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
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1 Introduction

Over the last few decades, there has been an unprecedented surge in foreign direct investment in Africa. During the 2000s it rose by almost sixfold, and the number of multinational enterprises (MNEs) has risen by almost 250% since the financial crisis.[1] As J. G. Ruggie notes in his book *Just Business*, some native people were able to take "*advantage of the opportunities created by this transformative process. But others were less fortunate.*" This included "*communities displaced without adequate consultation or compensation*."[2] The presence of MNEs can increase living standards (Méndez-Chacón and Van Patten, 2022), but at the same time, they may use scarce resources such as agricultural land, which can impact such things as food security and water access (Rulli et al., 2013), creating the potential for a violent reaction. In parallel to the arrival of MNEs, the number of conflicts in Africa has increased by almost fivefold.[3] Given the aforementioned, as governments compete to attract MNEs through costly public programs, it is crucial for policymakers to understand the role multinationals may play in mitigating or increasing conflict.[4]

This paper examines the impact of MNEs on civil conflict. I tackle this question by merging geolocalized information on conflict events with novel data on MNE affiliates and their headquarters for all African countries between 2007 and 2018. The units of analysis are cells of 0.5×0.5 degree latitude and longitude (approximately 55km $\times$ 55km at the equator) covering the entire African continent. The use of georeferenced information, together with a novel instrumental variables strategy and granular fixed effects, permits causal identification.

The case of Mozambique helps to illustrate the magnitude of the phenomenon. It gained independence from Portugal in 1975 after centuries of resistance, thus fulfilling the ideal of "la liberté de l'homme et de la terre" (freedom of man and land). In April 2011, a trilateral cooperation program called the ProSavana project was initiated, together with Japan and Brazil, in order to promote "sustainable and inclusive agricultural development." It involved well-known multinational agribusinesses and logging enterprises and covered a total of 10.7M hectares cultivated by 692 thousand rural families.[5] Case studies have found that the project violated local people's rights with little if any compensation, and often produced conflict situations.[6]

[1] Calculated by the author (details in Appendix C). FDI data is from World Bank (2014).

[2] Ruggie (2013). Ruggie was Professor of Human Rights and International Affairs at Harvard Kennedy School, and served as UN Assistant Secretary-General for Strategic Planning, focusing on businesses and human rights.

[3] *Armed Conflict Location Events Data* (Raleigh et al., 2010), see Appendix C for details.

[4] For example, tax holidays and subsidized industrial infrastructure (UNCTAD, 2018a). The number of Special Economic Zones increased from 76 in 47 countries in 1986 to 4 thousand globally by 2018 (UNCTAD, 2018b).

[5] The population of the target area was estimated at 4.3M in 2011, mostly living in rural areas where 80% of people depend on agriculture for subsistence and the typical farm size is 1.34 hectares (MASA, 2015).

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

The empirical analysis is based on an original dataset that combines the *Historical Ownership Dataset* and *Orbis*, two Bureau van Dijk datasets which provide the worldwide location and activities of MNE affiliates (the main explanatory variable), and the *Armed Conflict Location Events Data*, which provides the location and type of conflict events (the outcome). The analysis requires the identification of a multinational's affiliates and headquarters, and their geolocation. To accomplish this, a novel algorithm is used to combine historical information on the ownership of all firms worldwide that are connected through an ownership link. The algorithm maps the hierarchical structure of business groups by ascending the ownership structure in order to construct the network of business groups for more than 200 countries for the period 2007 to 2018. They are then geolocated using zipcodes. The headquarters-affiliate link in particular is a key ingredient of the instrumental variable strategy described below.

Evaluating the effects of MNE activities on violence constitutes a challenge due to various methodological issues, and in particular the possible reverse causality from local violence to MNE operations. Indeed, the presence of a conflict may reduce the probability of an affiliate locating its operations in that location. Relying on the internal capital market literature and exploiting the headquarters-affiliate credit link, the dataset created for the analysis provides a novel way to instrument MNE activity at the local level using a shift-share approach. Historical financial data at the headquarters level together with credit availability serve as the shifter. More specifically, I interact pre-period headquarters' dependence on external credit with a multinational's availability of credit, thus capturing exogenous variation in MNE activities over time.[7] This shifter is then interacted with the share component, i.e. the initial distribution of affiliates at the cell level in Africa. Given the potential endogeneity of the shares, consistency of the estimates relies on the quasi-random assignment of the shifter (Borusyak et al., 2022), a condition carefully tested in the paper. The exclusion restriction implies that shocks to non-African private sector credit – conditional on cells and country$\times$year fixed effects, and the controls – affect conflicts in African cells solely through the local presence of affiliates belonging to multinational groups.

MNE activity is found to have significant and heterogeneous effects on conflicts. On average, an increase in affiliates leads to a rise in the number of violent events. The evidence suggests that this result is primarily driven by the operations of affiliates involved in land-intensive activities. Land is a precious resource given that farming is the primary source of food and income in Africa, accounting for up to 60 percent of all employment on the continent (Sy, 2016; Coulibaly, 2020).

[7] The intuition is straightforward: some affiliates, in any given cell-year, are part of a relatively less healthy and less robust multinational that is particularly dependent on external credit, while others have more stable parent corporations. The former are expected to be significantly more affected by credit cycles and therefore their activities will be characterized by greater variation.

The number of violent events is shown to increase following large-scale land acquisitions. The data from *LandMatrix* are used to geolocate land deals that exceed 200 hectares, and it is shown that they are not harmful everywhere, but rather only where multinationals are active. Moreover, data on the use of land before the arrival of multinationals show that conflicts occur when the land was previously dedicated to agriculture. It is also shown that the type of conflict triggered by multinationals is primarily localised violent events, as described by case studies of land-grabbing. These events are likened to insurrections to protect a key resource for survival, which is land in this case. Finally, individual-level data from *Afrobarometer* show that MNE activity leads to an increase in complaints by locals about land management and that this result is entirely driven by land-intensive multinational activity.

The demonstrated effect is of a substantial magnitude. On average, the arrival of 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. Overall, more than 13% of the violent events can be attributed to the presence of multinational enterprises. Interestingly, the activity of multinational affiliates whose headquarters are located in the UK, France, the US, or Germany – the top four non-African home countries of multinationals – accounts for 6.7% of the events.

The results are robust to a large battery of robustness checks. Among others, a test for the potential endogeneity of shares and non-random exposure to exogenous shocks (see Borusyak et al., 2022 and Borusyak and Hull, 2020). A placebo test that replaces the shift component in the instrumental variable strategy with a simulated instrument. Adding potential time-varying cell-specific shocks to the demand for agricultural commodities produced in the cell and the heterogeneous impact this may have on cells where costs of trade are high (Berman and Couttenier, 2015). An event study where the effect of an increase in the number of affiliates in a cell-year is examined (de Chaisemartin and D'Haultfoeuille, 2022). An alternative instrumental strategy that is independent of the initial allocation of affiliates. The sample is restricted to only cells with multinational affiliates or to include their neighbouring cells as well (Acemoglu et al., 2012; Buonanno et al., 2015). Cells with valuable resources (gold, diamonds, oil, etc.), or that containing a capital, and the years of the financial crisis are excluded. Country$\times$year fixed effects are replaced by region$\times$year fixed effects in order to control for possible indirect effects of the crisis on specific areas within a country. Variables are added to control for weather conditions, population and development dynamics, and the presence of local firms. The main outcome variable is replaced with a dummy variable, and the robustness of the results is checked using an alternative data source on conflicts (GDELT). Finally, tests for alternative functional forms, different methods of data cleaning, and alternative clustering of the standard errors are also carried out.

