26% and 9% respectively, in the same years.[23]

Figure 3: South African affiliates



Notes: The graphs show aggregate numbers of affiliates by year focusing on South Africa. The histograms below show changes in number of affiliates.

Given the credit mechanism behind the 2008-2009 crisis, I exploit parent corporations' heterogeneity in dependence on external finance in the decade before my analysis. I interact this with the availability of credit to the multinationals. The intuition is that the crisis hits parent firms differently depending on their reliance on credit. To avoid endogeneity, I compute a headquarters-level measure of access to credit from the previous decade. I need to instrument the number of affiliates for each cell-year. To obtain it, I use a classic shift-share approach (in the spirit of Bartik, 1991). The procedure follows three steps. First, I measure the "role" of each parent company in each cell in the base year, 2007, considering the share of each parent m's affiliates in the cell.

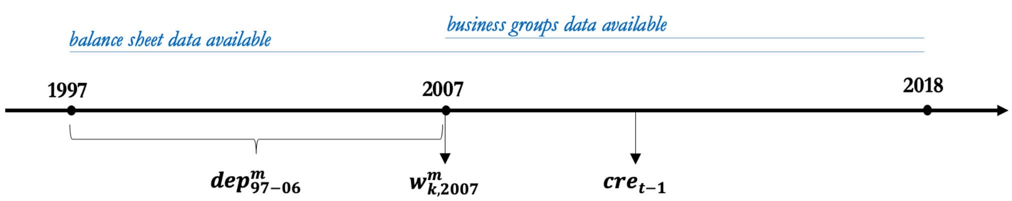
[23] As described in section 2, the dataset elaborated for this work only covers two years before the crisis due to data limitation, considering the *Historical Ownership Database* starts in 2007. However, UNCTAD's data on FDI flows confirm that before 2009 there was stable and rapid growth of FDI worldwide and in Africa (UNCTAD, 2009a; UNCTAD, 2009b), and this growth diminished sharply with the 2008-2009 crisis.

Specifically, $w^m_{k,c,2007}$ represents the parent m's share of affiliates in cell k year 2007.[24] This is the share part of the instrument. Second, I estimate the parent's dependence on external credit in the previous decade (1997-2006), denoted by dep^m_{97-06}.[25] Third, I then interact this firm-specific (time-invariant) variable with measures of credit availability at the international level, cre_{t-1}.[26] The interaction $dep^m_{97-06} \times cre_{t-1}$ represents the shift component. Figure 4 is a visual representation of the IV approach. For each cell-year, therefore, we obtain an instrument z for the number of MNE affiliates:

$$z_{k,c,t} = \sum_m w^m_{k,c,2007} \left(dep^m_{97-06} \times cre_{t-1} \right) \tag{2}$$

where I keep as constant the initial share of multinationals in each cell ($w^m_{k,c,2007}$) as weighting strategy for exogeneity. Consistency of the 2SLS estimates relies on the assumption that, other than multinationals' activity, non-African shocks to credit given to the private sector will – conditional to controls, cells and country×year fixed effects – impact conflict intensity in African cell k only through affiliates of multinational groups present in the cell.

Figure 4: IV strategy data timeline



Notes: The graph shows the time coverage of the data used for the IV strategy. Headquarters' balance sheet information is available from 1997 onward, while ownership information (essential to create the MNE dataset) is available from 2007.

This methodology presents several challenges. First, one could be worried that credit shocks might impact some areas/industries more intensively than others, therefore inducing differential effects within sub-national areas in Africa. Therefore, a detailed analysis taking into account the

[24] This is measured as the ratio between the number of m's affiliates in cell k year 2007, and the total number of affiliates in cell k in the same year. A limitation of the data is the poor coverage of affiliates' financial information. That is, I have rich balance-sheet data for the headquarters, but for almost half of the affiliates I cannot deduce useful information - even, say, their size. I record precisely where and when they are active. Presence thus serves as a proxy for MNE activity. Results are robust, and quantitatively comparable, if I focus only on affiliates with size information (augmenting the IV strategy with this additional margin as well), see Appendix C for details.

[25] Measured as the parent's total (non equity) liability-to-asset ratio (see, among others, Rajan and Zingales (1995), Rajan and Zingales (1998), and Manova (2013).

[26] World Bank data: worldwide domestic credit to private sector (financial resources provided to the private sector), excluding African countries. As a robustness, in section 3.3, I also use domestic credit provided by financial sector. Results are confirmed.

dynamic of local economic activity is needed. Second, multinationals' activity might be correlated with climatic variables and population dynamics, that might have an independent effect on conflicts. Third, even if the shares are constructed using data at the start of our sample period, one may still be concerned about non-random exposure to the shocks, which could potentially give rise to an omitted variable bias in the IV estimates. These points, together with a full battery of sensitivity and robustness checks, are tackled both in the main results' section 3.2, and in the robustness' section 3.3. The latter starts with a list of tests in support of the identification assumption, in particular, the recent tests about potential endogenous shares and non-random exposure to exogenous shocks in shift-share research design proposed by Borusyak et al. (2022) and Borusyak and Hull (2020).

3.2 Empirical results

Table 2 presents first-stage and 2SLS estimates of the model, equations (1) and (2). The dependent variable is the number of violent events at cell-year level. The main explanatory variable is the number of MNE affiliates in the cell-year. Given the nature of the data, particularly its high spatial resolution, the spatial correlation is important. As both conflicts and affiliates are clustered in space, standard errors are estimated with a spatial correction allowing for both cross-sectional spatial correlation and location-specific serial correlation, applying the method developed by Colella et al. (2019). Elaborating on Conley (1999), they develop an estimator for the variance-covariance matrix of OLS and 2SLS that allows for arbitrary dependence of the errors across observations in space (or network) structure and across time periods.[27] All specifications include cell and country$\times$year fixed effects. The former controls for time-invariant co-determinants of violence and MNE activity at cell level (a particular land conformation, say, distance to borders or to the capital, or ethnic cleavages). The latter cleans country features that impact both on conflicts and on MNE activity (e.g. property rights, change of political representation).

Column 1 presents OLS estimates, while in column 2 the 2SLS are reported. As we can see,

[27]This empirical strategy imposes no constraint on the temporal decay for the Newey-West/Bartlett kernel that weights serial correlation across time periods. The time horizon for vanishing of serial correlation is assumed infinite (100,000 years). A radius of 200km is set for the spatial kernel, which corresponds exactly to ten times the average distance among agglomerations with more than 10,000 inhabitants in Africa, as described by OECD and SWAC (2020). The authors recommend this spatial dimension to help identify unprecedented, multiscale territorial transformation processes, such as the development of metropoles and intermediary cities, the merging of villages into mega-agglomerations and the formation of new transnational metropolitan regions. In the robustness section 3.3, I show a full battery of alternative estimations modifying both the time horizon and the radius of these estimations, on top of the robustness of the results without taking any spatial correlation of the standard errors into account, and Moran's I statistics.

the coefficient of interest is significant at the 1% level in both specifications. In particular, an increase in MNE activity increases conflict probability. A few points are worth underlying. First, the IV approach confirms the downward bias of the OLS estimation, which underestimates the effect of MNE activity on violence, because of the lower probability of observing MNE activities in cells where there is violence. Second, the magnitude of the effect is substantial. Given the results in column 2, together with the average number of violent conflicts in a cell in the overall sample (0.47) and in cells with some affiliates (4.27), one additional affiliate increases the number of conflicts by 34% of the sample mean ($0.161/0.47$) and by 4% ($0.161/4.27$) in cells with some affiliates. At the bottom of the table, the estimates of the first-stage equation are reported. This shows that higher credit availability for multinationals leads to an increase in multinationals' activity. The Kleibergen-Paap Wald F statistic is reported, and it shows that we can reject the hypothesis that the instrument is weak.

Column 3 presents a preliminary sensitivity analysis of the main result. A full set of tests on the validity of the identification assumption, together with robustness checks, are presented in section 3.3. The exclusion restriction of this IV strategy relies on the assumption that credit shocks happening outside the African credit market will impact conflict intensity at the cell level only through the activity of headquarters' affiliates in African cells. However, one could be worried that credit crisis periods have direct impacts at the cell level. For example, if grid cells in host countries are experiencing income declines because they face common shocks, or because multinationals' home countries have ties to economic activity in the cell through other links besides the one that affects their own affiliates. One could be worried that this represents an alternative channel through which conflict is affected, given the effects of low income on conflict through opportunity cost effects unrelated to the presence of affiliates. In order to tackle this potential violation of the exclusion restriction, in column 3, country$\times$year fixed effects are substituted with region$\times$year fixed effects. This highly demanding set of fixed effects takes into account potential local time-varying differential effects of the crisis.[28] Moreover, in order to directly tackle the issue of local economic development, the lagged value of night lights at the cell level is included.[29] This specification is augmented also with the lag of population at the cell level, in order to check for population dynamics, together with three proxies for climatic conditions (log of temperature, log of rainfall, and water balance, i.e. the difference between evapotranspiration and precipitation,

[28] In the robustness section 3.3 I check the impact of the crisis at the cell level following Berman and Couttenier (2015) and Berman et al. (2021), namely taking into account price shocks of goods produced at the cell level.

[29] Night lights have been shown to proxy well for local economic activity, and are widely used in the literature, see Henderson et al., 2012. Moreover, in section 3.3, results are shown to be robust to the inclusion of local firms as controls.

see Harari and Ferrara, 2018, Brückner and Ciccone, 2011) and cell-specific time trends. This specification is particularly demanding, however, the coefficient maintains its significance at the 1% level. The lag of population and nightlights at the cell levels, despite being important controls, can be considered as bad controls, therefore the preferred specification is that of column 2.

Table 2: Multinational activity and conflict

	(1)	(2)	(3)
Estimator	OLS	2SLS	
Dep. Var.	Conflicts	Conflicts	
Affiliates	0.0932***	0.161***	0.178***
	(0.0183)	(0.0375)	(0.0415)
Cell FE	Yes	Yes	Yes
Country×year FE	Yes	Yes	No
Region×year FE	No	No	Yes
Population, nightlights, weather, cell trends	No	No	Yes
KP F		30.09	17.59
Obs	125,076	125,076	125,076
First stage		0.0730***	0.0567***
		(0.0132)	(0.0134)

Notes: OLS estimation in column 1, 2SLS estimation in columns 2 and 3. Dependent variable: number of violent conflict (ACLED). ***,**,* = indicate significance at the 1, 5, and 10% level, respectively. Controlling for: cell FE in columns 1-3, country×year FE in column 1 and 2, region×year FE together with (log of 1-period lag of) population, (log of 1-period lag of) nightlights, weather conditions (log of temperature, log of rainfall, and water balance, i.e. the difference between evapotranspiration and precipitation) and cell-specific trends in column 3. Conley (1999) standard errors in parenthesis, allowing for spatial correlation within a 200km radius and for infinite serial correlation. *Affiliates* indicates the number of MNE affiliates in the cell. In columns 2 and 3, the latter variable is instrumented, details are explained in section 3.1. The section *First stage* reports the coefficients of the first stage estimations. Kleibergen-Paap F-statistic are reported for columns 2 and 3.

3.3 Identification assumption and sensitivity analysis

In this section I first present a battery of tests in support of the identification assumption (Appendices D, E, F, G), then I show that the baseline estimates of Table 2 prove to be robust to a large battery of checks (Table 3, and Appendices H, I, J, K).

Identification assumption. Here I describe additional evidence in support of the identification assumption. First, in Appendix D, I perform a placebo analysis in which I substitute the shift component in the IV strategy. More specifically, the variation of the instrument comes from changes in credit availability for multinational enterprises, namely the cre_{t-1} component in equation (2). I show that substituting this component with a "simulated instrument" constructed by drawing many counterfactual credit shocks from the assignment process provides no significant effects. Second, one may be concerned about non-random exposure to the shocks, which could give rise to an omitted variable bias. To deal with this concern, also in Appendix D, I show that the 2SLS results are robust when applying the recentering methodology proposed by Borusyak and Hull (2020). Specifically, even if the shares capturing heterogeneous exposure to the shocks are constructed using data at the beginning of the sample period, concerns about non-random exposure to the shocks may still hold, potentially rising an omitted variable bias in the IV estimates. The authors explain how to purge omitted variable bias from non-random exposure to the shocks, without having to impose further assumptions (like parallel trends). They show that "recentering", i.e. by controlling for the simulated instrument or subtracting it from the IV, removes the bias from non-random shock exposure. Third, in Appendix E, the recent and frontier tests proposed by Borusyak et al. (2022) concerning potentially endogenous shares in shift-share research designs are presented. In our setting, the credit dependency interacted with global credit availability is what the authors call the shock, while the composition of multinationals in each grid cell is the exposure. Appendix E shows that: (i) the distribution of shocks in the whole dataset and residualized after extracting year fixed effects present significant variation, (ii) the inverse of the HHI of shock-level average exposure, i.e. a way to describe their effective sample size, shows a sizable degree of variation at the headquarter level, (iii) there is no correlation of potential confounders with our shocks, i.e. affiliates locations are uncorrelated with multinational shocks. Reassuringly, these three results are perfectly in line with what is requested by the authors in order to have robust results in settings with potentially endogenous shares (exposures). Fourth, one could be worried that worldwide credit shocks to private firms might have a direct impact on people's incentive to participate in violent actions, for example by changing the relative values of goods produced at the cell level. Therefore, in Appendix F, I present an analysis on cells' exposure to changes in commodity prices. Following Berman and Couttenier (2015) I check (i) for the time-varying cell-specific measure of external demand for the commodities produced by the cell, and (ii) for the heterogeneous impact this channel has on less naturally open cells (i.e., the cells for which trade costs are higher), proxied by the distance to the nearest major seaport.[30] Fifth, as proposed by Goldsmith-Pinkham et al. (2020) and Angrist and Pischke (2008), in Appendix G an alternative (maximum likelihood) estimation procedure is presented, together with overindentificaiton tests, and a different measure of credit shocks is used to check the robustness of the main estimation.[31]

[30] I am grateful to the authors for sharing updated data on cell-specific crops suitability and world import values, coming from an updated version of their two datasets used in Berman and Couttenier (2015) and Berman et al. (2021).

[31] The use of two instruments allows us to perform Hansen-J tests, which yields non-significant p-values, reassuring on the exogeneity of the instruments.

Sample. I now examine the robustness of the main result to changes in the sample. Having only 2% of our observations with some MNE activity could be seen as problematic. However, the fact that the sample does not consist only of cells with MNE activity but also has a large number of cells without MNE, conveys information that is essential to correctly estimating the effect we are interested in. In Table 3, I first restrict the sample to cells with some MNE activity during the period and their immediate neighbouring cells without MNE affiliates, row 1. In row 2, I implement a neighbour-pair fixed effect estimation, similar to Acemoglu et al. (2012) and Buonanno et al. (2015). I define a neighbourhood fixed effect that is specific to each couple of treated (affiliates$>$0) and untreated (affiliates$=$0) cells. Identification, therefore, relies on relative variations in conflict incidence in the affiliate-cell with respect to its neighbouring cells when the instrument changes. This exercise is similar in spirit to a matching estimator. In row 3, I restrict the sample to only cells with some MNE activity during the period. Needless to say, this reduces the sample size drastically. This exercise is particularly important to test the strength of the instrument. In fact, in cells that have no affiliates and do not add any during the period under analysis, the instrument perfectly predicts the correct number of affiliates – zero. So, restricting the sample to cells where there is MNE activity in at least one year tests whether the instruments correctly predict MNE activities. With this very demanding restriction, the Kleibergen-Paap Wald F statistic is still high, above 26, indicating that the instrument is not weak even when excluding all cells with no affiliates. As South Africa is the country with the majority of MNE affiliates, in row 4, I exclude it, to be sure the results are not driven by a single country. In row 5, I limit the analysis to Sub Saharian countries. One potential concern with the econometric specification proposed, and in particular with the use of the country$\times$year fixed effects, is that some cells may belong to more than one country, which is the case for almost 18% percent of the cells, therefore, in row 6, I exclude them. Potential critiques to the proposed specification could relate to the possibility of reverse causality in cells with affiliates in the resource sectors (mining and quarrying, oil, gas, etc.). The literature extensively documented the causal link between the presence of resources and violence (see, among others, Guidolin and La Ferrara, 2007; Caselli et al., 2015; Berman et al., 2017). For these reasons, row 7 restricts the sample to cells without valuable resources (gold, diamonds, oil, etc). Campante et al. (2019), studying the links between capital cities and conflict, find that conflict is more likely to emerge (and dislodge incumbents) closer to the capital. De Haas and Poelhekke (2019), in estimating the impact of local mining activity on firm-level business constraints, exclude firms in capital cities because limited fiscal redistribution may keep rents disproportional in the capital.[32] For these reasons, row 8 excludes capital cities.