The paper contributes to various strands of the literature. One strand examines the complex connection between trade and conflict using country-level aggregate trade data.[8] Despite the dominance of their activity worldwide (two thirds of world trade flows are somehow related to multinational firms, see UNCTAD 2011), much less attention has been paid to the relationship between multinational enterprises and conflict. Importantly, data on country-level foreign direct investment have been used as a proxy for MNE activities. This situation has been described by Helpman et al. (2004, pp.306) as the "*dearth of internationally comparable measures of the extent of FDI across both industries and countries*."[9] The novel dataset used here helps to fill that gap. By systematizing ownership links using the *Historical Ownership Database*, I introduce a novel algorithm that provides the network of business groups for more than 6.3 million business groups, which have 12.8 million affiliates in more than 200 countries. They are then geolocated using zipcodes. To the best of my knowledge, this is the first global, firm-level dataset that provides hierarchies and activities of multinationals in a panel setting.[10] Moreover, this work provides a novel way to instrument multinationals' activity based on the direct credit links between affiliates and headquarters.

Another strand of the literature uses disaggregated data to study the determinants of conflict in African countries.[11] It includes two studies that examine the role of firms, both of which focus exclusively on the mining sector. Christensen (2018) finds that the probability of protest is twice as large 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 demonstrate a sizeable and significant positive impact of mining on conflicts at the local level.[12] The current study contributes to this literature in three ways. First, it is the first work examining the impact of multinational enterprises on conflict. Second, the analysis covers multinational activity in *all* industries. This is a major contribution to the literature – which until now has focused exclusively on mining – given that the effect of MNE activity may vary by industry, depending on specific characteristics such as land intensity. Third, the analysis covers an entire continent over more than a decade, thus en-

[8] Oneal and Russet (1997); Oneal and Russett (1999, 2001); Barbieri (1996, 2002); Martin et al. (2008b,a).

[9] Polachek et al. (2012) shows theoretically that FDI can improve international relations, a result confirmed empirically by Bussmann (2010). Morelli and Sonno (2017) show how country-level asymmetries in foreign value added can be relevant in conflict analysis. Recent geocoded data on Chinese aid have facilitated the study of country-specific aid flows on protests, which has produced mixed results (Iacoella et al., 2021; Gehring et al., 2019).

[10] Although the analysis is limited to African affiliates of multinational enterprises, the MNE dataset is suitable for analyses anywhere in the world (e.g., Altomonte et al., 2021).

[11] Among many others, Guidolin and La Ferrara (2007); Brückner and Ciccone (2011); Nunn and Wantchekon (2011); Besley et al. (2011); König et al. (2017); Berman et al. (2017); Manacorda and Tesei (2020).

[12] Some recent work has studied the impact of MNEs on local firms in developing countries (e.g., Dhingra et al., 2021; Alfaro-Urena et al., 2022).

suring the external validity of the results, and overcoming country-specific and/or period-specific effects. Other studies have looked at the impact of agricultural income shocks on conflict (e.g., Dube and Vargas, 2013; Berman and Couttenier, 2015; Berman et al., 2021) and, more specifically, land conflicts (Hidalgo et al., 2010; Di Falco et al., 2020). The current analysis creates a link between the studies that focus on mining and conflict and those that focus on agriculture and conflict by examining land use in general by multinational firms.

Finally, the analysis fits into the expanding body of literature that leverages firm-level data to study conflict. It has been shown that conflict can impact a firm's choice of inputs (Amodio and Di Maio, 2018), labour supply (Ksoll et al., 2023), production strategies (Del Prete et al., 2023), location (Blumenstock et al., 2020), timing of shutdowns (Camacho and Rodriguez, 2013) and investment choices (de Roux and Martinez, 2021), and may induce a shift of workforce toward protection duties in response to predation risks (Besley and Mueller, 2018). For a review of the literature discussing these effects, see Rohner and Thoenig (2021). Couttenier et al. (2022) show that disruptions at the firm level due to local conflicts can ripple through production networks to impact the broader economy. The current analysis contributes to this literature by examining the inverse relationship, that is, the impact that private firms, and in particular multinationals, have on conflict.[13]

The paper is organized as follows. Section 2 describes the data and section 3 presents the empirical analysis. Section 4 proposes a potential mechanism to explain the results. 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.[14]

[13] This paper also contributes to the very lively policy debate surrounding what is referred to in the literature and by activists as "land grabbing", a phenomenon far more widespread in Africa than in any other continent (Nolte et al., 2016). Several factors link lang grabbing 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 land grabbing events and the conflicts they have brought about (Hall, 2011), no systematic study of the impact of large-scale land acquisition on conflicts has yet been done, and in particular not in areas where large multinationals are active. This paper contributes to the literature by attempting to fill this gap using novel panel and cross-country evidence.

[14] 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,

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 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.[15] I focus on the subset of affiliates 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

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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.

[15] 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).

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).[16] 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*.[17] This initiative provides information about large-scale land acquisitions in different years.[18] 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 con-

[16] 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).

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

[18] 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 analysis, only concluded land deals are considered.

sidering 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. Appendix B provides a detailed description of the *LandMatrix* data and discusses its reliability.

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.[19]

Other data. For population data I use data from *LandScan*.[20] 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 "develop 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.[21] 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 C.

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

[19] 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).

[20] 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.

[21] 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.

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.

Table 1: Descriptive statistics

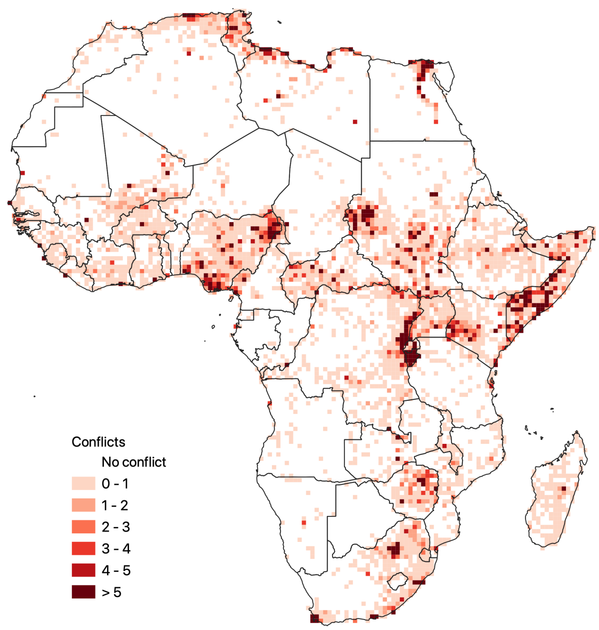
		Obs.	Mean	S.D.	Median
Conflict					
	# conflict, all cells	125,076	0.47	2.97	0
	# conflict, if affiliates $= 0$	122,114	0.37	2.52	0
	# conflict, if affiliates > 0	2,962	4.27	9.79	0
	Prob. conflict > 0, all cells	125,076	0.10	0.30	0
	Prob. conflict > 0, if affiliates $= 0$	122,114	0.09	0.29	0
	Prob. conflict > 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 C.

Appendix C 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 C, 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 A9 in Appendix C shows annual aggregates of the number of MNE affiliates and headquarters in the African sample. Over the period analysed, the number of affiliates increased by almost 250%. However, this growth was not linear, i.e. 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).[22] In terms of nationality, the most frequent non-African headquarters are British (10% of affiliate-year observations), American and French (both around 8%), and German (5%).

Figure 1: Conflict events



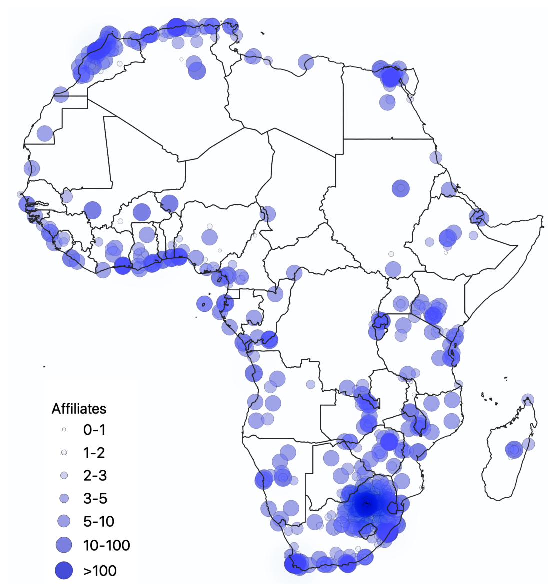
Notes: The map shows the average number of violent conflicts (ACLED) over the years 2007-2018.

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. Before delving into the econometric approach, I will first discuss the theoretical framework underpinning the analysis.

[22] 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).

Figure 2: MNE affiliates



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

3.1 Setting

The impact of firms on conflict dynamics is theoretically ambiguous. Their activity may increase wages and hence reduce labour supplied to conflict activity (Grossman, 1991; Collier and Hoeffler, 1998, 2004; Fearon and Laitin, 2003; Miguel et al., 2004), and it may detract land and labor opportunities, especially when multinationals arrive from outside and bring their own resources. The balance between the two effects depends on the scarcity of resources used by firms and on the potential changes in the quantity or type of employment. The greater is the scarcity of the contested resources (such as fertile land), the higher will be the probability of conflict following a firm's appropriation of those resources. Thus, a significant aspect of the heterogeneity in these effects is the extent to which they depend on the intensive use of fixed-stock resources. Farming is the primary source of food and income in Africa, contributing up to 60 percent of all jobs (Sy, 2016; Coulibaly, 2020). Consequently, if a firm in Africa makes extensive use of land, it could potentially stimulate conflict (keeping other factors constant).

Besides the scarcity and relevance of the contested resources, a second important determinant of grievances concerns the effect on jobs and wages: new firms may generate (or alter the nature of) employment, which may increase the opportunity cost of conflict for individuals (Dube and

Vargas, 2013).[23] In this context, distinguishing between local and multinational firms is particularly important. Economic activities undertaken by foreign firms may lead to positive spillovers, such as higher living standards (Méndez-Chacón and Van Patten, 2022), technology transfers (Alfaro-Urena et al., 2022) or improved labour standards, potentially raising wages and enhancing job quality (Dhingra et al., 2021).[24] However, in contrast to local firms, multinationals often have access to multiple labour markets. Thus, when other factors are held constant, the activity of multinational companies may result in relatively fewer or lower-quality jobs. Combining the same multinational data used in this analysis, together with 4.4 million geolocated DHS interviews in Sub-Saharan countries, it can be shown that, on average, multinational enterprise activity reduces local on-farm jobs (Mendola et al., 2021). This finding is supported by numerous case studies, particularly in the mining sector.[25]

Therefore, both the type of resources involved and the effects of firm ownership on labour demand should matter in understanding the impact of firms on conflict. The impact depends on the sector in which the company operates and its use of scarce resources, although it also hinges on the effect of its investments on the opportunity cost of conflict, influencing the quantity and quality of jobs created. For instance, MNE investment in a sector with abundant resources that creates quality jobs is likely to reduce conflict, because it reduces only marginally the expected rents that can be extracted from the resource while increasing the opportunity cost of engaging in conflict. Conversely, an MNE operating in a scarce resource industry that creates few or low-quality jobs, or even reduces job opportunities, is more likely to exacerbate conflicts, since it significantly reduces expected rents from the resource and does not increase (and perhaps even decreases) the opportunity cost of conflict. Between these two extremes lies a continuum of scenarios.[26] Appendix D further clarifies how the interaction of the two aforementioned factors can

[23] They show that a sharp decline in coffee prices during the 1990s led to reduced wages and an increase in violence in Colombian municipalities with extensive coffee cultivation (referred to as the *opportunity cost effect*). Conversely, a rise in oil prices resulted in increased municipal revenue and an increase in violence in oil-rich regions (referred to as the *rapacity effect*).

[24] For a detailed discussion, see for example the analysis of foreign direct investment's spillovers in Sub-Saharan Africa in World Bank (2012).

[25] An examination of multinational oil and mining companies' operations in Nigeria, South Africa, and Zambia in Eweje (2009) reveals that multinationals have faced extensive criticism from local governments and trade unions for favouring expatriate employment over local labour. The use of imported and subcontracted labour by Chinese investors in Africa has been described by various authors (Cooke, 2014; Mohan, 2013).

[26] Consider, for example, the manufacturing sector. It might rely on scarce resources like land but to a significantly lesser extent than the agriculture and forestry sectors. Additionally, the land used is usually not particularly fertile (e.g., close to a production area). Therefore, such activities do not greatly affect average land values and prices. As a result, sectors like manufacturing do not impact conflict, not because of a balance of opposing effects, but because they do not significantly influence conflict in either direction.

affect conflicts through other channels and in conjunction with other factors.

As a result, the impact of MNE investment on conflict remains ambiguous and ultimately is an empirical question. Notably, the increase in multinational activity is precisely what the instrumental variable strategy is designed to identify. The strength of the proposed strategy lies in its ability to detect changes in the presence of multinational affiliates in Africa, which are attributed to variations in credit available to their headquarters. Crucially, the validity of this empirical approach hinges on the assumption that changes in credit availability – measured as the credit availability in countries outside of Africa – affect only multinational affiliates which can access international credit markets, while not impacting local firms.

3.2 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:

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

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.[27] f_k and $f_{c,t}$ are cell and country $\times$ 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.[28]

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 E shows that results are confirmed, both qualitatively and quantitatively, when accounting for the intensive margin of multination-

[27] 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 3.4, I present estimates without winzorizing and with alternative functional forms, showing that this make no substantial difference to the results.

[28] Border cells are assigned to the country that represents the largest share of their territory. As a robustness check, in the sensitivity analysis (section 3.4), all cells belonging to multiple countries are dropped from the analysis.

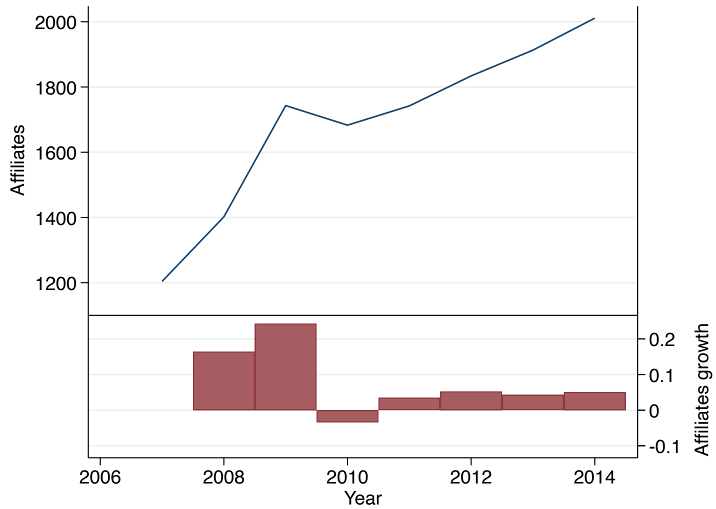
als' activity (affiliates' size).[29] The basic empirical strategy exploits the fact that some affiliates within a cell-year are part of relatively healthy and robust multinationals, whereas others belong to less healthy groups, which are more reactive to credit booms/downturns. More specifically, pre-period 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 positive/negative credit shock hits the parent company, if some constraint on the amount of borrowing or any general financial help is released/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). Indeed, the years of credit expansion or 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. Note the clear increase in affiliates over the overall period displayed in the figure (more than 65% between 2007 and 2014, and more than 120% over the whole period 2007–2018), with a drop in the number of affiliates around the crisis but a stable positive growth rate in the years before and after it.[30] Remarkably, the entire analysis is robust to the exclusion of the years around the crisis, as described in section 3.4.

Given the credit mechanism used in the work, 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 credit booms/shrinking hit parent firms differently depending on their reliance on credit. To avoid endogeneity, I compute a

[29] In Appendix E, 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 E. 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.

[30] Specifically, South African affiliate's growth rate decreased from 20% to an average of 3% in the first few years after 2009, i.e. 2010-2014. The same trend is confirmed in the overall sample, with an average of 26% and 9% respectively, in the same years. 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), this growth diminished with the 2008-2009 crisis but then increased constantly during the subsequent years (see Figure A9 in Appendix C).

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.