[32] Also the authors use, among others, a sample of mining firms from the *Orbis* dataset of Bureau van Dijk.

Additional controls. A potential concern with the identification strategy proposed is whether periods of credit crisis might have differentiating effects on different areas in African countries. For example, if the textile industry was particularly hard-hit, this might be expected to impact on specific African areas particularly specialised in textile production. To control for possible indirect effects of the crisis on specific areas within a country, in row 9 country×year fixed effects are substituted with region×year fixed effects. In row 10, cell-specific time trends are included. Where agriculture is largely rain-fed, i.e. countries that lack extensive irrigation systems and are not heavily industrialized, weather is crucial, and is also a key to conflict probability (Harari and Ferrara, 2018; Brückner and Ciccone, 2011; Miguel et al., 2004; Hendrix and Salehyan, 2012). For this reason, the results are checked after controlling for (the log of) rainfall, (the log of) temperature, together with a measure of water balance (the difference between evapotranspiration and precipitation), row 11. In row 12, I add the lagged and lead values of the dependent variable at the cell level. In rows 13 and 14 two important controls are added, which tho could be considered as bad controls, namely night lights and population at the cell level. They are important to proxy the level of development (or the disaggregated level of GDP), and to control for population density at the cell level, which can be directly related to conflict probability. To mitigate endogeneity problems, they are lagged by one period. In row 15, headquarters' country fixed affects are added, with dummy variables taking value 1 where a cell-year shows at least one affiliate of a parent corporation located in a specific region of the world.[33] In line 16, I control for the number of local firms at the cell level, lagged by one year, while in line 17 the same variable is lagged by 3 years.[34]

Different conflict variables. In line 18, a dummy variable assuming value 1 when we observe at least one violent event in the cell-year is used as dependent variable. Note that, as described in Table 1, the probabilities of observing a violent event are 0.10 in the overall sample and and 0.49 in cells where we observe some affiliates. This means that, on average, one additional affiliate increases conflict probability by 14.7% with respect to the overall sample mean, and by 3% in cells with some affiliates. In row 19, I study the effect on all ACLED events, therefore not limiting the analysis to violent events only. Section 4.2 extensively studies the different types of conflict in order to shed light on one of the mechanisms behind the main result. In row 20, I explore

[33] Specifically, I group headquarters nationality in eight macro regions: Eastern, Western, and Southern Asia, Eastern, Western, Southern, and Northern Europe, and North American. This aggregation allows me to avoid including more than 100 dummy variables (as many as headquarters' nationalities) in the estimation.

[34] This data come from the same source of the main MNE data, i.e. Bureau van Dijk, specifically from the *Orbis* database. Details on the data concerning local firms, and additional robustness including local firms' size, can be found in Appendix H.

robustness to using the alternative GDELT dataset. The coefficient of a completely different magnitude is not surprising, and it is common in the literature, considering the strongly higher number of records we find in the GDEL dataset. Indeed, the average number of GDELT events is above 15, while it is 0.47 in the ACLED dataset. This is due to the different type of data collection (the main difference being that GDELT collects event through an automated coding of news wires, as described in section 2).

Alternative functional forms. In Appendix I, I also consider additional transformation of the dependent and independent variables. One relevant feature of the conflict and multinational data is that their distribution is highly skewed to the right, with a few cells displaying a very high number of violent conflicts and/or affiliates. For this reason, in the baseline specification both the dependent and independent variables are winsorized at the top percentile. However, as alternative checks, in Appendix I, I present estimates without winzorizing and where I experiment with the logarithm transformation and the inverse hyperbolic sine transformation of these variables, with and without winzorizing.

Spatial correlation. The spatial resolution of the data used for this work is particularly high, therefore in all the analysis the spatial correlation is taken into account using a spatial correction allowing for both cross-sectional spatial correlation and location-specific serial correlation, as explained in the main result section. In Appendix J, results using a full battery of different settings for this correction (both in terms of time and space) are presented, together with results clustering standard error at the cell-level or different administrative levels without correcting for the spatial correlation. Finally, in Appendix K, I report Moran's I statistics, as suggested by Kelly (2019).

As we can see from Table 3, together with the listed Appendices D, E, F, G, H, I, J, and K, the results presented in section 3.2 are robust to all the checks described above, independently from the different samples used and/or different controls added to the main specification. In particular, the coefficient, its significance, and the Kleibergen-Paap Wald F statistic are stable in the large majority of these perturbations, reassuring the robustness of the estimated effect.

4 Land acquisition

In this section, I provide *supportive evidence* to spotlight *one* potential mechanism of the documented impact that MNE activities have on conflict. The past decades have been characterized by a vast increase in large-scale land acquisitions (LSLA) in developing countries. The acquisitions are usually made by national sovereign wealth funds or corporations based in wealthier, more

Table 3: IV - Sensitivity analysis

	Affiliates			
	Coeff.	Std. Err.	K-P F stat	Obs.
Sample				
(1) MNE cells and neighboring cells	0.162***	(0.0496)	33.94	28,608
(2) Neighbor-pair fixed effects	0.219***	(0.0356)	41.33	28,608
(3) Only cells with MNE activity	0.112***	(0.0375)	26.06	4,332
(4) Excluding South Africa	0.111**	(0.0443)	26.31	119,460
(5) Only Sub Saharian countries	0.178***	(0.0396)	23.05	99,264
(6) Excluding border cells	0.172***	(0.0403)	26.76	102,264
(7) Excluding cells with resources	0.186***	(0.0425)	23.81	120,960
(8) Excluding capitals	0.178***	(0.0478)	14.74	124,260
Additional controls				
(9) Region $\times$ Year FE	0.176***	(0.0415)	17.57	125,076
(10) Cell-specific time trends	0.160***	(0.0373)	29.93	125,076
(11) Precipitation, temperature, water balance	0.160***	(0.0375)	30.11	125,076
(12) Conflict (t-1) and (t+1)	0.058**	(0.0228)	30.41	104,230
(13) Nightlights (t-1)	0.162***	(0.0376)	30.13	125,076
(14) Population (t-1)	0.161***	(0.0375)	30.08	125,076
(15) Headquarter country FE	0.162***	(0.0376)	30.72	125,076
(16) Local firms (t-1)	0.185***	(0.0412)	26.76	125,076
(17) Local firms (t-3)	0.188***	(0.0439)	24.87	125,076
Different conflict variables				
(18) Dummy	0.0147***	(0.0032)	30.09	125,076
(19) All conflict events	0.535***	(0.137)	30.09	125,076
(20) GDELT	9.362***	(1.764)	30.09	125,076

Notes: The table reports 2SLS estimation results from 17 different specifications described in section 3.3. Dependent variable: number of violent conflicts (ACLED). ***,**,* = indicate significance at the 1, 5, and 10% level, respectively. Conley (1999) standard errors in parenthesis, allowing for spatial correlation within a 200km radius and for infinite serial correlation. *Affiliates* indicates the number of MNE affiliates in the cell. The latter variable is always instrumented, details are explained in section 3.1. Kleibergen-Paap F-statistic are reported for each specification.

developed countries. This phenomenon is known in the literature and by activists as "land grabbing". It is by far more widespread in Africa than in any other continent (Nolte et al., 2016), and several reasons link it to conflict, the greatest of which being that it directly threatens the local population's food security by taking agricultural land away from small farmers. In many countries where food insecurity is already high, large portions of the total arable land have been sold or leased to foreign investors (GRAIN, 2012).[35] Land tenure is complicated in many African countries and land rights are usually customary, without written evidence of usage or ownership. Local authorities can, therefore, often sell the land without consulting the local communities living there, they may then be displaced when their land is sold to foreign investors, and may not be compensated for it (Deininger and Byerlee, 2011).[36] For all these reasons, scholars and activists have argued in a series of case-studies that land grabs cause, or are likely to cause, violent social conflict, i.e. riots, in response to this accumulation and enclosure of land (Arslan et al., 2011; Von Braun and Meinzen-Dick, 2011; Oakland Institute, 2013).[37]

To provide supportive evidence that use of land by MNE is one of the mechanisms leading to the documented increase in conflicts, I first show that among MNE activities, sectors increasing conflict are the *land-intensive* ones. Secondly, using geocoded information on large-scale land acquisitions, I corroborate this evidence showing that the increase in violent conflict caused by multinationals' activity is amplified in areas targeted for this *large* (more than 200 hectares) conversion of land from smallholder production, local community use, or important ecosystem service provision to *commercial use*.[38] Moreover, I show that the type of conflict triggered by multinationals is mainly that outlined by case-studies on land-grabbing, namely *localized* violent events, likened to insurrections to protect a key resource for survival: land. Third, using individual-level data from Afrobarometer, I show that the higher the MNEs activity, the more likely it is that people living nearby these multinationals declare *land* and/or *farming/agriculture* as being among the "most important problems facing this country that government should ad-

[35] Moreover, intensive use of land often involves an intense use of water, depriving people in the surrounding areas of this very scarce resource. In fact, water control may well be the primary objective of a land grab (Rulli et al., 2013; Woodhouse and Ganho, 2011; Woodhouse, 2012). Furthermore, LSLA clash head-on with the ideal of food sovereignty, "the right of communities, peoples and states to independently determine their own food and agricultural policies" (Beuchelt and Virchow, 2012).

[36] It is important to underline that when locals lose access to land, even when there is a lot of alternative arable land, investors may buy the most fertile lands and locals who were using it could be moved to other areas with less suitable characteristics for agriculture (Cotula, 2011).

[37] In Africa, the emblematic case of the agreement between the government of Madagascar and Daewoo Logistics is often mentioned: a 99-year lease covering almost half of Madagascar's arable land, with the aim of producing maize and palm oil for export. This astonishing deal is often cited as a cause of the coup that toppled President Marc Ravalomanana (Meinzen-Dick and Markelova, 2009; Thaler, 2013).

[38] This is exactly the *Land Matrix*'s definition of land deals recorded in their dataset.

dress". Moreover, this section concludes by showing that this individual-level results are completely driven by people leaving in areas where land-intensive MNEs are active, while the activity of non land-intensive MNEs provides no significant results.

It is worth underlying that considering some limitation of the data at hands and a few methodological difficulties, as described below, the results of this section has to be taken as suggestive evidence of the mechanism presented. The reader could also think at alternative channels, which I cannot rule out with the data available in this work. For example, the presence of multinationals could potentially increase local labour demand in low-skilled industries, therefore, decreasing the probability of engaging in violent actions. In Mendola et al. (2021), we geolocate and match 4.4 million DHS interviews for Sub-Saharan countries over the period 2003-2019 with the dataset on multinational activity used in this work to show that this is not the case. Indeed, our results show that, on average, MNE activity decreases locals' on-farm job participation.[39]

4.1 Industry heterogeneity

Based on the extensive andecdotal evidence and on the literature on land grabbing in developing countries described above, this subsection aims at providing evidence confirming that *land intensive* MNEs industries are those related to conflict.

In order to study the heterogeneous effects of different MNE industries, we need to unpack the aggregate variable *number of affiliates* used in the main analysis in a set of variables counting the *number of affiliates in different industries*. I do so in Figure 5. Unfortunately, the instrumental variable strategy presented in section 3.1 does not allow the use of a 2SLS approach in a more disaggregated framework, therefore, any time a disaggregated version of the main variable will be used, OLS estimates will be implemented.[40] Importantly, the 2SLS and the OLS estimations of the main specification (columns 1 and 2 of Table 2) present the same sign, comparable magnitude, and the same level of significance. This allows us to internally compare the coefficients

[39]This finding is supported by numerous case studies, focused in particular in the mining sectors. Studying the activity of multinational oil and mining companies in Nigeria, South Africa and Zambia, Eweje (2009) finds that multinationals have been widely criticized by local governments and trade unions for employing expatriates at the expense of local labor. The use of imported and subcontracted labor by Chinese investors in Africa has been described by various authors (Cooke, 2014; Mohan, 2013).

[40]More technically, remember that the instrument described in details in section 3.1 is composed by a share, which is constant by construction like in any shift-share to avoid endogeneity, and a shifter, which changes over time. The latter, i.e. the worldwide credit availability for MNE (cre_{t-1}), is the only time-varying component of the shifter and does not vary by industry, considering that the headquarters' dependence on external credit, dep^{m}_{97-06}, are time-invariant. Therefore, computing a set of instruments at the industry level, for each cell, using the same shifter for all of them, would create serious issues of collinearity in the estimation when using the instruments simultaneously. An alternative would be to find additional industry-specific instruments, which is something I leave for future research.

presented in Figure 5, avoiding any comparison with 2SLS estimates and/or any quantification exercise.

In the first specification, the variable *affiliates* (indicating the number of affiliates in a cell-year in all industries) is split in two: *land intensive* and *non land intensive* affiliates. In the first category the primarily industries are included, while the latter includes the secondary and tertiary industries.[41] Interestingly, only the number of MNE affiliates in the *land intensive* industries show a positive and significant coefficient when regressed on the number of conflict.[42] This splitting in two groups of the main explanatory variable is the preferred specification, because it categorizes industries based on their intensity in the use of land and it is not based on any specific (and potentially ad-hoc) selection of industries. However, to corroborate even more the land-intensive mechanism, and to check the robustness of the result, I do two things. First, in the next paragraph, I split the *land intensive* group of affiliates even further, showing that the relatively more land intensive industries - among the primarily industries - are those driving the results. Second, in Appendix L, I split the *non land intensive* affiliates' variable in several ways, showing that independently on how we manipulate the data, the *land intensive* group is always the one driving the results.

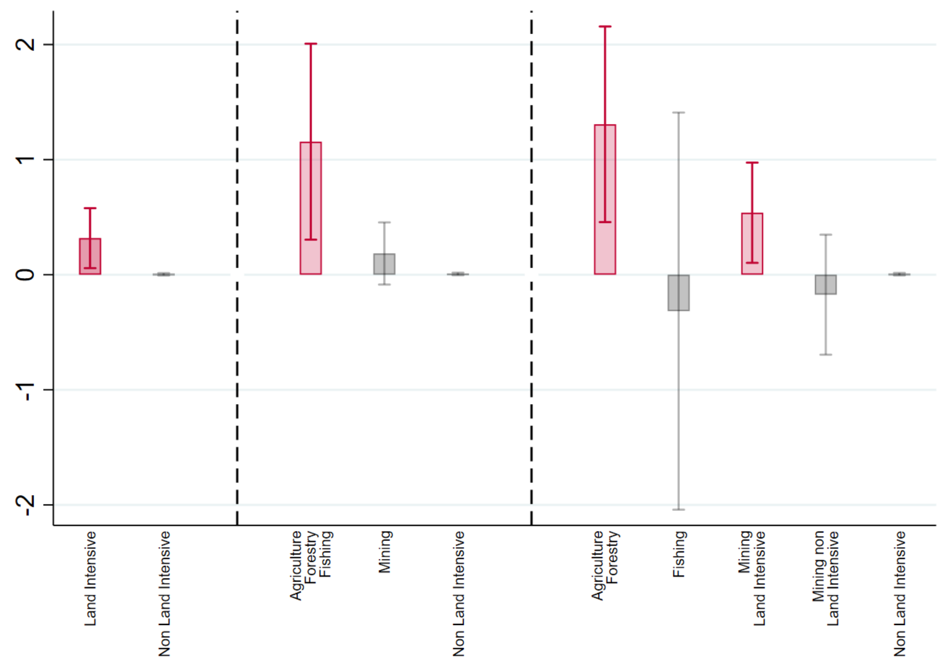
In order to better understand this channel, and strictly following the High-level SNA/ISIC industry aggregation, in Figure 5, the variable *land intensive* is split out even more into the two set of industries (i) *agriculture*, *forestry*, *fishing*, and (ii) *mining and quarrying*. The number of MNE affiliates in the *agriculture*, *forestry*, *fishing* industries present, once again, a positive and significant coefficient, while the affiliates in *mining and quarrying* show a positive coefficient, however, not well identified at standard levels. As a final step, in order to isolate the particularly land-intensive industries, in the third specification I group the two particularly land-intensive industries *agriculture* and *forestry* together, while leaving the non land-intensive *fishing* industry alone. In the same way, I group the relatively more land intensive industries in the *mining and quarrying* industry (e.g. *metal ores*, see Guidolin and La Ferrara, 2007), and I group together the least land intensive *mining and quarrying* industries (such as *petroleum* and other energy

[41] I follow the classic three-sector model widely used in development economics when analyzing least developed countries. Primary industries include: Agriculture, Forestry, Fishing; Mining and Quarrying. Secondary industries include: Industry; Manufacturing; Construction. Tertiary industries include all the rest. The industry aggregation proposed is mainly based on the High-level ISIC/NACE sector aggregation, which is the most aggregated classification identified by national accountants to be used for reporting Systems of National Accounts data from a wide range of countries (Eurostat, 2008). More details in Appendix L.