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. Specifically, $w^m_{k,c,2007}$ represents the parent *m*'s share of affiliates in cell *k* year 2007.[31] 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}.[32] Third, I then interact this firm-specific (time-invariant) variable with measures of credit availability at the international level, cre_{t-1}.[33] 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

[31] 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. As explained in the data section 2, 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 E for details.

[32] 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).

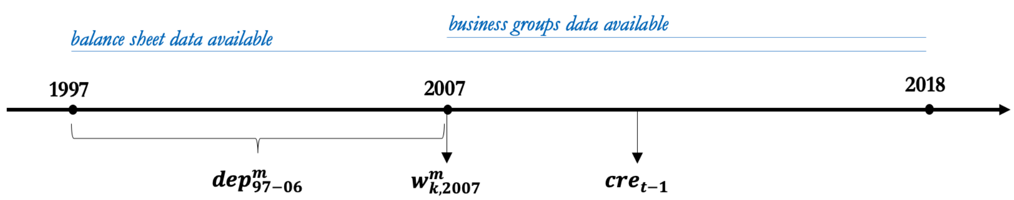
[33] World Bank data: worldwide domestic credit to private sector (financial resources provided to the private sector, weighted by GDP), excluding African countries. As a robustness, in section 3.4, I also use domestic credit provided by financial sector. Results are confirmed.

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 non-African shocks to credit given to the private sector will – conditional to controls, cells and country$\times$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 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 3.3, and in the robustness' section 3.4. The latter starts with a list of tests in support of the identification assumption, in particular, the 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).

3.3 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.[34] All specifications include cell and country×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, the coefficient of interest is significant at the 1% level in both specifications. In particular, an increase in MNE activity increases the number of conflicts. 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. 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 3.4. 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 periods with significant changes in credit have direct impacts at the cell level. For example, if grid cells in host countries are experiencing income declines because they face com-

[34] 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 3.4, 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.

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 3.2. The section *First stage* reports the coefficients of the first stage estimations. Kleibergen-Paap F-statistic are reported for columns 2 and 3.

mon 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×year fixed effects are substituted with region×year fixed effects. This highly demanding set of fixed effects takes into account potential local time-varying differential effects of the credit shocks.[35] Moreover, in order to directly tackle the issue of local economic development, the lagged value of night lights at the cell level is included.[36] 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, see Harari and Ferrara, 2018, Brückner and Cic-

[35] In the robustness section 3.4 I check the impact of significant changes in credit at the cell level following Berman and Couttenier (2015) and Berman et al. (2021), namely taking into account import values shocks of goods produced at the cell level.

[36] 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 3.4, results are shown to be robust to the inclusion of local firms as controls.

cone, 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.

Before turning to the sensitivity analysis, it is worth dwelling a bit more on the magnitude of the identified effect. Given the results in column 2 of Table 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. In Appendix F, I calculate the contribution of multinational affiliates to observed violence in each country. The role of MNEs in this context is notably heterogeneous.[37] Using the counterfactual exercise's results, we find that MNEs' presence accounts for a significant 13.39% of violent conflicts in Africa over the 12-year study period. Additionally, in the same appendix, two other counterfactual analyses are conducted. Firstly, we predict the conflict events attributable to the affiliates whose headquarters are located in the top four non-African home countries as described in the descriptive statistics in section 2 (UK, France, the US, and Germany), representing 6.75% of the total number of observed conflict events in the period. Interestingly, we then assess that this magnitude is comparable to the share of conflicts explained by the overall increase in affiliates from 2007 to 2018, comparing the actual events with a counterfactual scenario where the number of affiliates remained constant at the beginning-of-period level. This latter scenario accounts for 6.30% of the total number of observed events.

3.4 Identification assumption and sensitivity analysis

In this section, I first present a battery of tests in support of the identification assumption (Appendices G, H, I, J, K), I describe an alternative instrumental strategy that is independent of the initial allocation of affiliates (Appendix L), then I show that the baseline estimates of Table 2 prove to be robust to a large battery of checks (Table 3, and Appendices M, N, O, P).

Identification assumption. Here I describe additional evidence in support of the identi-

[37] The procedure follows six steps. First, we estimate the same specification as in our baseline (Table 2, column 2). Second, we predict the number of conflicts using the observed number of affiliates. Third, we predict the counterfactual number of events setting affiliates to zero. Fourth, we compute the difference between the two predictions in all cells and years. Such differences are interpretable as the number of events explained by multinational affiliates. Fifth, we sum the number of explained events (i.e. the differences) across all cells and years within countries. Finally, we take the ratio of these *explained* events over the actual number of events observed in the country during the 2007-2018 period.

fication assumption. First, in Appendix G, 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 G, 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 H, the tests proposed by Borusyak et al. (2022) concerning potentially endogenous shares in shift-share research designs are presented. In this 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 H shows that: (i) the distribution of shocks in the whole dataset and residualized after extracting year fixed effects presents 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 I, I present an analysis of cells' exposure to changes in import values. Following Berman and Couttenier (2015) (i) I add as controls the time-varying cell-specific measure of external demand for the commodities produced by the cell, and (ii) I check the robustness of the results with respect to 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.[38] Fifth, as proposed by Goldsmith-Pinkham et al. (2020)

[38] I am grateful to the authors for sharing updated data on cell-specific crops suitability and world import values,

and Angrist and Pischke (2008), in Appendix J 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.[39] Sixth, in Appendix K, an event study where the effect of an increase in the number of affiliates in a cell-year is presented, following the estimation procedure presented by de Chaisemartin and D'Haultfoeuille (2022), which allows for staggered and repeated treatments.

Alternative instrument. In Appendix L, an alternative instrumental strategy is introduced. This strategy relies on cells' pre-period geographical characteristics, and it is therefore independent of the initial affiliate allocation in the cells. It is, however, applicable to a subset of industries (agriculture, forestry, and mining). Reassuringly, the results using this strategy are confirmed, despite the lower strength of the first stage.

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

coming from an updated version of their two datasets used in Berman and Couttenier (2015) and Berman et al. (2021).

[39] 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.

to Sub Saharian countries. One potential concern with the econometric specification proposed, and in particular with the use of the country×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.[40] For these reasons, row 8 excludes capital cities. Row 9 tests the robustness of the result when excluding the years of the financial crisis, i.e. 2009 and 2010.[41]

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 10 country×year fixed effects are substituted with region×year fixed effects. In row 11, 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 12. In row 13, I add the lagged and lead values of the dependent variable at the cell level. In rows 14 and 15 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 16, I group headquarters in eight

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

[41] Remarkably, results are robust and comparable both in magnitude, significance and power of the F-statistics if we exclude a larger window of years around the period of credit shrinking, e.g. 2009-2012 or 2008-2013.

macro-regions and a dummy variable taking value 1 is added when a cell-year shows at least one affiliate of a parent corporation located in one of these regions.[42] In line 17, I control for the number of local firms at the cell level, lagged by one year, while in lines 18 and 19 the same variable is lagged by 2 and 3 years respectively.[43]

Different conflict variables. In line 20, 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. This result is especially important for confirming the robustness of our findings when using a non-count dependent variable. In row 21, 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 22, I explore 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 GDELT 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 N, additional transformation of the dependent and independent variables are considered. 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 N, 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. The same appendix also includes results from IV Poisson estimations, which incorporate a reduced number of fixed effects due to computational constraints.

[42] Specifically, I group headquarters nationality in eight macro-regions: Eastern, Western, and Southern Asia, Eastern, Western, Southern, and Northern Europe, and North American. If I include one dummy variable for each parent company nationality (more than 100), the main coefficient remains positive (beta 0.441) but loses its statistical significance (standard error 0.751). In particular, the F-statistics of this regression drops below one.

[43] 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 M.

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 O, 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 P, I report Moran's I statistics, as suggested by Kelly (2019).

As we can see from Table 3, together with the listed Appendices G, H, I, J, K, L, M, N, O, and P, the results presented in section 3.3 are robust to 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), with the African continent representing one of the key targeted areas.[44] The acquisitions are usually made by national sovereign wealth funds or corporations based in wealthier, more 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).[45] Land

[44] Comprehensive datasets on land deals are scarce, complicating the provision of official figures (Schoneveld, 2014). Nonetheless, the African continent has been highlighted as one of the main targets for LSLAs since early insights (Deininger and Byerlee, 2011). This "global rush for land" intensified in the early 2000s (Arezki et al., 2015; Cotula, 2012), partly due to the food price spikes in 2007/08 and expectations of consistently higher agricultural commodity prices, although the number of deals has decreased since 2015 (Lay et al., 2021). Using data from *Land-Matrix*, Appendix B corroborates these trends, showing a marked increase in African land deals around the 2009 and 2011 spikes, with a subsequent stabilization.

[45] 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).

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	0.166***	(0.0453)	14.57	108,912
(8) Excluding capitals	0.178***	(0.0478)	14.74	124,260
(9) Excluding crisis	0.107***	(0.0363)	30.41	104,230
Additional controls				
(10) Region×Year FE	0.176***	(0.0415)	17.57	125,076
(11) Cell-specific time trends	0.160***	(0.0373)	29.93	125,076
(12) Precipitation, temperature, water balance	0.160***	(0.0375)	30.11	125,076
(13) Conflict (t-1) and (t+1)	0.058**	(0.0228)	30.41	104,230
(14) Nightlights (t-1)	0.162***	(0.0376)	30.13	125,076
(15) Population (t-1)	0.161***	(0.0375)	30.08	125,076
(16) Headquarters macro-region FE	0.162***	(0.0376)	30.72	125,076
(17) Local firms (t-1)	0.188***	(0.0422)	25.70	125,076
(18) Local firms (t-2)	0.196***	(0.0465)	22.67	125,076
(19) Local firms (t-3)	0.191***	(0.0450)	23.80	125,076
Different conflict variables				
(20) Dummy	0.015***	(0.0032)	30.09	125,076
(21) All conflict events	0.535***	(0.137)	30.09	125,076
(22) GDELT	9.362***	(1.764)	30.09	125,076

Notes: The table reports 2SLS estimation results from 17 different specifications described in section 3.4. 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 3.2. Kleibergen-Paap F-statistic are reported for each specification.

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).[46] 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).[47]

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*.[48] 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, it is shown that multinational activity increases conflict specifically in those areas which were allocated to *agriculture before* the arrival of the MNEs, specifically with an increase in localised violent events, i.e. riots. Fourth, 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 address". Moreover, this section concludes by showing that these individual-level results are completely driven by people living in areas where land-intensive MNEs are active, while the activity of non land-intensive MNEs provides no significant results.

Considering the potential role of local firms in the dynamics previously described, as discussed in the theoretical framework in section 3.1, Appendix M replicates the analyses from sections 4.1 to 4.3, this time focusing on local firms. The results show that the primary channel

[46] 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).

[47] 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).

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

outlined in this section, namely activity in land-intensive industries, is significant only for multinational affiliates.[49]

It is worth underlying that considering some limitation of the data at hand 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 of alternative channels, which I cannot rule out with the data available in this work.[50]

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 3.2 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.[51] 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 presented in Figure 5, avoiding any comparison with 2SLS estimates and/or any quantification exercise.

[49] A limitation, however, is that while we can causally identify the role of multinational affiliates in several empirical exercises using the strategy described in section 3.2, the identification for local firms is not as robust. Consequently, a detailed causal analysis of local firms' impact on conflict and the involved channels remains a subject for future research.

[50] One example is the potential increase in local labour demand in low-skilled industries induced by the activity of multinationals. As already described in the section 3.1, in Mendola et al. (2021) we show that this is not the case, a piece of evidence confirmed by numerous case studies. Indeed, while large-scale farms do require labor for operations, potentially generating gainful wage employment over time, large-scale land acquisitions are typically more capital-intensive and less labor-intensive compared to smallholder farms (Lay et al., 2021). Recent case studies in Africa, which also consider indirect employment effects such as income and local demand, reveal no impact on employment (Ali et al., 2019, in Ethiopia), or very limited and short-term employment impacts on neighbouring farmers, but paired with an overall decrease in perceived well-being (Deininger and Xia, 2016, in Mozambique).

[51] More technically, remember that the instrument described in details in section 3.2 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.

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.[52] 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.[53] 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 primary industries - are those driving the results. Second, in Appendix Q, 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 minerals, which are more capital intensive rather than land intensive).[54] In line with our priors, only the number of affiliates in the land-intensive industries present a positive and significant

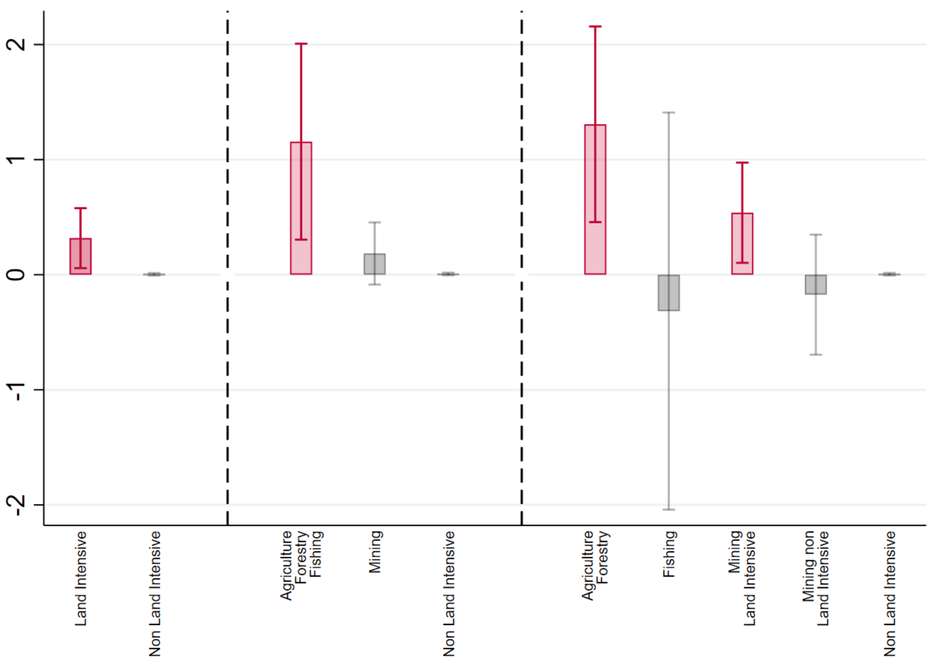
[52] I follow the classic three-sector model widely used in development economics when analyzing least developed countries. Primary industries include: Agriculture, Forestry, Fishing; Mining and Quarrying. Secondary industries include: Industry; Manufacturing; Construction. Tertiary industries include 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 Q.

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

[54] Details about industries grouping and regression results can be found in Appendix Q.

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). 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 Q). In each specification cell and country×year fixed effects are included. The regressions' table of this Figure can be found in Appendix Q, Table A20.

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 conflicts 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 with case studies cited above where locals start rioting to protect their land, i.e. the main resource for their survival. Moreover, the effects of MNE on conflicts are shown to be present, in particular, in areas that were previously devoted to agriculture. Column 1 of Table 4, Panel A, 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.[55] Looking at column 1, 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. Anecdotally, they show that the impact multinationals' activity has on conflict is amplified in areas targeted for large-scale temporary or permanent land acquisitions.[56]

At the same time, the linear term *Land Deals* alone exhibits a negative correlation with conflicts, i.e. $\pi < 0$. This suggests, anecdotally, that in the absence of multinational affiliates, land deals may be associated with a reduction in conflicts. As discussed in the theoretical framework in section 3.1, this could be attributed to local firms involved in land deals potentially employing local workers, thus providing more or better jobs compared to multinationals, which may rely on foreign labor (Eweje, 2009; Cooke, 2014; Mohan, 2013). Alternative explanations could include the impact of infrastructure development promises. These promises can be believed or not, creating a situation of commitment problem (Fearon, 1995), as documented by Hufe and Heuermann (2017). If (incentive compatible) promises, often related to infrastructure (see Deininger and Byerlee 2011), are credible and honoured, local communities might benefit, leading to a decrease in grievances, as detailed in Appendix D.