[42] Note that the empirical specification of Figure 5 completely mimics the main specification, equation (1), e.g. with cell and country$\times$year fixed effects.

minerals, which are more capital intensive rather than land intensive).[43] In line with our priors, only the number of affiliates in the land-intensive industries present a positive and significant coefficient when regressed on the number of conflict, while the rest show a not significant effect.

Figure 5: Industry heterogeneity



Notes: The figure reports the coefficients of three OLS estimations described in section 4.1. The three different specifications are divided by vertical dashed lines. Dependent variable in all specifications: number of violent conflicts (ACLED). ***,**,* = indicate significance at the 1, 5, and 10% level, respectively. Controlling for: cell and country×year FE. Conley (1999) standard errors in parenthesis, allowing for spatial correlation within a 200km radius and for infinite serial correlation. Each group of affiliates indicated below represent the number of affiliates belonging to that specific group in a cell-year (e.g. *Land intensive* represent the number of affiliates belonging to land intensive industries - for details see Section 4.1 and Appendix L). In each specification cell and country×year fixed effects are included. The regressions' table of this Figure can be found in Appendix L, Table A17.

4.2 Land acquisitions and localised violence

As described in the section 2, I use geocoded data from *LandMatrix* to map the percentage of each cell targeted by a land deal. When a cell is targeted for a large-scale land acquisition, the average percentage of surface covered is around 10%. In this section, I provide suggestive evidence that the increase in violent conflict caused by MNEs' activity is amplified in areas targeted for large-scale land deals, and that the type of conflicts triggered are *localized* violent events, in line

[43]Details about industries grouping and regression results can be found in Appendix L.

with case studies cited above where locals start rioting to protect their land, i.e. the main resource for their survival. Column 1 of Table 4 presents the 2SLS result of the following specification:

$$conflicts_{k,c,t} = \sigma + \delta\ affiliates_{k,c,t} + \pi\ ld_{k,c,t} + \rho\ affiliates_{k,c,t} \times ld_{k,c,t} + f_k + f_{c,t} + v_{k,c,t} \quad (3)$$

where (*k,c,t*) stands for cell, country, and year as in the other specifications, and $ld_{k,c,t}$ is the percentage of cell *k* which is part of a large-scale land deal. As in the other specifications, $conflicts_{k,c,t}$ is the number of violent conflicts in the cell, $affiliates_{k,c,t}$ is the number of multinational affiliates in the cell, and f_k and $f_{c,t}$ are cell and country×year fixed effects.[44] Looking at column 1 of Table 4, the coefficient ρ is estimated positive and significant at the 1% level. As stated in the description of the data, the precision of the land-deal data is not particularly high, moreover, I use simultaneous land-deals, which could suffer from endogeneity issues (despite better mapping the dynamics of land deals, which are key in this specific analysis), therefore, these results have to be taken with a grain of salt. Anecdotically, they show that the impact multinationals' activity have on conflict is amplified in areas targeted for large-scale temporary or permanent land acquisitions.[45]

Having shown that MNE impact on conflict is amplified in areas targeted for land grabbing, here I provide some additional evidence on the specific type of conflicts induced. The type of conflicts MNE trigger are in line with the mechanism described, i.e. local violent events. Remember that farming is the primary source of food and income for Africans, providing more than sixty percent of all jobs on the continent (Sy, 2016; Coulibaly, 2020). Therefore, if the channel described is true, when this *scarce* and *key* resource is detracted from the locals, often without compensation (Deininger and Byerlee, 2011), we expect people's grievances to escalate mainly to violent localised actions, such as riots. Columns 2-5 of Table 4 replicates the baseline specification for each of the four categories of violent events covered by the ACLED dataset: *battles*, *explosions and remote violence*, *riots*, *violence against civilians*.[46] Interestingly, the only type

[44] Note that the interaction term $affiliates_{k,c,t} \times ld_{k,c,t}$ is instrumented as well. I instrument the $affiliates_{k,c,t} \times ld_{k,c,t}$ variable by interacting the instrument for the variable $affiliates_{k,c,t}$ with the $ld_{k,c,t}$ variable.

[45] Note that this is not the case for all land deals. Indeed, the effect of *Land Deals* alone seems to be negatively related to conflict intensity (this might be due to the fact that, often, LSLA projects are proposed with the formal aim of investing in local infrastructures and/or human capital), however, when they take place in areas together with multinationals' activity, this magnifies the effect of MNE on conflict.

[46] ACLED codes four categories of violent events. These four types of violent events represents the disaggregated version of the main dependent variable used in the paper. First, *Battles*, defined as "a violent interaction between two politically organized armed groups at a particular time and location". Second, *Explosions and Remote Violence*, "one-sided violent events in which the tool for engaging in conflict creates asymmetry by taking away the ability of the target to respond". Third, *Violence against Civilians*, "violent events where an organised armed group deliberately inflicts violence upon unarmed non-combatants". Fourth, *Riots*, "violent events where demonstrators or mobs engage in disruptive acts, (...) may target other individuals, property, businesses, other rioting groups or armed actors".

of violent event allowing the detection of a significant role of MNE activity alone, even unconditionally with respect to others, is riots, as we can see from column 4.[47] Moreover, the magnifying effect of large-scale land deals seems to be always correlated with an increase in conflict when they take place in areas with MNE, as we can see from the interaction terms of Table 4.

Table 4: Land acquisition and localized violence

	(1)	(2)	(3)	(4)	(5)
Estimator	2SLS			2SLS	
Dep. Var.	Conflicts	Battles	Expl./Rem.	Riots	Viol. Civ.
Affiliates	0.160***	-0.00175	0.00816	0.143***	0.0152
	(0.0375)	(0.00841)	(0.00957)	(0.0246)	(0.00956)
Affiliates×Land Deals	0.352***	0.0894**	0.0315***	0.315***	0.0328
	(0.0573)	(0.0364)	(0.0120)	(0.0318)	(0.0352)
Land Deals	-0.601***	-0.258*	-0.150***	-0.116	-0.456***
	(0.188)	(0.140)	(0.0338)	(0.0826)	(0.130)
Cell FE	Yes	Yes	Yes	Yes	Yes
Country×year FE	Yes	Yes	Yes	Yes	Yes
FP F	15.03	15.33	15.33	15.33	15.33
Obs	125,076	125,076	125,076	125,076	125,076

Notes: 2SLS estimation. Dependent variables: number of violent conflict (column 1), number of battles (column 2), explosions and remote violence (column 3), riots (column 4), violence against civilians (column 5). ***,**,* = indicate significance at the 1, 5, and 10% level, respectively. Controlling for: cell and country×year FE. Conley (1999) standard errors in parenthesis, allowing for spatial correlation within a 200km radius and for infinite serial correlation. *Affiliates* indicates the number of MNE affiliates in the cell. The latter variable is instrumented, details are explained in section 3.1. *Land Deals* indicates the percentage of the cell covered by a large-scale land acquisition. Kleibergen-Paap F-statistic are reported for each specification.

4.3 MNE and locals' complains about land management

In this section, I finally turn to individual data from the Afrobarometer survey to further investigate the effect of MNE activity on conflict. Microdata from the Afrobarometer, by providing information about the major problems the government should face according to respondents, allow shedding some light on potential mechanisms of impact. Note that the results in this section should be taken with caution, as using them I have to ignore their potential nonrandom allocation of coverage across areas.

Among the Afrobarometer survey, there is one question which is particularly interesting for our analysis. The respondent is asked "*In your opinion, what are the most important problems facing this country that government should address?*". The interviewer is then provided with the

[47] Importantly, note that if we replicate columns 2-5 of Table 4 without the interaction with land deals, *riots* is again the only type of event significantly impacted by MNEs' activity. Note also that, as in Berman et al. (2017), the unconditional probability of observing specific types of events is smaller than the probability of observing any type of event, as shown in column 2 of Table 2.

following instructions related to the above question "*[Do not read options. Code from responses. Accept up to three answers. If respondent offers more than three options, ask 'Which three of these are the most important?'; if respondent offers one or two answers, ask 'Anything else?']*". This is particularly relevant in our settings, because it outlines that the respondent does not answer selecting the issue(s) from a list, but she/he answers the question freely and then the interviewer codes the answer from a list of entries. Two (among more than 30) entries belonging to the list available (only) to the interviewer are *land* and *farming/agriculture*.[48] I use this question to test whether in areas where MNEs activity is more intense people lament one of the main issues to be addressed as being related to land or agriculture and farming. Columns 1 and 2 of Table 5 reports estimations of the following specifications:

$$issue_{i,k,c,t} = \kappa + \psi \; affiliates_{k,c,t} + \bar{x}_{i,k,c,t} + f_k + f_{c,t} + e_{k,c,t} \tag{4}$$

where i stands for individual, (k,c,t) stands for cell, country, and year as in the other specifications, and $\bar{x}$ are individual controls.[49] The dependent variable $issue_{i,k,c,t}$ is a dummy assuming value 100 if the respondent i located in cell k declares *land* (or *farming/agriculture*, depending on the specification) to be one of the three main problems the government should address. As in the other specifications, $affiliates_{k,c,t}$ is the number of multinational affiliates in cell k (instrumented at the cell-level as in the main specification), and f_k and $f_{c,t}$ are cell and country×year fixed effects. Columns 1 and 2 of Table 5 show that, on average, complains about both land management or farming/agriculture significantly increases in areas with higher MNEs activity. An increase of the mean number of affiliates nearby the respondents (around 10 affiliates) increases the probability of respondents listing *land* or *farming/agriculture* as one of the main problems to be tackled by the government by 18% (10×0.0398/2.2) and 6.4% (10×0.0703/10.96) with respect to the sample mean, respectively.

In columns 3 and 4 of Table 5, I split the *number of affiliates* variable in the two groups *land intensive* and *non land intensive affiliates* described in subsection 4.1, in order to understand whether the increase in complains documented in columns 1 and 2 can be attributed to the activity of land intensive MNEs. As stressed in subsection 4.1, this procedure requires to switch to an OLS estimation (see footnote 40) and, therefore, prevents any type of comparison between the results in columns 1-2 and 3-4. Interestingly, both specifications highlight that only the activity of land intensive MNEs increases the likelihood that individuals complain about land management and/or farming/agriculture.

[48] More details and the full list of answers can be found in Appendix M.

[49] The individual controls are age and age squared, educational dummies, a dummy for urban residence, dummies for religion, and number of adults in the household.

Table 5: MNE and locals' complains about land management

Estimator	(1)	(2)	(3)	(4)
	2SLS		OLS	
Dep. Var.	Issue: Land	Issue: Farm./Agric.	Issue: Land	Issue: Farm./Agric.
Affiliates	0.0398*	0.0703**		
	(0.0219)	(0.0334)		
Land intensive affiliates			0.123*	0.140*
			(0.0712)	(0.0804)
Non land intensive affiliates			-0.00599	-0.00606
			(0.00410)	(0.00441)
Cell FE	Yes	Yes	Yes	Yes
Country×year FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
FP F	23.52	23.52		
Obs	127,794	127,794	127,794	127,794

Notes: 2SLS estimation in columns 1 and 2. OLS estimation in columns 3 and 4. Dependent variables: number of violent conflict. ***,**,* = indicate significance at the 1, 5, and 10% level, respectively. Controlling for: cell, country×year FE, and a set of individual level variables (age, age squared, educational dummies, dummy for urban residence, dummies for religion, number of adults in the household). Conley (1999) standard errors in parenthesis, allowing for spatial correlation within a 200km radius and for infinite serial correlation. *Affiliates* indicates the number of MNE affiliates in the cell. The latter variable is instrumented in columns 1 and 2, details are explained in section 3.1. *Land intensive affiliates* and *Non land intensive affiliates* indicates number of MNE affiliates in land intensive (primarily industries) and non land intensive industries (secondary and tertiary industries), respectively. Kleibergen-Paap F-statistic are reported for specifications 1 and 2.

This set of results, with the evidence presented in the previous sections, depicts a coherent dynamic in line with the extensive anecdotal evidence documented by the policy debate and specific case-studies (among others, The Economist, 2011; Arslan et al., 2011). We can conclude that among multinationals' activity, those increasing conflicts are documented to be mainly the land-intensive ones. MNEs' impact is magnified in areas targeted for large-scale land acquisitions, where smallholder producers are often forced to relocate due to the conversion of the land to commercial use, and the specific type of conflict induced turns out to be local, potentially comparable to insurrections to protect land, a principle resource for locals' survival. Finally, individuals living nearby multinationals lament significantly more land management and farming/agriculture as key problems to be addressed by the government, and the increase in these complains seems to be driven by the activity of land intensive MNEs.

5 Conclusion

In this paper, I provide novel systematic evidence on the impact of multinational enterprises' activity on conflict. Using novel and fine-grained worldwide panel data on multinational groups, both at the headquarters' and affiliates' level, together with georeferenced data on violent conflicts in Africa, I document a quantitatively important impact of multinationals' activity on conflict intensity. A battery of sensitivity tests confirms that the result is robust to a variety of alternative specifications and additional controls. This disaggregated study of the causal impact of multinational corporations' activities on conflict also attempts to shed light on one potential mechanism through which these activities can lead to the escalation of violence: land expropriation. First, I provide suggestive evidence that industries increasing conflict marginally more are, in particular, land-intensive ones. Second, I show that these effects are magnified in areas targeted for large-scale land acquisitions. These multinationals put the primary local sources of food and income at risk, increasing local grievance, which then escalates into localized violent events. Finally, using individual level data, I show that people living by multinationals are more likely to lament land management and agriculture/farming as major problems the government should tackle.

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Online Appendix

A Multinational enterprise dataset

In this appendix, I provide additional information on the multinational enterprises (MNE) dataset, which identifies MNE, disentangles their hierarchical structure, and geolocalizes the worldwide population of affiliates and headquarters. The dataset covers years 2007 to 2018, but it is possible to update it as soon as more recent data is available from Bureau van Dijk.

Subsection A.1 describes in detail how the dataset is constructed. In subsection A.2 it is compared with existing dataset in order to validate its coverage. Subsection A.3 validates affiliates' geographical location.

The literature on MNE has always struggled with strict constraints on data availability. Most studies use aggregated data on MNE activity at the country of origin (or industry) level from Foreign Affiliates Statistics (FAPS) or FDI flows from Balance-of-Payments Statistics. A small number of works use firm-level micro-data from various sources. Examples of such sources are *Orbis* from Bureau van Dijk, *Compustat*, the *BEA* for US Multinational. While all of these sources have their pros and cons, *Orbis* is the most popular because of its completeness and global scale.

The first global-scale micro-study on MNE is Alfaro and Charlton (2009): using data from *Dun & Bradstreet* the authors elaborate a cross-section for the year 2005, covering 650K multinational subsidiaries in 400 industries and 90 countries. While, the first data-set covering all countries of the world was produced by Altomonte and Rungi (2013). The authors use data from Bureau van Dijk to map control chains of corporate activities (both domestically and internationally) for more than 1,5M affiliates of around 270K headquarters in 2010, across more than 200 countries and all industries.

A.1 Dataset construction

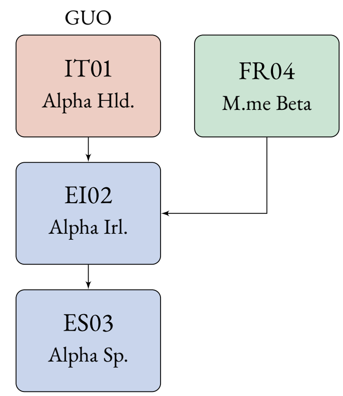
As far as the dataset on multinationals used in this work is concerned, I construct it as follows. First, I collect all ownership information in the *Historical Ownership Database* of Bureau van Dijk for years 2007-2018. The information of the database is stored in the form of binary links: each company is linked to all of its shareholders (SHH), direct controllers (ISH) and ultimate owners (GUO).

Some definitions are in order: I rely on the concept of corporate Global Ultimate Owner (GUO) developed by Bureau van Dijk in agreement with the notion of corporate control estab-

Figure A1: An example from the Historical Ownership Database

Data-base snippet

BvD ID	Shareholder	Relation	Share	Year
IT01	IT01	GUO	100	2018
EI02	IT01	GUO	70	2018
EI02	IT01	ISH	70	2018
EI02	IT01	SHH	70	2018
EI02	FR04	SHH	30	2018
ES03	IT01	GUO	-	2018
ES03	EI02	ISH	100	2018
ES03	EI02	SSH	100	2018



Notes: The figure shows a simplified example of how the group of Alpha Holdings would look in the historical ownership folder of the *Orbis* database. Notice that Alpha Holdings owns a majority share in the capital of Alpha Ireland and controls Alpha Spain indirectly trough Alpha Ireland. Also, notice that M.me Beta owns a minority participation in the capital of Alpha Ireland.

lished by international accounting standards (OECD, 2005; Eurostat, 2007; UNCTAD, 2011).[50] Company A is considered the GUO of another company B if it can control, either directly or indirectly through other subsidiaries, more than 50% of the voting rights in company B. I acknowledge that this definition excludes other forms of control such as minority control, golden shares, or market characteristics (e.g. monopsony or monopoly). However, the inclusion of such forms would complicate the construction of the dataset significantly and would generate unclear group boundaries. Direct controllers, on the other hand, are immediate (direct) shareholders that control subsidiaries and stand on the path between the subsidiary and its ultimate owner.

Each link specifies the type of relation and the share of capital rights that each party detains. This is called direct share on *Orbis*. However, links describe one ownership relations at a time, so, for example, if shareholding company A is also the direct controller and the ultimate controller of company B, *Orbis* would record three different links relating B to A. The procedure is repeated every year and saved in a separate file, so that it is possible to assess the evolution of ownership on a year to year basis. Figure A1 presents an illustrative example of how data in the historical ownership folder looks.

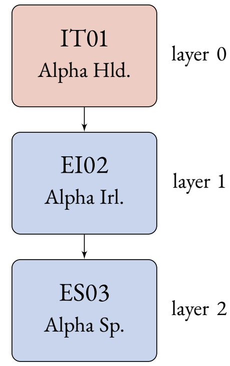
With this information at hand I can identify the perimeter of business groups. I define business groups as the set of all firms who share the same ultimate owner, including the owner itself. Since the focus of this research is on multinational business groups, I then drop groups that are

[50] Specifically, this is called the GUO 50C on *Orbis*. The letter C stands for Corporate. For simplicity, in this Appendix I will refer to it as GUO.

Figure A2: An example from the MNE panel

Data-set snippet

BvD ID	GUO	Year	Layer	C. Firm	C. GUO
IT01	IT01	2018	0	ITA	ITA
EI02	IT01	2018	1	IRL	ITA
ES03	IT01	2018	2	ESP	ITA



Notes: An example of how the group of Alpha Holdings (same as figure A1) would look like in the MNE Panel.

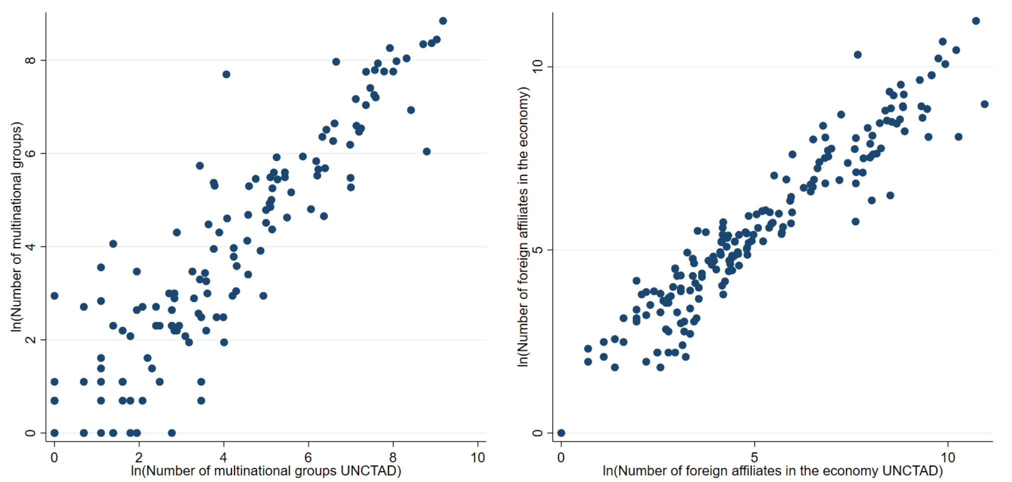
not multinational, that is, in this setting, groups whose entities are all located in the same country. At this point, I proceed by disentangling the hierarchical structure of groups. I divide the hierarchy into layers on the basis of the distance between the ultimate owner and the subsidiary. Ultimate owners are assigned to layer 0, subsidiaries that are directly controlled by (whose ISH is) the ultimate owner to layer 1, subsidiaries who are controlled by other subsidiaries at layer 1 are assigned to layer 2, and so on. With this novel recursive algorithm, this procedure is able to assign layers to more than 99.5% of the subsidiaries in the sample. Figure A2, gives an example of how the dataset looks.

At this point, then, since the identification codes of firms are the same of those in the *Orbis* database, I can match them with the information on industry, balance-sheets, location, etc., that is available on *Orbis*.

A.2 Dataset validation - Coverage

As already discussed, data on MNE are quite scarce. Therefore, it is not easy to validate this novel dataset. I do so with three different datasets. First, following Alfaro and Charlton (2009), I compare my data with the data from UNCTAD (2011), for the year 2009. The left panel of Figure A3 shows on the x-axis the (log of) number of MNE headquarters in each country according to UNCTAD (2011), and on the y-axis the corresponding (log of) number of MNE headquarters in that specific country in my dataset. The correlation between the two datasets is 0.90. On the right panel, instead, with the same logic, I plot the number of foreign affiliates. In this case the correlation is 0.95.[51]

Figure A3: Data validation with UNCTAD (2011)



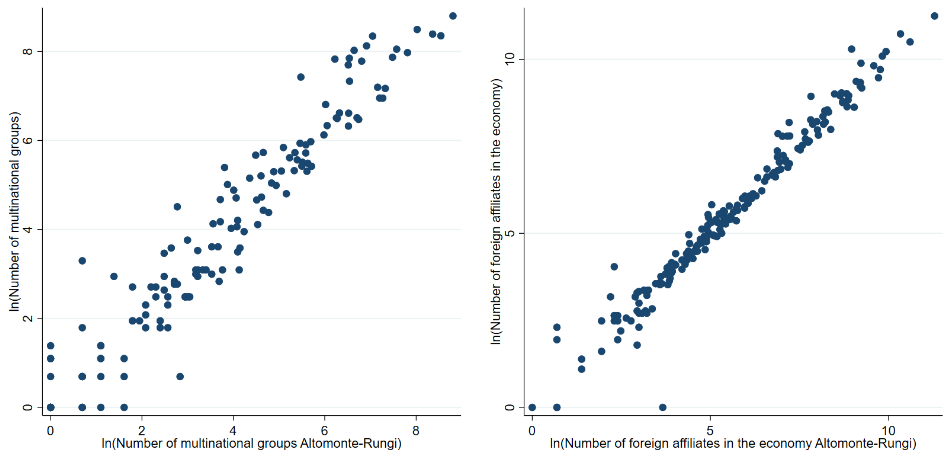
Notes: On the horizontal axis of the left panel we have the (log of the) number of MNE recorded in the UNCTAD (2011) dataset, and on the vertial axis the same variable, but from the dataset elaborated for this paper. On the right panel, the horizontal axis is again the (log of the) number of affiliates in the UNCTAD (2011) dataset, and the vertical axis is the same variable elaborated for this paper.

Second, I can validate my dataset with data for the year 2010 from Altomonte and Rungi (2013). Following the logic described above, the correlation for the (log of) number of MNE headquarters in each country is 0.96, while for the (log of) number of foreign affiliates it is 0.98, as shown in Figure A4.

Finally, I focus on African MNE affiliates, i.e. the main explanatory variable in this work, and I compare my dataset with Outwards FATS from OECD Countries in the same years as the analysis (2007-2018). FATS report the number of subsidiaries that multinationals of OECD countries have in each country of the world. For example, they report the number of subsidiaries of US multinationals that were located in Kenya in 2017. Therefore, I compare those statistics with the ones I obtain in my panel MNE dataset. The results are reported in Figure A5 that clarifies how much the two dataset correlate (correlation = 0.78). Readers might be surprised that there are more registered subsidiaries in *Orbis* than in the official statistics (slope <1), but this is because

[51] A possible source of differences between these datasets is, in particular, the fact that UNCTAD (2011) refers to data updated to 2009, while the data elaborated for this work started from a dataset updated to 2019, and Bureau Van Djik has changed a significant amount of information providers in recent years, also for very large countries like the US and Canada. For a detailed description of the changes in data sources, please check the manual of the *Historical Ownership Database*, were all the changes in coverage are documented by year and by country.

Figure A4: Data validation with Altomonte and Rungi (2013)



Notes: On the horizontal axis of the left panel we have the (log of the) number of MNE recorded in the Altomonte and Rungi (2013) dataset, and on the vertial axis the same variable, but from the dataset elaborated for this paper. On the right panel, the horizontal axis is again the (log of the) number of affiliates in the Altomonte and Rungi (2013) dataset, while the vertical axis is the same variable elaborated for this paper.

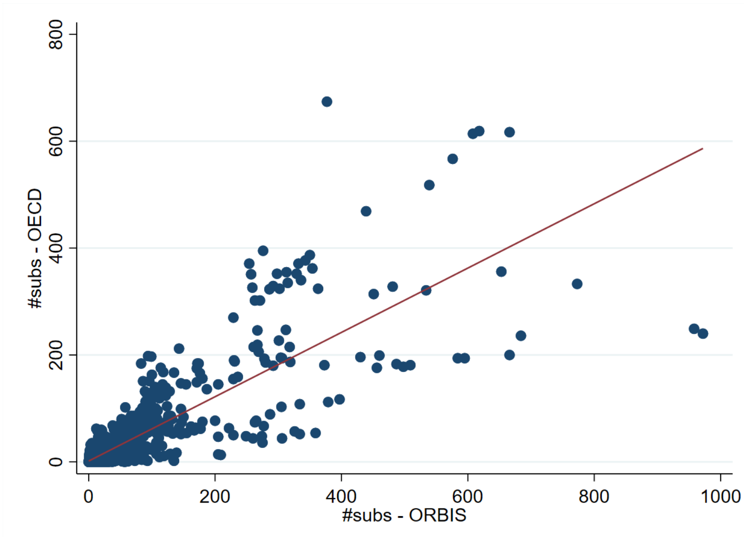
the official FATS only count subsidiaries with a turnover of more than 25 million dollars (and other dimensional prerequisites that *Orbis* does not have).

More in general, the validation of Bureau van Dijk micro data has been documented by several works. One of the latest is Fons-Rosen et al. (2013), revised in 2019, where the authors use Bureau van Dijk data to create a dataset of foreign ownership and productivity which is representative for both foreign and domestic firms. They focus on the manufacturing sectors of the eight advanced European countries for which OECD data is available (Belgium, Finland, France, Germany, Italy, Norway, Spain, and Sweden) for the years 1999-2012. Interestingly, the "aggregated foreign investment", obtained from the authors' dataset by summing up the output produced by foreign owned firms in their sample, tracks one-to-one the "official foreign investment" from the OECD, as the authors show in Figure A6.

A.3 Dataset validation - Locations

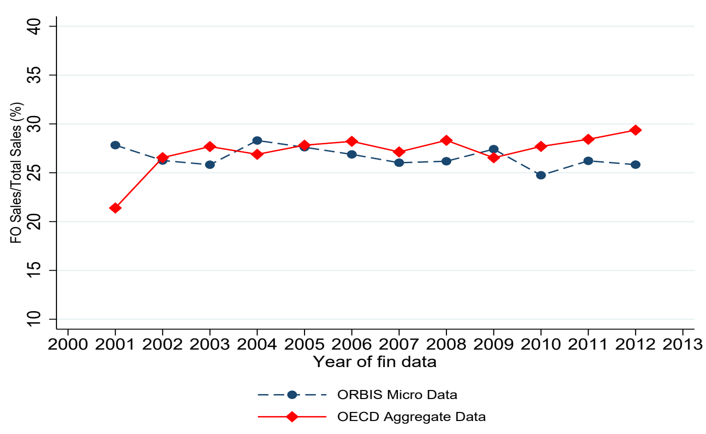
Multinationals' are geolocated from information included in the Bureau van Dijk (BvD) database (firms' country, region, city, and postcode). The reader could be worried that this information does not identify the actual affiliate's location, but potentially their legal offices. In other words, it could be challenging to distinguish between affiliates' legal base of operations and their actual location of economic activities. In order to address this potential concern, several tests are pre-

Figure A5: Data validation with OECD FATS



Notes: Observations are the number of subsidiaries in one country that belong to multinationals of a given country in a given year. The official FATS are reported on the vertical axis while the statistics computed from Orbis are on the horizontal one. Subsidiaries active in the agricultural sectors are excluded from the figure because they are excluded in the OECD FATS. Vertical axis cropped at 800 and horizontal axis cropped at 1000 for readability.

Figure A6: Foreign Firms' Share in Manufacturing Sales: ORBIS vs. OECD Data (%)



Source: Fons-Rosen et al. (2013), revised in 2019.
Notes: The shares from the ORBIS data (blue dashed line with circles) are computed as the ratios of the aggregated sales of firms in manufacturing with foreign ownership of at least 10% to total manufacturing sales across all ORBIS firms. Foreign multinational activity from the OECD data (red solid line with diamonds) is the sum of sales of multinational manufacturing companies reported by the AFA and AMNE databases of the OECD divided by total manufacturing sales in these countries from the OECD STAN database. The figure represents average of countries for which the OECD data is available: Finland, France, Italy, Norway, and Spain.

sented in this section.

First, I search all affiliates' name on Google Maps API and download the location(s) provided by the server. If the reader is worried that BvD provides mainly (or only) legal locations of affiliates, searching affiliates' names on Google Maps API for sure provides not only the legal locations but also all operating (plants) locations. Reassuringly, the correlation between the locations provided by BvD and the locations obtained by Google Maps is above 99% (specifically, the correlations between the two latitudes and the two longitudes are 99.86% and 99.56%, respectively).[52]

Note that Google Maps provides *all* locations related to a specific firm, therefore, this procedures might return multiple locations for each firm. Therefore, as a second check, I study more in details the cases where Google Maps provides multiple locations for the same affiliate's name. In particular, almost 91% of affiliates' name return one single location on Google Map, 9% return two locations, and less than 0.1% of names return more than two locations. The median distance between the location obtained from BvD and the one retrieved online is 4.1 km for affiliates with only one correspondence on Google Maps and 5.7 km for those with two locations. Remembering that the size of the cells used as unit of analysis in the paper is 55 km $\times$ 55 km, this is reassuring that, even assuming a potential error, this should not affect the analysis in a significant way.

In Table A1, I replicate the main results of the paper (Table 2) focusing only on affiliates which names provided a single location with the use of Google Maps API.[53] Reassuringly, results are confirmed both in terms of significance and magnitudes, with either OLS or 2SLS estimations.

It is important to underline that this procedure using Google Maps API is likely to introduce noise in the analysis. Indeed, while the BvD data provides homogenized locations for all the affiliates in terms of cities and/or zipcodes, a searching engine such as Google API might e.g. not include all the affiliates, or follow different recording logic in terms of locations, or simply find results which are not affiliates but have similar names with respect to affiliates' names. This is why this exercise is used as a robustness, while in the main analysis we rely on the locations provided by BvD, which is not only dedicated to this, but also more comprehensive and proven to be accurate with the robustness analysis presented in this Appendix.

[52] Note that this procedure identifies the location in Africa of more than 84% of affiliates' name. The names not found could be the results of different reasons. First, this is a completely automatize process using Google Maps API, therefore no cleaning is performed on the firms' names provided by BvD (which, often, includes particular signs, parenthesis, etc.), therefore increasing the noise in the search. Second, affiliates' name on the BvD data might be different with respect to the name firms' use to register their location on Google Maps. Third, some affiliates might simply not be present on Google.

[53] Note that this procedure is particularly demanding, considering we are excluding from this analysis the 16% of affiliates which name was not found by Google.