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 MNEs 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. Therefore, if the channel described is true, when this *scarce* and *key* resource is detracted from the locals, often without compensation (Cotula, 2009), 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

[55] 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.

[56] Note that the *Land Deals* variable has a median of 0.0146 and its 95^{th} percentile is 0.382. In the median cell with 3 affiliates and a land deal share of 0.0146, the total effect of multinational affiliates on conflict would be 0.487.

for each of the four categories of violent events covered by the ACLED dataset: *riots*, *battles*, *explosions and remote violence*, *violence against civilians*.[57]

Interestingly, the only type 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.[58] 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.

Panel B of Table 4 further explores the mechanism behind the observed effects. It hypothesizes that the increase in MNE activity may provoke relatively more violent reactions in areas previously dedicated to agriculture. This could be a particularly relevant channel in contexts like the African continent, where consultation is often limited or absent and land tenure is weak (Nolte and Voget-Kleschin, 2014; Vermeulen and Cotula, 2013). Utilizing data documenting land use in the year 2000, I create a dummy variable, *Agr. Land Pre*, to identify cells where agriculture was significant before multinationals' arrival.[59] This approach mirrors equation (3), interacting *Agr. Land Pre* with the number of affiliates. *Agr. Land Pre* assumes a value of one when a cell's agricultural share in 2000 was above the average of cells with some agricultural activity.[60] Results are presented in Panel B of Table 4. Column 1 confirms our hypothesis, i.e. MNE activity tends to increase conflicts in areas that were significantly dedicated to agriculture. Column 2 further specifies that this effect is mainly due to localized violence, such as *riots*, aligning with Panel A's findings.

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[57] ACLED codes four categories of violent events. These four types of violent events represent the disaggregated version of the main dependent variable used in the paper. First, *Riots*, "violent events where demonstrators or mobs engage in disruptive acts, (...) may target other individuals, property, businesses, other rioting groups or armed actors". Second, *Battles*, defined as "a violent interaction between two politically organized armed groups at a particular time and location". Third, *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". Fourth, *Violence against Civilians*, "violent events where an organised armed group deliberately inflicts violence upon unarmed non-combatants".

[58] 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.

[59] *ISAM-HYDE* database (Meiyappan and Jain, 2012), aggregated at the cell-year level by PRIO-GRID. Selecting the year 2000 as a reference point enables the study of land use before the widespread increase in FDI across the African continent (World Bank, 2014; UNCTAD, 2009a,b).

[60] The distribution of this variable is particularly skewed, with a median below 3% and an average around 9%. About 22% of observations exceed the mean. Indeed, the validity of the results is upheld when replacing this variable with a dummy that represents cell-years in the top quartile of the distribution. Moreover, results are confirmed also if the dummy *Agr. Land Pre* is defined over the overall distribution and not with respect to cells with some agricultural activity in 2000.

Table 4: Land acquisition and localized violence

	(1)	(2)	(3)	(4)	(5)
Panel A					
Estimator	2SLS	2SLS			
Dep. Var.	Conflicts	Riots	Battles	Expl./Rem.	Viol. Civ.
Affiliates	0.160***	0.143***	-0.00175	0.00816	0.0152
	(0.0375)	(0.0246)	(0.00841)	(0.00957)	(0.00956)
Affiliates×Land Deals	0.352***	0.315***	0.0894**	0.0315***	0.0328
	(0.0573)	(0.0318)	(0.0364)	(0.0120)	(0.0352)
Land Deals	-0.601***	-0.116	-0.258*	-0.150***	-0.456***
	(0.188)	(0.0826)	(0.140)	(0.0338)	(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
Panel B					
Estimator	2SLS	2SLS			
Dep. Var.	Conflicts	Riots	Battles	Expl./Rem.	Viol. Civ.
Affiliates	0.0136	0.0533*	-0.0103	-0.000684	-0.0120
	(0.0282)	(0.0311)	(0.00713)	(0.00167)	(0.0239)
Affiliates×Agr. Land Pre	0.190***	0.126***	0.00943	0.0123	0.0294
	(0.0566)	(0.0467)	(0.0146)	(0.0147)	(0.0265)
Cell FE	Yes	Yes	Yes	Yes	Yes
Country×year FE	Yes	Yes	Yes	Yes	Yes
FP F	10.35	10.35	10.35	10.35	10.35
Obs	123,084	123,084	123,084	123,084	123,084

Notes: 2SLS estimation. Dependent variables: number of violent conflicts (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 3.2. *Land Deals* indicates the percentage of the cell covered by a large-scale land acquisition. *Agr. Land Pre* is a dummy variable assuming value one if the share of the cell devoted to agriculture in 2000 is above the mean of cells with some agricultural activity. 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 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*.[61] 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:

$$\mathit{issue}_{i,k,c,t} = \kappa + \psi \; \mathit{affiliates}_{k,c,t} + \bar{x}_{i,k,c,t} + f_{k} + f_{c,t} + e_{k,c,t} \tag{4}$$

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.[62] The dependent variable $\mathit{issue}_{i,k,c,t}$ 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, $\mathit{affiliates}_{k,c,t}$ 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$\times$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

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

[62] 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.

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 51) 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.

Table 5: MNE and locals' complaints about land management

	(1)	(2)	(3)	(4)
Estimator	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: binary variable taking value 100 if the respondent declares land to be one of the three main problems the government should address (columns 1 and 3); binary variable taking value 100 if the respondent declares farming/agriculture to be one of the three main problems the government should address. ***,**,* = 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 3.2. *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. Moreover, conflicts occur when the land was previously dedicated to agriculture. 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

This paper presents novel and systematic evidence for the effect of multinational enterprises on conflict. The analysis uses fine-grained global panel data on multinational groups, both at the headquarters and affiliate level, together with georeferenced data on violent conflicts in Africa. Multinationals' activity is found to have a positive and quantitatively important impact on conflict intensity. A battery of sensitivity tests confirms that the results are robust to a variety of alternative specifications and additional controls. This disaggregated study also sheds light on land expropriation as a potential mechanism through which the activity of multinational enterprises can lead to the escalation of violence. Suggestive evidence is presented that land-intensive industries have the largest impact on conflict. It is then shown that these effects are magnified in areas targeted for large-scale land acquisitions. The effects are shown to be particularly present in areas that were previously devoted to agriculture. The presence of multinationals threatens the primary local sources of food and income, thus increasing local grievances that often escalate into localized violent events. Finally, using individual-level data, it is shown that locals living nearby multinational activities are more likely to complain about the government's land management and agricultural policy.

A limitation of the current work is its focus on only the short-run effects of multinational activity. Future research should examine the medium- and long-run implications of this phenomenon, as well as the spillover effects in neighbouring areas. Another limitation of the proposed analysis is its reliance on non-comprehensive data on land deals. A promising direction for future research would therefore be to explore the interaction between multinational investment and more detailed data on the locations of land deals. Future research might also investigate the potential role of local firms in conflict dynamics in a causal manner.

Several policy implications emerge from the analysis. The intensive use of land is demonstrated to be a potential channel for the observed increase in conflict, which argues for the implementation of land governance reforms in developing countries. Implementation should be based on the Voluntary Guidelines on the Responsible Governance of Tenure (FAO, 2012) and the Principles for Responsible Investment in Agriculture and Food Systems (FAO, 2014). Second, the emphasis should be shifted to local development, with the goal of more inclusive land management that can be expected to reduce social tension. Third, continual monitoring is called for, both by government institutions and NGOs, which currently carry most of the burden. The monitoring should be public and transparent, such that actors engaged in large-scale investment projects will make information publicly available, with the goal of avoiding a situation of asymmetric information that might encourage social tension. Fourth, governments should link incentives, such as tax reductions or subsidies for multinational firms, to the fulfilment of the aforementioned conditions. Specifically, investments should adhere to international standards, and business strategies should prioritize positive spillovers to rural development, especially by including the local population. Finally, a firm commitment to transparency and active participation in monitoring initiatives should be mandatory.