Table A1: Multinational activity and conflict - Restricted affiliates' sample

	(1)	(2)	(3)
Estimator	OLS	2SLS	
Dep. Var.	Conflicts	Conflicts	
Affiliates	0.106***	0.181***	0.223***
	(0.0217)	(0.0430)	(0.0513)
Cell FE	Yes	Yes	Yes
Country×year FE	Yes	Yes	No
Region×year FE	No	No	Yes
Population, nightlights, weather, cell trends	No	No	Yes
KP F		28.31	15.64
Obs	125,076	125,076	125,076
First stage		0.0696***	0.0530***
		(0.0130)	(0.0133)

Notes: OLS estimation in column 1, 2SLS estimation in columns 2 and 3. Dependent variable: number of violent conflict (ACLED). ***,**,* = indicate significance at the 1, 5, and 10% level, respectively. Controlling for: cell FE in columns 1-3, country×year FE in column 1 and 2, region×year FE together with (log of 1-period lag of) population, (log of 1-period lag of) nightlights, weather conditions (log of temperature, log of rainfall, and water balance, i.e. the difference between evapotranspiration and precipitation) and cell-specific trends in column 3. Conley (1999) standard errors in parenthesis, allowing for spatial correlation within a 200km radius and for infinite serial correlation. *Affiliates* indicates the number of MNE affiliates in the cell. Note that in this table the number of affiliates is restricted to affiliates which are (i) found through the Google Maps API procedure described in Appendix A.2, and (ii) which Google indicates having a single location. In columns 2 and 3 the latter variable is instrumented, details are explained in section 3.1. The section *First stage* reports the coefficients of the first stage estimations. Kleibergen-Paap F-statistic are reported for columns 2 and 3.

B Additional descriptive statistics

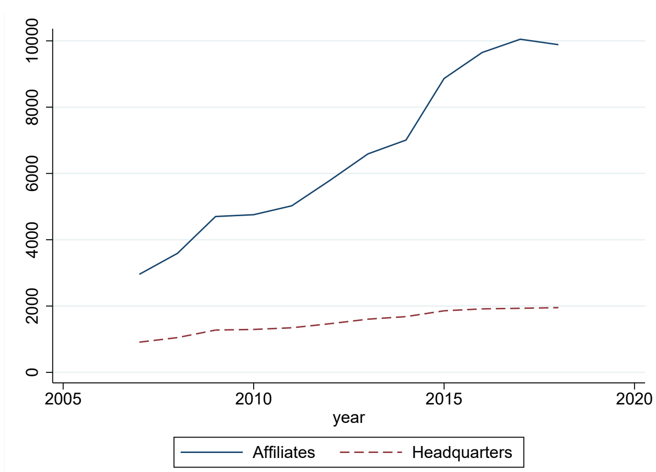
In this section, I provide additional information on the data used in the paper. Table A2 disaggregates ACLED events. Figure A7 shows the evolution of African affiliates (with location and industry information) and their headquarters (with balance-sheet information) around the world. In Table A3, I document data sources not described in the main text. Table A4 presents additional descriptive statistics on the variables used in the analysis at the cell level. Table A5 presents descriptive statistics about the individual level data from Afrobarometer.

Table A2: Conflict statistics

Type of event	Frequency	Percent
Battle	28,567	22.26
Explosions/remote violence	11,513	8.97
Protests	36,437	28.40
Riots	17,609	13.72
Strategic development	7,179	5.60
Violence against civilians	27,005	21.05
Total	128,310	100

Notes: Author's computation from the ACLED dataset. The types of events classified as violent are battles, exposions/remote violence, riots, and violence against civilians.

Figure A7: African MNE affiliates and headquarters



Notes: Author's computation from the MNE dataset obtained from *Historical Ownership Database*, Bureau Van Djik.

Table A3: Additional data sources

	Source	Short Description
Temperature	Berkeley Hearth	Data is available in monthly rasters. Yearly rasters were created by taking the mean of each pixel value over the year, and then extracted by taking the mean of all pixel values in each PRIO-GRID cell.
Precipitation	Global Precipitation Climatology Project	Data is available in monthly rasters. Yearly rasters were created by taking the mean of each pixel value over the year, and then extracted by taking the mean of all pixel values in each PRIO-GRID cell.
Evapotranspiration Index	Standardized Precipitation Evapotranspiration Index	The 12th time scale Global 12-month 1901-2015 SPEI was used. It provides a raster for each month since 1901. For each year, the December raster was used, then averaged by taking the mean of all pixels in each PRIO-GRID cell.
Night lights	Harmonized global nighttime light dataset 1992-2018	Data from Li et al. (2020). The authors generate an integrated and consistent nightlights dataset at the global scale by harmonizing the inter-calibrated observations from different datasets (DMSP, OLS, VIIRS).
Border distance (km)	PRIO-GRID	Spherical distance in kilometer from the cell centroid to the border of the nearest land-contiguous neighboring country. Cells belonging to island states with no contiguous neighboring country were originally coded as missing, therefore I assigned them a distance of 1 million km. Year 2014 (last available on PRIO-GRID).
Distance to capital (km)	PRIO-GRID	Spherical distance in kilometers from the cell centroid to the national capital city in the corresponding country, based on coordinate pairs of capital cities. Year 2014 (last available on PRIO-GRID).
No resources (dummy)	PRIO-GRID	Dummy variable indicating the absence of: primary (kimberlite) or secondary (alluvial) diamond deposits, placer gold deposits, vein gold deposits, surface gold deposits, onshore petroleum deposits.
Agricultural shock	Berman and Couttenier (2015) and Berman et al. (2021)	Cell-specific suitability for cultivating45 crops from the FAO's global agroecological zones (GAEZ) interacted with world import value of the specific crop in the same year, minus the imports of the specific country where the cell is located.
Distance to port (10m)	Berman and Couttenier (2015)	Distance in kilometers between a cell's centroid and the closest seaports with a maximum draft larger than or equal to 10 meters. Data available only for South Saharian countries. Year 2006 (last available in the authors' dataset).
Distance to port (12m)	Berman and Couttenier (2015)	Distance in kilometers between a cell's centroid and the closest seaports with a maximum draft larger than or equal to 12 meters. Data available only for South Saharian countries. Year 2006 (last available in the authors' dataset).

Notes: The table briefly present the sources and a few characteristics of the variables not described in the paper.

Table A4: Additional descriptive statistics (cell level)

	Obs.	Mean	S.D.	Median
Instrument[(a)]	125,706	11.87	93.19	0
Population (log)	125,706	8.44	3.98	9.81
Temperature (log)	125,706	0.68	0.18	0.67
Precipitation (log)	125,706	2.59	1.25	2.95
Evapotranspiration Index	125,706	-0.44	0.93	-0.40
Night lights (log)	125,706	0.40	0.67	0.01
Border cell (dummy)	125,706	0.18	0.37	0
Distance to capital (km)	125,706	642.91	414.19	541.25
No resources (dummy)	125,706	0.97	0.18	1
Land Deal	125,706	0.002	0.027	0
ACLED events	125,706	0.84	10.35	0
GDELT events	125,706	15.41	105.34	0
ACLED Battles	125,706	0.15	1.27	0
ACLED Remote violence/Explosions	125,706	0.06	1.34	0
ACLED Protests	125,706	0.19	1.76	0
ACLED Riots	125,706	0.11	1.02	0
ACLED Strategic Developments	125,706	0.04	0.49	0
ACLED Violence against civilians	125,706	0.16	1.36	0
Agricultural shock	125,706	49.03	30.24	55.65
Distance to port (10m)	100,404	769.87	436.47	743.93
Distance to port (12m)	100,404	860.99	438.15	862.26
Alternative instrument	125,706	2.38	30.65	0

Notes: Author's computation. (a) The mean headquarters' dependence on external credit in cells with some MNE activity is 0.54 (S.D. 0.40), while the mean of the worldwide credit given to private firms (expressed in trillion for the construction of the instrument) over the 12 years of the analysis is 1,196 (S.D. 130). The two variables *Distance to port (10m)* and *Distance to port (12m)* are available only for Sub-Saharan countries, this explain the lower number of observations.

Table A5: Descriptive statistics Afrobarometer data (individual level)

	Obs.	Mean	S.D.	Median
Issue: Land	130,225	2.21	14.69	0
Issue: Farming/Agriculture	130,225	11.96	32.45	0
Land-intensive Affiliates	148,069	1.30	9.30	0
Non Land-intensive Affiliates	148,069	18.81	173.40	0
Age	146,979	36.93	14.53	34
Female	146,929	0.50	0.50	1
Urban	148,069	0.39	0.49	0
Number of adults	147,855	3.60	2.62	3
Years of education	147,696	5.29	3.95	5
Christian (dummy)	148,069	0.59	0.49	1
Muslim (dummy)	148,069	0.30	0.46	0
Other religion (dummy)	148,069	0.11	0.31	0

Notes: Author's computation, based on the Afrobarometer data, rounds from 4 to 7 (Afrobarometer, 2017).

C Affiliates' size

The main analysis is performed focusing on the extensive margin of multinationals' activity, i.e. the opening/closing of affiliates in a specific cell-year. This is due to data limitation, as detailed information on affiliates' size is available only for a sub-sample of affiliates (approximately half of them, see details below). In this appendix, I do two things. First, I provide additional details about this data limitation. Second, the core results are replicated restricting the sample to those affiliates with size information, incorporating this additional (intensive margin) dimension in the estimation. Reassuringly, the results are robust to this perturbation and new estimation procedure, as we will see below.

Obtaining size information about affiliates in Africa is not an easy exercise, considering the heterogeneity of fiscal and accounting regulations in these countries. I proceed in two steps. First, the affiliate-year level of *capital* is compared to the overall sample distribution, allocating the affiliate-year in one of the four quartiles of the overall *capital* distribution (considering both local firms and affiliates in Africa) over the period analysed. By doing so, a variable indicating whether affiliates (in a specific year) are small, medium, large, or very large is created. I start with capital as it is the most populated variable allowing to proxy affiliates' size (more than 92% of coverage). When this variable is missing, the same procedure is followed using *revenues*, then *fixed assets*, *totalassets*, *profit/loss before tax* and, only lastly, *number of employees*, as it is the variable with lower coverage (7%).[54] Second, the mean of this categorical variable over the whole period is computed for each affiliate, in order to obtain an average proxy of affiliates' size over the period.[55]

This methodology allows us to obtain a categorical size variable assuming values from 1 (small) to 4 (very large) for each affiliate, using all (different) information available to proxy affiliates' size and maximizing the coverage of this variable. Specifically, it allows us to enrich more than 55% of affiliate-year observations with size details.

In order to better understand the role of size in our main specification, we proceed as follow. First, Table A6 replicates the main Table 2 focusing only on affiliates for which we have size information, for comparison purposes. Second, Table A7 replicates Table 2 with two important modifications, (i) focuses only on affiliates for which we have size information and, remarkably, (ii) includes this intensive margin dimension in the estimation procedure. Third, we compare the different estimates of the two tables.

[54] Results are completely consistent if we invert the order, starting from *number of employees* as a first proxy to fill the categorical variable for affiliates' size, followed by *profit/loss before tax* an continuing backward until *capital*.

[55] An alternative would have been to compute the size of affiliates at the beginning of the period, 2007, however, this is not feasible as a significant share of affiliates starts operating after 2007.

Specifically, in Table A7, the estimation equation, ignoring controls, becomes:

$$\textit{conflicts}_{k,c,t} = \alpha + \beta \; \textit{affiliates}{\times}\textit{size}_{k,c,t} + f_{k} + f_{c,t} + u_{k,c,t} \tag{5}$$

where, as before, k indicates a generic cell, with $k \in c$, where c denotes a country and t denotes a generic year, $\textit{conflicts}_{k,c,t}$ denotes the number of violent events in cell k in country c in year t, f_{k} and $f_{c,t}$ are cell and country × year fixed effects. Remarkably, in this specification, the independent variable becomes $\textit{affiliates}{\times}\textit{size}_{k,c,t}$, indicating that each affiliate is multiplied by its size (the categorical variable described above). An example might help here. Assume in a cell-year there are 10 affiliates, 2 small, 3 medium, 4 large, and 1 very large; then this variable will assume value $(2 \times 1) + (3 \times 2) + (4 \times 3) + (1 \times 4) = 24$. In comparison with the main specification in equation 1, where this variable would have had a value of 10, here we are considering affiliates' size dimension as well.

In line with this reasoning, also the instrument used for the 2SLS estimation has to take into consideration this new dimension. For each cell-year, therefore, we obtain an instrument z for the $\textit{affiliates}{\times}\textit{size}_{k,c,t}$ variable:

$$z_{k,c,t} = \sum_{m} s^{m}_{k,c,2007} \left(\textit{dep}^{m}_{97-06} \times \textit{cre}_{t-1} \right) \tag{6}$$

where $s^{m}_{k,c,2007}$ is the share of affiliates, multiplied by their size, of multinational m, in year 2007, in cell k. Following our example above, assume the number of 10 affiliates relate to year 2007, and in cell k there are two multinational groups, i.e. *m1* and *m2*. If the small (2), medium (3), and large (4) affiliates belong to *m1*, while the very large (1) affiliates belong to *m2*, then (approximating) $s^{m1}_{k,c,2007} = 0.83$ and $s^{m2}_{k,c,2007} = 0.17$. The two components of the shifter, instead, remain the same as described in section 3.1.

Reassuringly, Table A7 shows that our main results hold with this new specification, both in OLS and 2SLS. The coefficient of interest is still positive and highly significant. If we trust the implicit assumption that the size variable is a categorical one (e.g. one very large affiliate corresponds to approximately four small affiliates), it is then interestingly to compare the magnitudes of Table A7 with those of Table A6. Let's compare the effect on conflict of an increase of the explanatory variable equal to a one tenth of a standard deviation in both cases. In Table A7, such an increase of the independent variable (approximately 1.7) increases conflict by 25% with respect to the sample mean (0.47), while in Table A6 an equal increase in the independent variable (approximately 0.5) induces an increase in conflict of 23% with respect to the sample mean. Magnitudes are comparable also if we focus only on cells with some affiliates, where an increase of one tenth of a standard deviation of the independent variable in Table A7 (approximately 11) increases conflict by 17%

with respect to the sub-sample mean (4.66), and the same increase in Table A6 (approximately 3.3) increases conflict by 15% with respect to the sub-sample mean (4.62).

Table A6: Multinational activity and conflict - Only affiliates with size information

	(1)	(2)	(3)
Estimator	OLS	2SLS	
Dep. Var.	Conflicts	Conflicts	
Affiliates	0.145***	0.216***	0.286***
	(0.0374)	(0.0572)	(0.0741)
Cell FE	Yes	Yes	Yes
Country×year FE	Yes	Yes	No
Region×year FE	No	No	Yes
Population, nightlights, weather, cell trends	No	No	Yes
KP F		34.86	22.78
Obs	125,076	125,076	125,076
First stage		0.0620***	0.0461***
		(0.0104)	(0.00961)
Mean Conflicts overall sample	0.47	0.47	0.47
Mean Conflicts cells with affiliates	4.62	4.62	4.62

Notes: OLS estimation in column 1, 2SLS estimation in columns 2 and 3. Dependent variable: number of violent conflict (ACLED). ***,**,* = indicate significance at the 1, 5, and 10% level, respectively. The estimation includes only affiliates with size information. Controlling for: cell FE in columns 1-3, country×year FE in column 1 and 2, region×year FE together with (log of 1-period lag of) population, (log of 1-period lag of) nightlights, weather conditions (log of temperature, log of rainfall, and water balance, i.e. the difference between evapotranspiration and precipitation) and cell-specific trends in column 3. Conley (1999) standard errors in parenthesis, allowing for spatial correlation within a 200km radius and for infinite serial correlation. *Affiliates* indicates the number of MNE affiliates in each cell. In columns 2 and 3 the latter variable is instrumented, details are explained in section 3.1. The section *First stage* reports the coefficients of the first stage estimations. Kleibergen-Paap F-statistic are reported for columns 2 and 3.

Table A7: Multinational activity and conflict - Affiliates' size in the analysis

	(1)	(2)	(3)
Estimator	OLS	2SLS	
Dep. Var.	Conflicts	Conflicts	
Affiliates $\times$ size	0.0441***	0.0715***	0.0908***
	(0.0114)	(0.0180)	(0.0223)
Cell FE	Yes	Yes	Yes
Country$\times$year FE	Yes	Yes	No
Region$\times$year FE	No	No	Yes
Population, nightlights, weather, cell trends	No	No	Yes
KP F		34.04	22.11
Obs	125,076	125,076	125,076
First stage		0.192***	0.140***
		(0.0328)	(0.0297)
Mean *Conflicts* overall sample	0.47	0.47	0.47
Mean *Conflicts* cells with affiliates	4.66	4.66	4.66

Notes: OLS estimation in column 1, 2SLS estimation in columns 2 and 3. Dependent variable: number of violent conflict (ACLED). ***,**,* = indicate significance at the 1, 5, and 10% level, respectively. The estimation includes only affiliates with size information. Controlling for: cell FE in columns 1-3, country$\times$year FE in column 1 and 2, region$\times$year FE together with (log of 1-period lag of) population, (log of 1-period lag of) nightlights, weather conditions (log of temperature, log of rainfall, and water balance, i.e. the difference between evapotranspiration and precipitation) and cell-specific trends in column 3. Conley (1999) standard errors in parenthesis, allowing for spatial correlation within a 200km radius and for infinite serial correlation. *Affiliates$\times$size* indicates the number of MNE affiliates in each each multiplied by a categorical variable assuming value from 1 (small) to 4 (very large) indicating the affiliate's size. In columns 2 and 3 the latter variable is instrumented, details are explained in Appendix C. The section *First stage* reports the coefficients of the first stage estimations. Kleibergen-Paap F-statistic are reported for columns 2 and 3.

D Placebo analysis and Omitted Variable Bias

To check the validity of the presented instrumental strategy, I construct counterfactual shocks by randomly choosing country-level measures of credit and credit dependence. More specifically, starting from the distribution of the actual shifter ($dep^{m}_{9706} \times cre_{t1}$) at group level, I conduct 1,000 independent random draws assigning a random value for the shock to each group. Now, weighting for the true $w^{m}_{k,c,2007}$ and collapsing, I then obtain 1,000 placebo instruments $z^{P}_{k,c,t}$ and estimate the baseline regression on them. Among our 1,000 randomizations, the number of significant coefficients are well below 5%, thus confirming that substituting the real instrument with this "simulated instrument" provides no significant effects.[56]

Second, I address omitted variable concerns. As discussed in Section 3.1, the identification strategy relies on the key assumption that changes in worldwide credit availability (for private firms) will impact conflict intensity in specific African cells only through multinationals' affiliates present in these cells. Even if the shares capturing heterogeneous exposure to the shocks are constructed using data from the first year available, namely 2007, one may be still concerned about non-random exposure to the shocks, which could give rise to an omitted variable bias (OVB) in the IV estimates. In a recent work, Borusyak and Hull (2020) explain how to effectively purge OVB from non-random exposure to the shocks, without having to impose further assumptions, such as parallel trends. Their methodology, called "recentering", proposes to control for the simulated instrument described above (or subtracting it from the IV) in order to remove the bias from non-random shock exposure.

I apply the recentering methodology by averaging across the 1,000 randomizations described above, therefore obtaining an average simulated instrument $\bar{z}^{P}_{k,c,t}$. In Table A8, I include the simulated instruments constructed based on the randomization in the main specifications (column 2, Table 2). The coefficient of *Affiliates* is always positive and significant, and almost identical in magnitude to the corresponding estimates in Table 2, therefore, confirming that our results on the impact of multinationals' activity on conflict are robust to addressing OVB concerns.

[56] Considering the large number of results, these results are available upon request.

Table A8: Omitted Variable Bias

Estimator	2SLS
Dep. Var.	Conflicts
Affiliates	0.161***
	(0.0376)
Average Simulated Instrument	0.0192
	(0.0144)
Cell FE	Yes
Country×year FE	Yes
FP F	30.10
Obs	125,076

Notes: 2SLS estimation. Dependent variable: number of violent conflict (ACLED). ***,**,* = indicate significance at the 1, 5, and 10% level, respectively. Controlling for: cell and country×year FE. Conley (1999) standard errors in parenthesis, allowing for spatial correlation within a 200km radius and for infinite serial correlation. *Affiliates* indicates the number of MNE affiliates in the cell (instrumented, details are explained in section 3.1). *Average Simulated Instrument* indicates the average of 1,000 simulated (randomized) instruments, detailed in Appendix D. Kleibergen-Paap F-statistic is reported.

E Instrument validity

The 2SLS strategy presented in section 3.1 relies on a standard shift-share framework. The methodology proposed combines a shifter, i.e. the volume of global credit, and a share component, i.e. the interaction between the pre-period (1997-2006) parent's dependence on external credit and the cell-specific distribution of affiliates within different multinationals in the baseline year (2007).

The direct effect of global credit shocks on conflict is captured by the country$\times$year (or, alternatively, region$\times$year) fixed effects. Moreover, in Appendix F, I perform additional robustness with respect to potential income shocks at the cell level (and their interaction with cell-specific openness to trade). On the other hand, cell fixed effects capture the time-invariant differences in conflict which could be correlated with the affiliate composition. A potential concern is, however, that the initial distribution of multinational affiliates (the share) may be correlated with conflict dynamics in the cells independently of multinational activity. For example, a particularly high concentration of affiliates in the primary sector could be indicative of environmental destruction from large-scale mining, forestry, or industrial agricultural activity in general and, therefore, could be linked to conflict. Therefore, I strictly follow the tests proposed by Borusyak et al. (2022), who show that the instrument is valid even if the exposure component of a shift-share is endogenous as long as the shocks are as good as randomly assigned. As suggested by the authors, first, I display the distribution of the shock and the exposure variables and, second, I perform a falsification test.

E.1 Distribution of shock and exposure variables

In this section, we replicate the first part of Table 1 of Borusyak et al. (2022), section 6.2.2. First, in Table A9 I show the distribution of the shock variable $\left(dep^m_{97-06} \times cre_{t-1}\right)$. In particular, in column 1 the mean, standard deviation and interquartile range of the distribution of the shock variable at the headquarter level are presented. In column 2, I present the same statistics after residualizing it on year-fixed effects. The shock presents a standard deviation of around 250 with or without controlling for year-fixed trends, while the interquartile range remains well above 300 in both cases. These statistics show a significant degree of variation of the shock, a key requirement highlighted by Borusyak et al. (2022) to ensure the robustness and unbiasedness of the results. Second, I display the inverse of the HHI of shock-level average exposure as a simple way of describing the effective sample size. The bottom part of Table A9 shows the 1/HHI of the exposure variable ($w^m_{k,c,2007}$), i.e. the share of affiliates from one parent corporation within each cell. Reassuringly, this number is particularly high, as recommended by the authors.

Table A9: Distribution of shock variable

Shock Variable		
Mean	659.5	0
Standar deviation	255.82	248.75
Interquartile range	331.37	316.52
Specification		
Residualizing on year FE	No	Yes
Exposure variable		
Effective sample size: 1/HHI of weights	(Year 2007)	158

Notes: In the panel above, the table replicates the first part of Table 1 of Borusyak et al. (2022), section 6.2.2. Columns 1 and 2 show the mean, standard deviation, and interquartile range of the distribution of the shock variable, without (column 1) and with (column 2) residualizing it on year-fixed effects, as requested by the authors. In the bottom panel, instead, presents the inverse of the HHI of shock-level average exposure, to present in a simple way the effective sample size (again, as suggested by Borusyak et al., 2022).

E.2 Falsification test

Here the correlations of potential confounders with the affiliate weighted shocks are presented (see Borusyak et al., 2022, pages 206-207). Validity requires that locations are uncorrelated with our instrument, i.e. shocks to multinationals. To test this, I use the pre-period credit exposure (dep^{m}_{97-06}) and correlate it with the multinational share weighted cell characteristics. In other terms, I correlate the multinationals' pre-period credit exposure with the multinationals' share weighted cell characteristics for conflict, i.e. the average number of conflicts for each multinational at the beginning of the period, using the number of multinationals in each grid cell as weights. Results are presented in Table A10, where we can see that, reassuringly, we do not find any significant correlation neither when we consider all types of conflicts together (column 1) nor when we split the conflict variables in different types (columns 2-5). Remarkably, not only the coefficients are not significant, but also the magnitudes of the correlations are very close to zero.

Table A10: Falsification test

Estimation	OLS				
Dependent Variable	Credit Dependence				
Conflict	-0.000981				
	(0.00122)				
Battles		0.00305			
		(0.00385)			
Explosion / Remote Violence			0.00926		
			(0.00625)		
Riots				-0.00221	
				(0.00138)	
Violence against Civilians					0.00177
					(0.00470)
Observations	865	865	865	865	865

Notes: In this table, following Borusyak et al. (2022, pages 206-207), we show the correlation of potential confounders with our affiliate weighted shocks. Dependent variable: pre-period credit exposure (dep^{m}_{97-06}). Independent variables: multinationals' share weighted cell characteristics for conflict; in other words, the average number of conflicts (of different types depending on the column, i.e. conflict for columns 1, battles for column 2, etc) for each multinational at the beginning of the period, using the number of multinationals in each grid cells as weights.

F Cell-level commodity price shocks and remoteness

In this section, I check the robustness of the main result with respect to income shocks at the cell level. This is a particularly important test in order to check the validity of the exclusion restriction presented in section 3.1. Indeed, the consistency of the 2SLS estimates relies on the assumption that differences in multinationals' credit availability have an impact on conflict probability only through the effect of multinationals' affiliates in the cells. Therefore, we need to control for potential effects that periods of worldwide private-firm credit shocks might have on the probability of conflict at the cell level independently of multinationals' activity.

I use data from Berman and Couttenier (2015) and Berman et al. (2021), who create time-varying cell-specific measures of external demand for the commodities produced by the cell for all African countries. I focus on the measure based on the cell-specific suitability for cultivating 45 crops from the FAO's global agroecological zones (GAEZ). These data are derived from models that combine location characteristics such as climate information and soil characteristics.[57] These are then matched with crops' characteristics in terms of growing requirements, in order to generate a global mapping of the suitability of a grid cell for cultivating each crop.[58] This cell-specific measure of grid suitability is then interacted with the world import value of the specific crop in the same year, minus the imports of the specific country where the cell is located. More formally, for each cell-time the following measure of external demand for the commodities potentially produced by the cell is computed:

$$WD_{k,t} = \sum_{p} \alpha_{p,k} \times M^{W}_{c,p,t} \tag{7}$$

where $\alpha_{p,k}$ is the share of agricultural commodity p in cell k and $M^{W}_{c,p,t} = \sum_{j \neq p} M^{W}_{j,p,t}$ is the world import value of commodity p in year t minus the imports of country c. This methodology presents two main advantages. First, crop suitability is exogenous to conflicts because it is not based on actual production. Second, the use of world value imports – instead of world prices – allows to consider a wider range of commodities, in particular to include commodities that do not have a world price.

Column 1 of Table A11 shows the result from the main specification (column 2, Table 2) con-

[57] The climate information is based on the average information over the period 1961-1990. See Nunn and Qian (2011) for a very detailed description of the FAO-GAEZ data.

[58] In this framework, suitability is defined as the percentage of the maximum yield that can be attained in each grid cell. The authors, following Nunn and Qian (2011) and Alesina et al. (2013), define a cell as suitable for a crop if it can achieve at least 40% of the maximum yield.

trolling for $WD_{k,t}$. As we can see, the coefficient of interest is almost unchanged, still positive and significant at the 1% level. In a second step, $WD_{k,t}$ is combined with cell-specific information reflecting their natural level of trade openness, proxied by the distance to the nearest major seaport.[59] This procedure ensures that these controls are identifying the effect of (exogenous) external foreign demand shocks and not some other, potentially internal, shocks that may be correlated with them. For each cell, the distance (in kilometers) between the cell's centroid and the closest major seaport with a maximum draft of at least 10 meters is identified. Note that the closest seaport is not always located in the same country, as some countries are landlocked or some cells are closer to a foreign port. Column 2 shows the result from a specification controlling for this interaction. Again, the main result is significant at the 1% level.[60]

Table A11: Commodity price shocks and remoteness

	(1)	(2)
Estimator	2SLS	
Dep. Var.	Conflicts	
	Controlling for	
	Agricultural Shocks	Agricultural Shocks × Remoteness
Affiliates	0.161***	0.178***
	(0.0375)	(0.0396)
Cell FE	Yes	Yes
Country×year FE	Yes	Yes
FP F	30.09	23.06
Obs	125,076	100,404

Notes: 2SLS estimation. Dependent variable: number of violent conflict (ACLED). ***,**,* = indicate significance at the 1, 5, and 10% level, respectively. Controlling for: cell and country×year FE in column 1 and 2, *Agricultural shocks* at the cell level (see details in Appendix F) in column 1, *Agricultural shock* interacted with the cell distance from the closest port (*Remoteness*) in column 2. Conley (1999) standard errors in parenthesis, allowing for spatial correlation within a 200km radius and for infinite serial correlation. *Affiliates* indicates the number of MNE affiliates in the cell (instrumented, details are explained in section 3.1). Kleibergen-Paap F-statistic is reported.

[59] In the authors' paper, this data is available only for Sub-Saharian countries, therefore the number of observations in column 2 is lower with respect to column 1.

[60] This result is completely robust also to considering seaports with a maximum draft larger than or equal to 12 meters, the threshold used internationally to consider a port as a deepwater one, due to the fact that they can accommodate loaded "Panamax" ships, whose dimensions are determined by the ones allowed by the Panama Canal's lock chambers.

G Alternative estimations

In this section, I test the robustness of the main result outlined in section 3.2 using a different estimation procedure with overidentified estimations. I also check the robustness of the main result if I substitute the credit variable used to construct the instrument.

In their recent work, Goldsmith-Pinkham et al. (2020) suggest to follow Angrist and Pischke (2008) with: "Check over-identified 2SLS estimates with LIML. LIML is less precise than 2SLS but also less biased. If the results come out similar, be happy. If not, worry, and try to find stronger instruments." In order to run over-identified regressions, I create an alternative instrument by substituting the worldwide credit component of the instrument in equation (2), namely cre_{t-1}, with the contemporaneous parent company's number of affiliates outside of Africa. The correlation between the two instruments is 0.63. Column 1 of Table A12 presents the results of the over-identified 2SLS model. Column 2 uses the LIML estimator.[61] As we can see, the coefficients are almost unchanged not only among each other, but also to the one in our main specification in 3.2, both in magnitude and level of significance. Moreover, the use of two instruments allows us to perform the Hansen-J test, which yields a non-significant p-value in both estimations, reassuring about the exogeneity of the instruments.

Finally, in column 3 of Table A12, I substitute the credit variable used to construct the instrument in equation (2), namely financial resources provided to the private sector, with a variable indicating the financial resources provided to the private sector specifically from the financial sector (World Bank data). The main result is confirmed and still significant at the 1% level.

[61]Because the option for the LIML estimation is not available in the *acreg* Stata package used to perform the Conley (1999) correction, in columns 1 and 2 I cluster standard error at the cell level.

Table A12: Alternative estimations

Estimator	(1) 2SLS	(2) LIML	(3) 2SLS
Dep. Var.		Conflict	
Affiliates	0.159***	0.159***	0.153***
	(0.03431)	(0.03432)	(0.03632)
Cell FE	Yes	Yes	Yes
Country×year FE	Yes	Yes	Yes
FP F	15.47	15.47	30.47
Hansen-J	0.416	0.416	
Obs	125,076	125,076	125,076

Notes: 2SLS estimation in column 1 and 3. LIML estimation in column 2. Dependent variable: number of violent conflict (ACLED). ***,**,* = indicate significance at the 1, 5, and 10% level, respectively. Controlling for: cell and country×year FE. Standard errors are clustered at the cell level in columns 1 and 2. Conley (1999) standard errors in parenthesis in column 3, allowing for spatial correlation within a 200km radius and for infinite serial correlation. *Affiliates* indicates the number of MNE affiliates in the cell. The latter is instrumented with the instrument described in 3.1 together with a second instrument described in Appendix G in columns 1 and 2, with an instrument constructed by substituting the credit component of the instrument described in 3.1 with a measure of credit given to private firms specifically by the financial sector in column 3. Kleibergen-Paap F-statistic is reported.

H Local firms

In this appendix, the data on local African firms used as control variables in Section 3.3 are described. These are firms not belonging to a multinational enterprise.

Starting from the *Orbis* database, from Bureau van Dijk, I focus on all firms located in African countries for which we are able to obtain the geolocalization (therefore, with information on their zipcode or, when missing, their city). The dataset contains approximately 2.2M firm-year observations for around 1.1M distinct local firms. Within our time span of 12 years (2007-2018), on average, a local firm is active for 1.9 years (standard deviation 1.8).

In section 3.3, the number of local firms (lagged by 1 and 3 years) are used as additional controls in the main specification (rows 16 and 17). In columns 1 and 2 of Table A13, we replicate these results but reporting the estimation coefficients of local firms as well. To corroborate the robustness of the results, in this section, I add another layer of information, namely the size of local firms. Following the same procedure explained in Appendix C, a categorical variable ranging from 1 (small) to 4 (very large) is associated with each local firm-year observation. This categorical variable describes the size of the local firm in each year with respect to the size of the overall distribution of firms (locals and affiliates) over the overall period.