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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

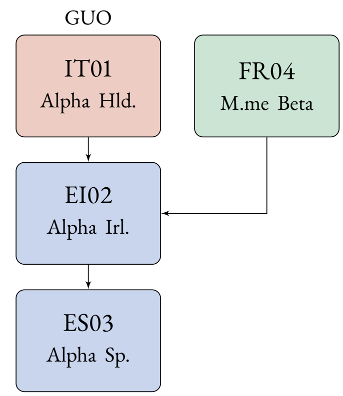
As far as the dataset on multinationals used in this work is concerned, I construct it as follows. First, I collect all ownership information in the *Historical Ownership Database* of Bureau van Dijk for years 2007-2018. The information of the database is stored in the form of binary links: each company 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).[63] 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.

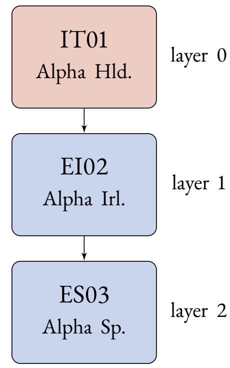
With this information at hand I can identify the perimeter of business groups. I define business groups as the set of all firms who share the same ultimate owner, including the owner itself. Since the focus of this research is on multinational business groups, I then drop groups that are

[63]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.

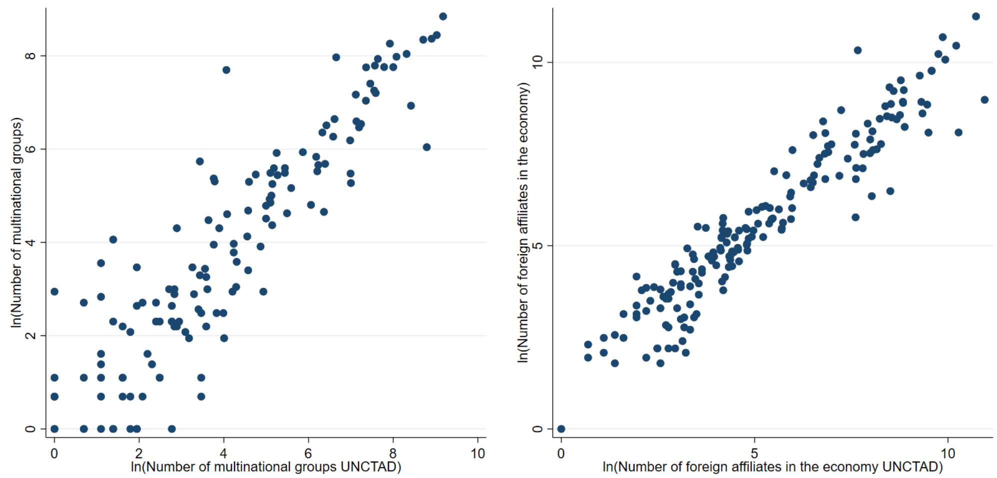
not multinational, that is, in this setting, groups whose entities are all located in the same country. At this point, I proceed by disentangling the hierarchical structure of groups. I divide the hierarchy into layers on the basis of the distance between the ultimate owner and the subsidiary. Ultimate 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.[64]

Figure A3: Data validation with UNCTAD (2011)



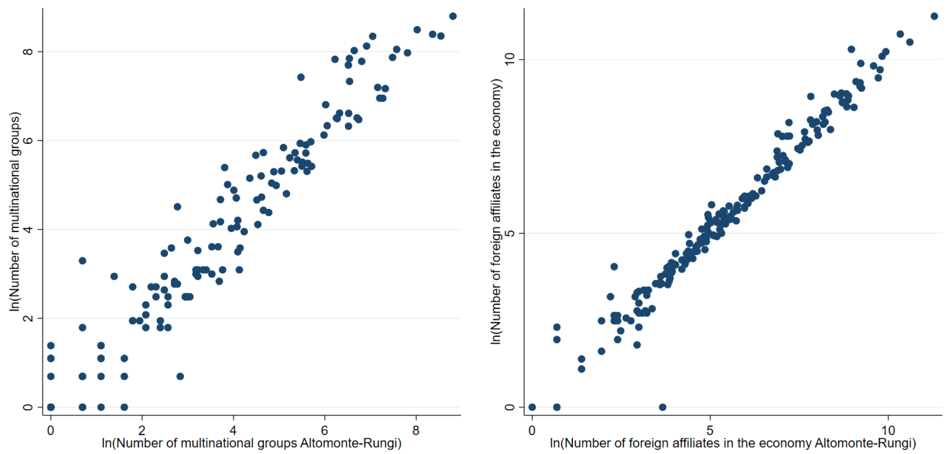
Notes: On the horizontal axis of the left panel we have the (log of the) number of MNE recorded in the UNCTAD (2011) dataset, and on the vertial axis the same variable, but from the dataset elaborated for this paper. On the right panel, the horizontal axis is again the (log of the) number of affiliates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

[64] 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.

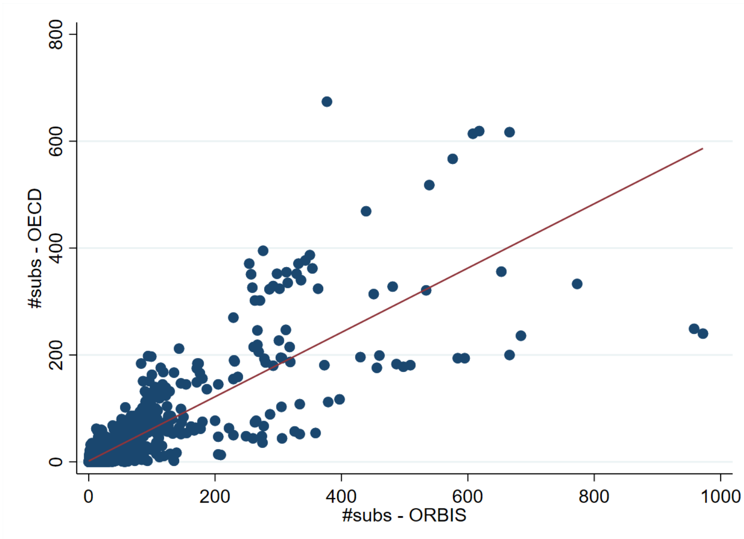
the official FATS only count subsidiaries with a turnover of more than 25 million dollars (and other dimensional prerequisites that *Orbis* does not have).

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

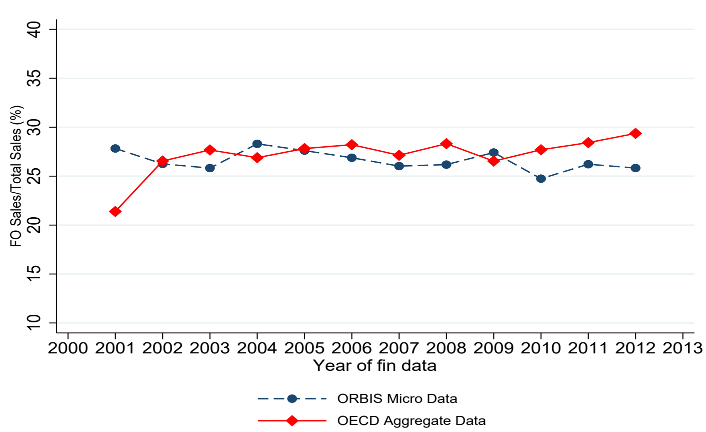
Multinationals' are geolocated from information included in the Bureau van Dijk (BvD) database (firms' country, region, city, and postcode). The reader could be worried that this information does not identify the actual affiliate's location, but potentially their legal offices. In other words, it could 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).[65]

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.[66] 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.

[65] 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.

[66] 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 3.2. The section *First stage* reports the coefficients of the first stage estimations. Kleibergen-Paap F-statistic are reported for columns 2 and 3.