In columns 3 and 4 of Table A13, I control for the number of affiliates in each cell-year multiplied by their size (see Appendix C for details on this procedure), lagged by 1 and 3 years, respectively. As we can see, results are confirmed. In columns 5 and 6, instead, I include as controls four variables counting the number of local firms in each of the four size category. Again, the main effect of affiliates in increasing conflict is confirmed with comparable magnitudes. Due to the potential endogeneity issues these variables describing local firms might have (despite the use of lags), I do not elaborate any causal interpretation of their estimating coefficients.

Table A13: Local firms

	(1)	(2)	(3)	(4)	(5)	(6)
Estimator	2SLS					
Dep. Var.	Conflicts					
Affiliates	0.189***	0.181***	0.192***	0.181***	0.188***	0.188***
	(0.0421)	(0.0414)	(0.0431)	(0.0414)	(0.0422)	(0.0415)
Local firms (lag 1)	-0.000344***					
	(0.000099)					
Local firms (lag 3)		-0.000383***				
		(0.000103)				
Local firms × size (lag 1)			-0.000160***			
			(0.000036)			
Local firms × size (lag 3)				-0.000139***		
				(0.000038)		
Local firm size 1 (lag 1)					-0.000547**	
					(0.000241)	
Local firm size 2 (lag 1)					-0.000875**	
					(0.000397)	
Local firm size 3 (lag 1)					0.00330	
					(0.00229)	
Local firm size 4 (lag 1)					-0.00304**	
					(0.00154)	
Local firm size 1 (lag 3)						0.000322
						(0.000645)
Local firm size 2 (lag 3)						-0.00235**
						(0.00120)
Local firm size 3 (lag 3)						0.000217
						(0.00149)
Local firm size 4 (lag 3)						-0.00100
						(0.00164)
Cell FE	Yes	Yes	Yes	Yes	Yes	Yes
Country×year FE	Yes	Yes	Yes	Yes	Yes	Yes
FP F	26.02	26.08	25.13	26.08	26.67	26.62
Obs	125,076	125,076	125,076	125,076	125,076	125,076

Notes: 2SLS estimation. Dependent variable: number of violent conflict (ACLED). ***,**,* = indicate significance at the 1, 5, and 10% level, respectively. Controlling for: cell FE in columns 1-3, country×year FE in column 1 and 2, region×year FE together with (log of 1-period lag of) population, (log of 1-period lag of) nightlights, weather conditions (log of temperature, log of rainfall, and water balance, i.e. the difference between evapotranspiration and precipitation) and cell-specific trends in column 3. Conley (1999) standard errors in parenthesis, allowing for spatial correlation within a 200km radius and for infinite serial correlation. *Affiliates* indicates the number of MNE affiliates in the cell. This variable is instrumented in all specifications, details are explained in section 3.1. *Local firms* indicate the number of local firms (not belonging to a multinational company) in each cell-year. *Local firms × size* indicates the number of local firms in a cell-year multiplied by a categorical variable assuming value from 1 (small) to 4 (very large) indicating the local firms' size. Details aboht the size categories are explained in Appendix C. *Local firms size n*, with $n \in (1, 2, 3, 4)$, indicates the number of local firms in each size category n in the cell-year. Kleibergen-Paap F-statistic are reported for columns 2 and 3.

I Alternative functional forms

In this section, I test alternative transformations of the key variables used in the analysis. A key characteristic of the data on multinational firms and conflict, as widely recognised in the literature, is that their distribution is highly skewed to the right. Locations such as Mogadishu or Tripoli, for example, record a number of violent conflict events which is above the top percentile consistently for more than half of the period analysed, and an average of 350 events per year (with respect to an average equal to 5 in cells with conflicts, but different from these two locations). On the other hand, among the entire African continent, four specific locations show a particularly high number of multinationals' concentration: Johannesburg, Pretoria, Capetown, and Casablanca. In these specific locations, the average numbers of affiliates is more than 720 per year, while all other locations with affiliates (but different from these four cities) have an average of around 10. Due to these very few locations, in order to correctly estimate the effect of multinationals on conflict, in the main specification both the dependent and independent variables are winsorized at the top percentile.

In Table A14, I show that using alternative functional forms does not change the main result. In the first two columns, I use the hyperbolic sine transformation, winzorizing (column 1) and not (column 2) the two key variables. In columns 3 and 4, I replicate the same procedure using the logarithmic (of the variable plus one) transformation. In column 5, I present the results without winsorizing at the top 1 percentile. As we can see from the table, the effect is still precisely identified, only the Kleibergen-Paap Wald F statistic decreases due to the difficulty in predicting the number of affiliates in the four outlier locations mentioned above. Indeed, dropping the cells where Johannesburg, Pretoria, Capetown, and Casablanca are located (column 6) the Kleibergen-Paap Wald F statistic also becomes comparable to the one in the main specification, confirming the robustness of the main result.

Table A14: Alternative functional forms

	(1)	(2)	(3)	(4)	(5)	(6)
Estimator	2SLS					
Dep. Var.	Conflict					
	Hyperbolic Sine		Logarithm		Level	
	Winsorizing	No Winsorizing	Winsorizing	No Winsorizing	No Winsorizing	
Affiliates	0.974***	0.963***	0.889***	0.878***	0.104**	0.228***
	(0.141)	(0.137)	(0.129)	(0.125)	(0.0485)	(0.0850)
Cell FE	Yes	Yes	Yes	Yes	Yes	Yes
Country×year FE	Yes	Yes	Yes	Yes	Yes	Yes
FP F	88.44	92.82	93.87	98.64	5.719	36.36
Obs	125,076	125,076	125,076	125,076	125,076	125,076

Notes: 2SLS estimation. Dependent variable: number of violent conflict (ACLED). ***,**,* = indicate significance at the 1, 5, and 10% level, respectively. Controlling for: cell and country×year FE. Conley (1999) standard errors in parenthesis, allowing for spatial correlation within a 200km radius and for infinite serial correlation. *Affiliates* indicates the number of MNE affiliates in the cell. The latter is instrumented with the instrument described in 3.1. In column 1 the hyperbolic sine transformation of the dependent and independent variables is applied to the variables winsorized at the top percentile, while in column 2 it is applied to non-winsorized variables. In column 3 the logarithmic transformation of the (one plus) dependent and (one plus) independent variables is applied to the variables winsorized at the top percentile, while in column 4 it is applied to non-winsorized variables. In column 5 both dependend and independent variables are not-winsorized. In column 6 the cells where Johannesburg, Pretoria, Capetown, and Casablanca are located are excluded. Kleibergen-Paap F-statistic are reported for each specification.

J Standard errors

In this section, I allow for different levels of cross-sectional spatial correlation and cell-specific serial correlation. Remember that in all tables of the work I allow the serial correlation to be present as a benchmark for an infinite horizon (i.e. 100,000 years) and a spatial radius of 200 kilometers. This radius corresponds exactly to ten times the average distance among agglomerations with more than 10,000 inhabitants in Africa. In a recent report, OECD and SWAC (2020) recommend this spatial dimension in disaggregated analysis to identify important and unprecedented territorial transformation processes (e.g. the development of metropoles and intermediary cities, the merging of villages into mega-agglomerations).

In Table A15, I replicate the main specification (column 2 of Table 2) but allow alternatively for spatial correlation of 100, 500, or 1,000 kilometers, and for a serial correlation over 1, 5 years or an infinite horizon. I also show combinations among these possible variations. I then provide alternative results, where I simply cluster the standard errors at the cell-, region-, or country-level. In all cases, the standard errors are such that the coefficients of interest remain statistically significant at conventional levels.

Table A15: Alternative estimations

	Affiliates			
	Coeff.	Std. Err.	K-P F stat	Obs.
	0.161			125,076
(1) Spatial: 100km; Time: Infinite		(0.0361)***	29.02	
(2) Spatial: 500km; Time: Infinite		(0.0389)***	30.13	
(3) Spatial: 1000km; Time: Infinite		(0.0419)***	30.04	
(4) Spatial: 200km; Time: 1		(0.0324)***	83.10	
(5) Spatial: 200km; Time: 5		(0.0329)***	52.45	
(6) Spatial: 100km; Time: 1		(0.0308)***	75.43	
(7) Spatial: 100km; Time: 5		(0.0312)***	49.29	
(8) Spatial: 500km; Time: 1		(0.0341)***	83.44	
(9) Spatial: 500km; Time: 5		(0.0345)***	52.59	
(10) Spatial: 1000km; Time: 1		(0.0374)***	82.79	
(11) Spatial: 1000km; Time: 5		(0.0378)***	52.33	
(12) Cell-level		(0.0342)***	30.68	
(13) Region-level		(0.0254)***	141.8	
(14) Country-level		(0.0427)***	49.82	

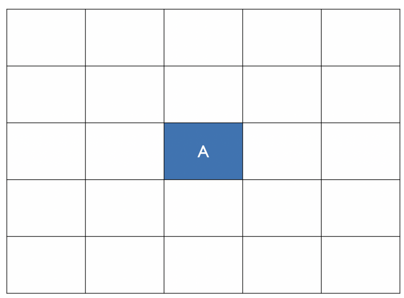
Notes: The table shows different standard errors of 2SLS estimations. Dependent variable: number of violent conflict (ACLED). ***,**,* = indicate significance at the 1, 5, and 10% level, respectively. Controlling for: cell and country×year FE. Conley (1999) standard errors in parenthesis at different radius and serial correlations from row 1 to 11. Standard error clustered at the cell-level in row 12, at the region-level (13), at the country-level (14). *Affiliates* indicates the number of MNE affiliates in the cell. The latter is instrumented with the instrument described in 3.1. Kleibergen-Paap F-statistic are reported for each specification.

K Moran's I statistics

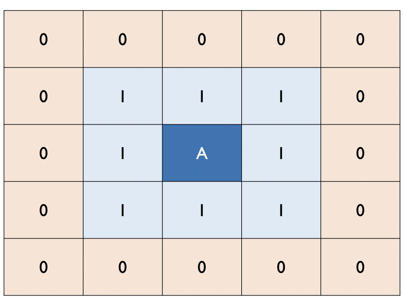
In this section, I first briefly review the methods used to perform spatial correlations, and then I present Moran's statistics for multinationals and conflicts data.

Relative spatial positions are represented with spatial weight matrices (W). These are created according to two criteria: (i) binary contiguity (BC) weights matrices, (ii) inverse distance weights matrices. There are two types of BC weights matrices: *Rook*: the four neighbours of each cell in the cardinal directions are given value 1, all others 0; *Queen*: the eight neighbours of each cell in all directions are given value 1, all others 0. Suppose that we are interested in the cell A, then the following applies:

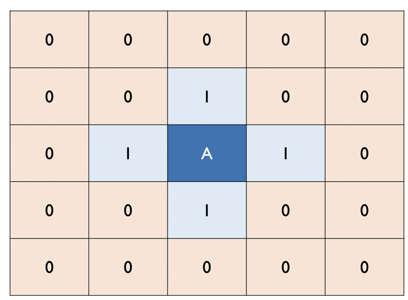
Figure A8: Spatial weight matrices



Base Map



Queen-distance band 1

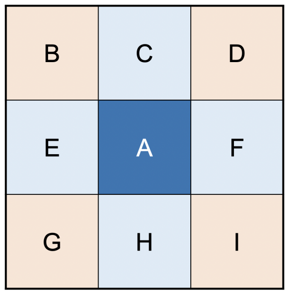


Rook-distance band 1

Hence, considering a smaller set of cells, the Rook 1 weights matrix is presented in Figure A9. As far as the inverse distance type of matrices are concerned, we record the distance between neighbours as 1, then reciprocals (1/d) of all pairs of distances are calculated and entered in W. Thanks to these matrices we are able to compute the spatial lag of a given variable. In particular, given a variable y, the spatial lag is defined as Wy.

A common way to assess whether there is spatial autocorrelation involves a statistic called

Figure A9: Rook 1 weights matrix



Cells

	B	C	D	E	A	F	G	H	I
B	0	1	0	1	0	0	0	0	0
C	1	0	1	0	1	0	0	0	0
D	0	1	0	0	0	1	0	0	0
E	1	0	0	0	1	0	1	0	0
A	0	1	0	1	0	1	0	1	0
F	0	0	1	0	1	0	0	0	1
G	0	0	0	1	0	0	0	1	0
H	0	0	0	0	1	0	1	0	1
I	0	0	0	0	0	1	0	1	0

Rook 1 weights matrix

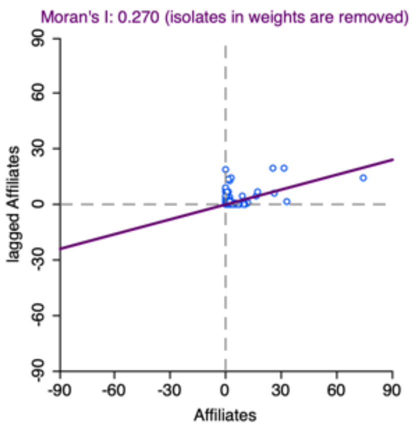
Moran's I Moran (1950):

$$I = \frac{\sum_i \sum_j w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\sum_i (x_i - \bar{x})^2} \approx N(0, \sigma^2) \tag{8}$$

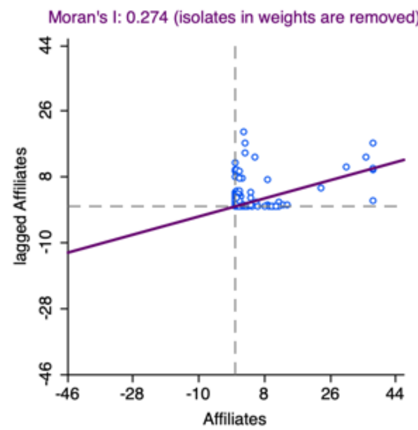
where $\bar{x}$ is the average, and w_{ij} is the element of the weight matrix for the couple (x_i, x_j). This index compares the value of the variable at any location with the value at all other locations. By construction $-1 < I < 1$. When I is close to 1 (-1) there is evidence of a strong positive (negative) spatial autocorrelation.

Here I present Moran's I statistics for the two main variables, namely the number of MNE affiliates and violent conflicts at the cell level. For each of them, I present both *Rook 1* and *Queen 1* statistics for three different periods: at the beginning of the period (2007), at the end of the period (2018), and the average over the 12 years covered by the sample. Reassuring, Moran's I statistics are always very close to zero.

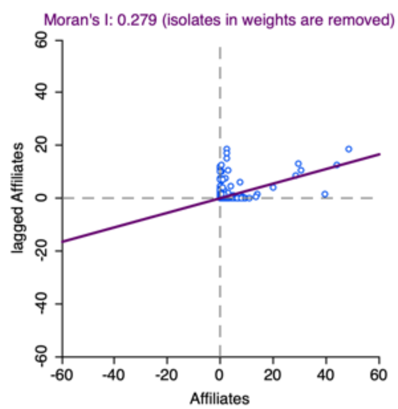
Figure A10: Rook 1 Moran's MNE



Year 2007

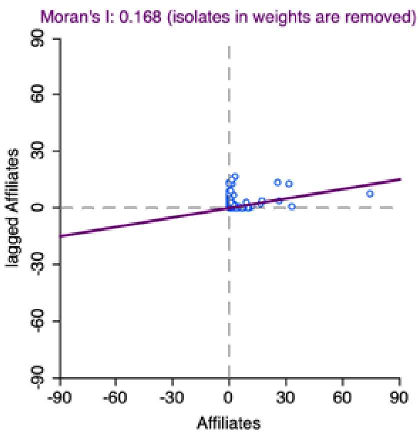


Year 2018

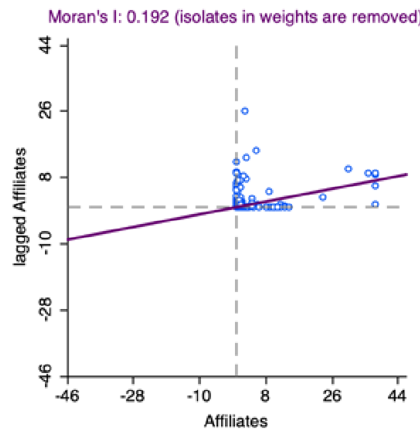


Average years 2007-2018

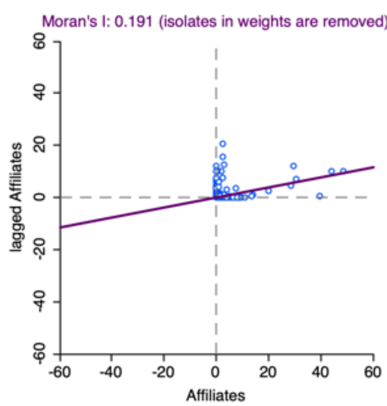
Figure A11: Queen 1 Moran's MNE



Year 2007

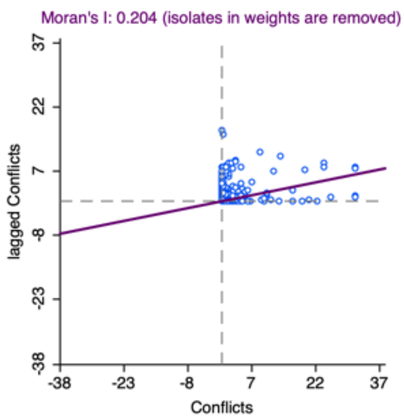


Year 2018

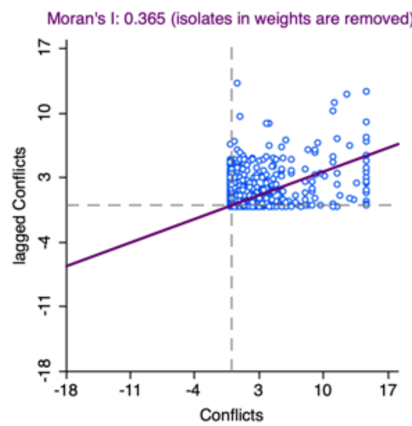


Average years 2007-2018

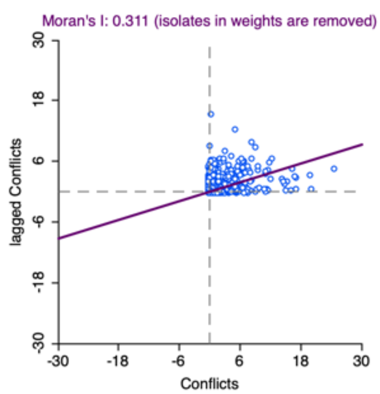
Figure A12: Rook 1 Moran's Conflicts



Year 2007

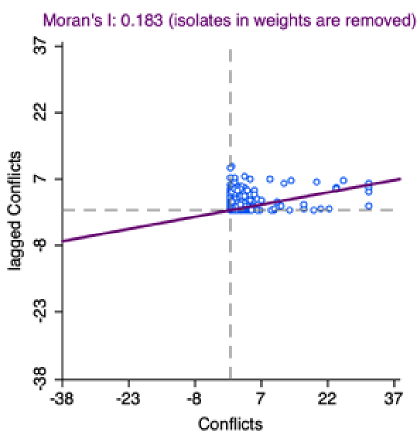


Year 2018

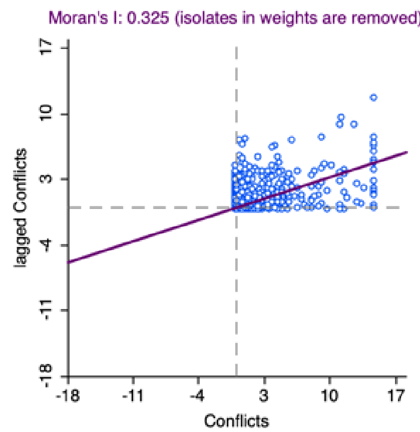


Average years 2007-2018

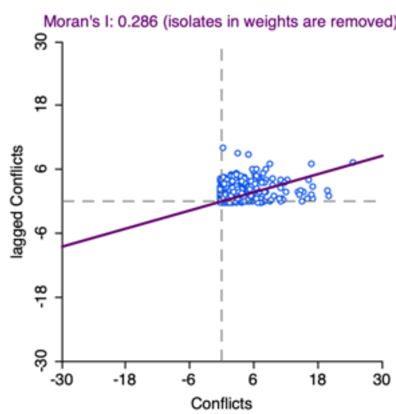
Figure A13: Queen 1 Moran's Conflicts



Year 2007



Year 2018



Average years 2007-2018

L Industries aggregations

In this Appendix, I document more in details the industry aggregation of multinational activities. First, I briefly describe the ISIC/NACE sector aggregation. Second, I show alternative ways of aggregating the multinational industries, confirming that independently on how we group them, land intensive activities always drive the main result. Third, I report the regression Tables which allow the construction of Figures 5, A14, and A15.

L.1 ISIC/NACE sector aggregation

The ISIC/NACE sector aggregation is widely recognised as the main reference for aggregated classification, indeed, it is identified by national accountants to be used for reporting Systems of National Accounts data (Eurostat, 2008). Based on their most aggregated categorization, the *high-level aggregation*, we group multinational activities in 10 categories:

Table A16: Industry aggregation

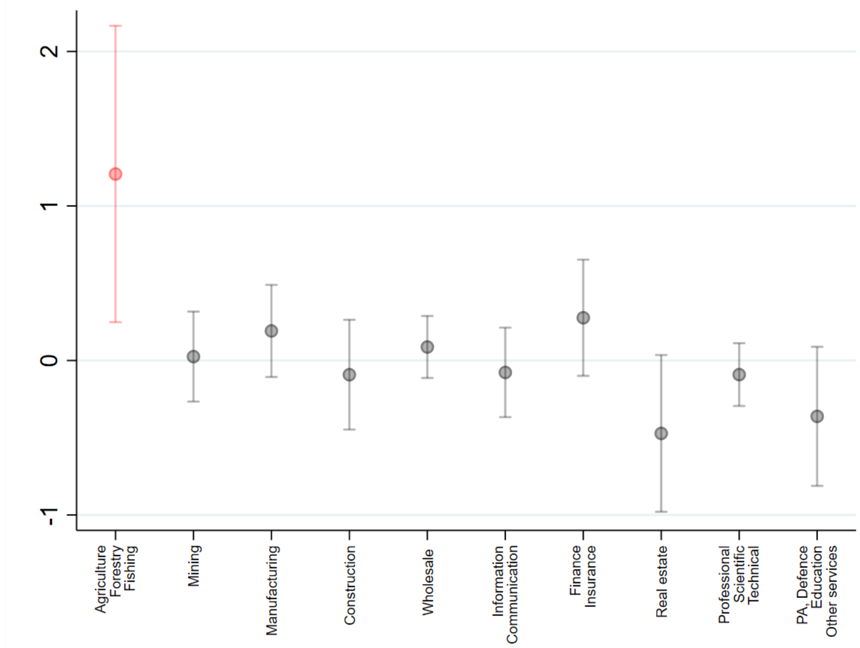
Industry
Agriculture, forestry and fishing
Mining and quarrying
Manufacturing and other industries
Construction
Wholesale and retail trade, transportation and storage, accommodation and food service activities
Information and communication
Financial and insurance activities
Real estate activities
Professional, scientific, technical, administration and support service activities
Public administration, defence, education, human health and social work activities, and other services

Notes: The table show industries aggregation based on the High-level Aggregation of the ISIC/NACE aggregation (see Eurostat, 2008).

L.2 Alternative industries grouping

In Section 4.1, I show that unpacking the *land intensive* industries in several ways provide consistent results with the channel analysed: the higher the land intensity of multinationals' activity, the higher the impact on conflict. In this Section, I show that, on the other hand, the non-significance of *non land intensive* industries does not depend on the way they are grouped. First of all, it is relevant to stress that the alternative groupings of industries are still based on the ISIC/NACE high-level aggregation of industries, to avoid any ad-hoc decision. First, Figure A14 shows that following the aggregation described above in Section L.1, once again, the result on conflict is driven by the most land intensive industries.[62]

Figure A14: Alternative industries aggregation: 10 categories

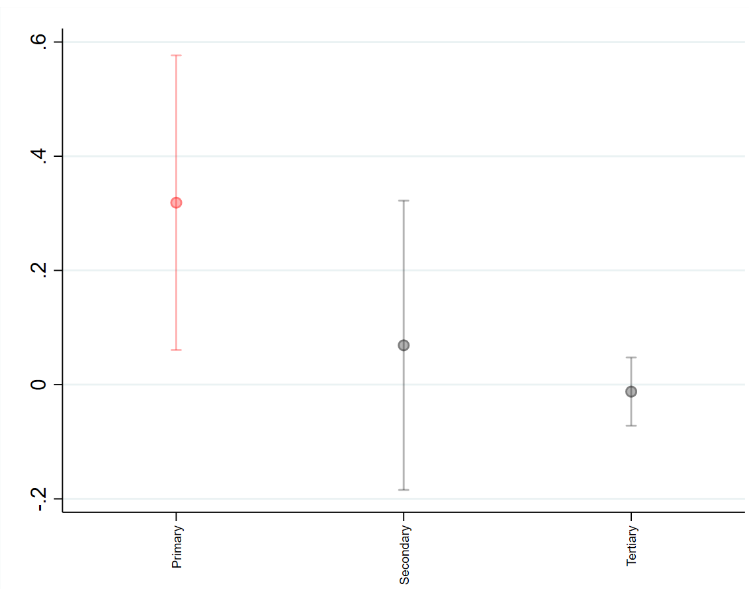


Notes: The figure reports the coefficients of an OLS estimation. Dependent variable: number of violent conflicts (ACLED). ***,**,* = indicate significance at the 1, 5, and 10% level, respectively. Controlling for: cell and country×year FE. Conley (1999) standard errors in parenthesis, allowing for spatial correlation within a 200km radius and for infinite serial correlation. Each group of affiliates indicated below represent the number of affiliates belonging to that specific group in a cell-year (e.g. *Agriculture, Forestry, Fishing* represent the number of affiliates belonging to these three industries - for details see Section 4.1 and Appendix L). In each specification cell and country×year fixed effects are included. The regressions' table of this Figure can be found in Appendix L, Table A18.

Second, I show that also following the classic three-sector model widely used in development economics (primary/secondary/tertiary industries), results are consistent. More specifically, primary industries include: Agriculture, Forestry, Fishing; Mining and Quarrying; secondary industries include: Industry; Manufacturing; Construction; while tertiary industries include all the rest. As Figure A15 shows, also with this more aggregated way of grouping the non land intensive affiliates, the result is driven by the more land intensive group (i.e. primary).

[62] The specification mimic perfectly the specifications of Figure 5 (number of violent conflicts as dependent variables, with cell and country×year fixed effects) but with a larger number of industries.

Figure A15: Alternative industries aggregation: 3 categories



Notes: The figure reports the coefficients of an OLS estimation. Dependent variable: number of violent conflicts (ACLED). ***,**,* = indicate significance at the 1, 5, and 10% level, respectively. Conley (1999) standard errors in parenthesis, allowing for spatial correlation within a 200km radius and for infinite serial correlation. Each group of affiliates indicated below represent the number of affiliates belonging to that specific group in a cell-year (e.g. *Primary* represent the number of affiliates belonging to the primary industries - for details see Section 4.1 and Appendix L). In each specification cell and country×year fixed effects are included. The regressions' table of this Figure can be found in Appendix L, Table A19.

L.3 Additional tables

In this Section I include the regressions' tables which correspond to Figures 5, A14, and A15.

Table A17: Regressions' table for Figure 5

	(1)	(2)	(3)
Estimator		OLS	
Dep. Var.		Conflicts	
Land intensive affiliates	0.318**		
	(0.158)		
Agriculture, Forestry, Fishing		1.156**	
		(0.518)	
Agriculture, Forestry			1.307**
			(0.517)
Fishing			-0.316
			(1.049)
Mining and quarrying		0.185	
		(0.164)	
Land intensive mining and quarrying			0.539**
			(0.265)
Non land intensive mining and quarrying			-0.173
			(0.317)
Non land intensive affiliates	0.00378	0.00682	0.00506
	(0.00619)	(0.00669)	(0.00644)
Cell FE	Yes	Yes	Yes
Country×year FE	Yes	Yes	Yes
Obs	125,076	125,076	125,076

Notes: OLS estimation. Dependent variable: number of violent conflict (ACLED). ***,**,* = indicate significance at the 1, 5, and 10% level, respectively. Controlling for: cell and country×year FE. Conley (1999) standard errors in parenthesis, allowing for spatial correlation within a 200km radius and for infinite serial correlation. *Land intensive avviliates* indicates the number of MNE affiliates in the primarily sector. *Non land intensive affiliates* indicates the number of MNE affiliates in the secondary and tertiary industries. The *Primarly* industry is detailed even more distinguishing the number of MNE affiliates in *Agriculture, Forestry, Fishing* (then decomposed even more among *Agriculture, Forestry*, and *Fishing*) and *Mining and Quarrying* (then decomposed even more among *land intensive mining and quarrying*, e.g. precious ores, and *non land intensive mining and quarrying*, such as petroleum and other energy industries).

Table A18: Regressions' table for Figure A14

Estimator	OLS
Dep. Var.	Conflicts
Agriculture, forestry and fishing	1.207**
	(0.583)
Mining and quarrying	0.0250
	(0.177)
Manufacturing and other industries	0.191
	(0.181)
Construction	-0.0919
	(0.216)
Wholesale and retail trade, transportation and storage, accommodation and food service activities	0.0872
	(0.122)
Information and communication	-0.0774
	(0.176)
Financial and insurance activities	0.276
	(0.229)
Real estate activities	-0.472
	(0.308)
Professional, scientific, technical, administration and support service activities	-0.0914
	(0.123)
Public administration, defence, education, human health and social work activities, and other services	-0.361
	(0.274)
Cell FE	Yes
Country×year FE	Yes
Obs	125,076

Notes: OLS estimation. Dependent variable: number of violent conflict (ACLED). ***,**,* = indicate significance at the 1, 5, and 10% level, respectively. Controlling for: cell and country×year FE. Conley (1999) standard errors in parenthesis, allowing for spatial correlation within a 200km radius and for infinite serial correlation. Each independent variable indicates the number of MNE affiliates in that specific industry at the cell level.

Table A19: Regressions' table for Figure A15

Estimator	OLS
Dep. Var.	Conflicts
Primary	0.319**
	(0.157)
Secondary	0.0689
	(0.154)
Tertiary	-0.0122
	(0.0363)
Cell FE	Yes
Country×year FE	Yes
Obs	125,076

*Notes:*OLS estimation. Dependent variable: number of violent conflict (ACLED). ***,**,* = indicate significance at the 1, 5, and 10% level, respectively. Controlling for: cell and country×year FE. *Primary* indicates the number of MNE affiliates in Agriculture, Forestry, Fishing, Mining and Quarrying industries. *Secondary* indicates the number of MNE affiliates in the Industry, Manufacturing, and Construction industries. *Tertiary* indicates the number of affiliates in all other industries.

M Afrobarometer's questionnaire

Here I include a copy of one of the Afrobarometer's questionnaire (round 4) which details the main question used for the individual-level analysis. This question is present in each Afrobarometer's round.

Figure A16: Question Afrobarometer

56. In your opinion, what are the most important problems facing this country that government should address? *[Do not read options. Code from responses. Accept up to three answers. If respondent offers more than three options, ask "Which three of these are the most important?"; if respondent offers one or two answers, ask "Anything else?"]*

	1st response	2nd response	3rd response
Economics			
Management of the economy (Including prices and inflation)	1	1	1
Wages, incomes and salaries	2	2	2
Unemployment	3	3	3
Poverty/destitution	4	4	4
Rates and Taxes	5	5	5
Loans / credit	6	6	6
Food / Agriculture			
Farming/agriculture	7	7	7
Agricultural marketing	32	32	32
Food shortage/famine	8	8	8
Drought	9	9	9
Land	10	10	10
Infrastructure			
Transportation	11	11	11
Communications	12	12	12
Infrastructure / roads	13	13	13
Government Services			
Education	14	14	14
Housing	15	15	15
Electricity	16	16	16
Water supply	17	17	17
Orphans/street children/homeless children	18	18	18
Services (other)	19	19	19
Health			
Health	20	20	20
AIDS	21	21	21
Sickness / Disease	22	22	22
Governance			
Crime and Security	23	23	23
Corruption	24	24	24
Political violence	25	25	25
Political instability/political divisions/ ethnic tensions	26	26	26
Discrimination/ inequality	27	27	27
Gender issues/women's rights	28	28	28
Democracy/political rights	29	29	29
War (international)	30	30	30
Civil war	31	31	31
Other responses			
Other (i.e., some other problem)	995	995	995
Nothing/ no problems	0		
No further reply		996	996
Don't know	999		

Notes: Source: Afrobarometer questionnaire, round 4.