B Data on land deals

In this section, we detail the information contained in the *LandMatrix* dataset and assess its validity and robustness.[67]

B.1 The *LandMatrix* dataset

LandMatrix is a global and independent initiative that compiles the only available multinational dataset on large-scale land acquisitions. As of now, it stands as the most comprehensive database on such acquisitions in the Global South (Giger et al., 2019). The database includes details about the location, size, development, legal status, purpose, stakeholders, and local impacts of each transaction. This wealth of information offers invaluable insights into the social, economic, and environmental effects of land utilization and ownership.

Due to the opaque nature of land acquisitions, providing a comprehensive and accurate figure of land deals worldwide is a complicated task (Schoneveld, 2014). The Land Matrix Initiative employs a range of sources for data collection, including central and local government records, media reports, academic studies, and reports from NGOs and other organizations. Moreover, researchers, activists, and stakeholders globally contribute by reporting new deals and providing additional information. This information undergoes cross-verification using land-specific documents, contracts, on-the-ground sources, satellite checks, and more. To enhance source proximity, the Initiative operates four Regional Focal Points (in Africa, Asia, Eastern Europe, and Latin America) and five National Land Observatories (in Argentina, Cameroon, Philippines, Senegal, and Uganda), where local partners supply direct information about deals. The sources are public, bolstering data transparency. Notably, among the listed variables in the *LandMatrix*, location and size are the most accurate, and reassuringly, these are the two aspects utilized in this work.

Figure A7 features two panels. The first is a line chart displaying the number of concluded land deals from 2000 to around 2020, segmented by region: Africa, Asia, Eastern Europe, Latin America, and Oceania. The second panel is a line chart depicting the area (in million hectares) of these land deals. In Africa, the first chart shows a marked increase in deals beginning around 2004, peaking in 2009, indicating a period of heightened acquisition activity. Though the number of deals declined after this peak, another surge occurred around 2011, followed by a gradual decrease. The second chart reveals significant peaks in African land coverage around 2009 and 2011. This data convergence highlights the significant impact of land deals in Africa, marked by

[67] I would like to extend my particular thanks to Christof Althoff for not only initially sharing the *LandMatrix* data but also for his ongoing support and advice regarding its content.

frequent transactions and extensive land coverage, positioning Africa as a key target for large-scale land investments during this period.

Figure A7: Number/Area of Concluded Land Deals by Year

Notes: The graphs show the number (top panel) and cumulative area (bottom panel) of land deals reported in each macro-region by year.

B.2 Validation

Considering the scarcity of comparable databases for Land Acquisitions, the accuracy of the *LandMatrix* database was verified using Google Earth Pro satellite images. For this purpose, 50 entries were randomly selected from the 183 land deals with precise coordinates. These were then cross-referenced with Google Earth to ensure compatibility with the information provided by *LandMatrix*.

B.2.1 Existence and location of land deals

Not all land deals result in visible changes observable from space, particularly those related to forest management, tourism, or natural conservation, where ground modifications may not be evident. However, for deals in agriculture or forestry, visible signs of intensive cultivation are expected. From our 50 randomly selected land deals, 36 met the criteria of (a) being active for at least a year and (b) being related to agriculture or forestry. Using Google Earth and coordinates from *LandMatrix*, we identified intensive farming or plantations in 28 out of these 36 deals (nearly 78%). This confirms that (i) the land deals occurred, (ii) were implemented, and (iii) the locations in *LandMatrix* are accurate. The remaining 8 did not meet one or more of these conditions.

B.2.2 Area of land deals from Google Earth

Among the 28 deals where intensive farms or plantations were observed, 16 cases featured establishments that were unique and clearly distinguishable from their surroundings. Under these conditions, we compared satellite images from different years to monitor the development and measure the area over time. This comparison revealed that the area measured from Google Earth aligns closely with the *LandMatrix* data, showing a correlation of more than 82%.

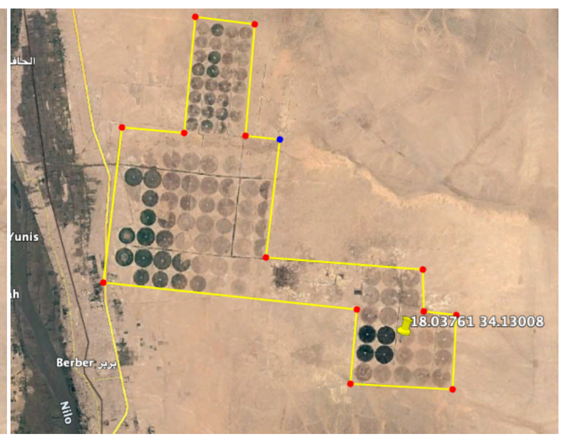
Figure A8 exemplifies this procedure. It traces the evolution of a land deal in Sudan near Berber (coordinates 18.03761; 34.18008). Initially, in 2008, the area was just desert. By 2010, 5,000 hectares of intensive farms had been established. This area expanded to 6,800 hectares in 2011, with further small expansions noted in 2014 and 2019 (not shown in the figure). Finally, by 2020, the productive area reached its peak at 10,100 hectares.

Figure A8: The Evolution of a Land Deal close to Berber, Sudan

(a) 2008 – 0 ha

(b) 2010 – 5,000 ha

(c) 2011 – 6,800 ha



(d) 2020 – 10,100 ha

Notes: Satellite images from Google Earth Pro in years 2008, 2010, 2011, and 2020 showing the evolution of an intensive farm close to the town of Berber, Sudan. The yellow pin marks the coordinates (18.03751; 34.13008) where Land Matrix reports a land deal operative from 2008.

C Additional descriptive statistics

In this section, I provide additional information on the data used in the paper. Table A2 disaggregates ACLED events. From a temporal perspective, the overall number of events increased by 390% over the years 2007-2018, after data cleaning as described in Section 2 (which included focusing on precisely located events and removing duplicates). This significant increase is confirmed when examining the period between 2000 and 2018.

Figure A9 shows the evolution of African affiliates (with location and industry information) and their headquarters (with balance-sheet information) around the world. This figure allows us to estimate that the number of African affiliates of multinational groups increased by 246% over the analyzed period.

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.

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.
Nightlights	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 milion 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).
Resources (dummy)	PRIO-GRID	Dummy variable indicating the presence of: primary (kimberlite) or secondary (alluvial) diamond deposits, placer gold deposits, vein gold deposits, surface gold deposits, gems deposits, onshore petroleum deposits. Defined before 2000.
Agricultural area	PRIO-GRID	Coverage of agricultural areas in 2000. *ISAM-HYDE* database (Meiyappan and Jain, 2012), aggregated at the cell-year level by PRIO-GRID.
Forest area	PRIO-GRID	Coverage of forest areas in 2000. *ISAM-HYDE* database (Meiyappan and Jain, 2012), aggregated at the cell-year level by PRIO-GRID.
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).

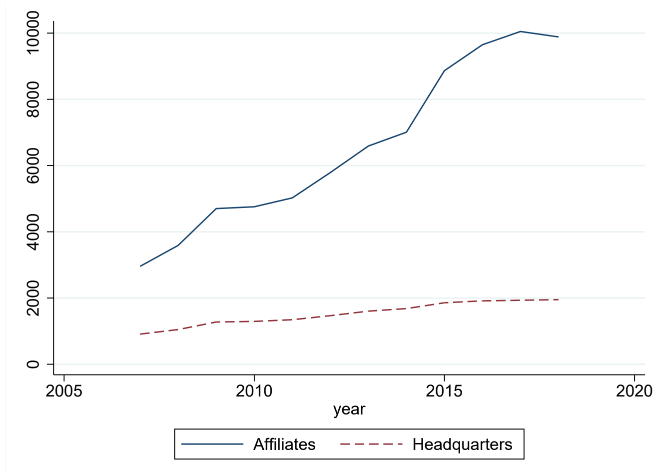
Notes: The table briefly presents the sources and a few characteristics of the variables not described in the paper.

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
Nightlights (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
Resources (dummy)	125,706	0.129	0.33	0
Land Deal	125,706	0.002	0.0274	0
Agr. Land Pre (dummy)	123,084	0.223	0.42	0
Agr. Land Pre	123,084	7.06	13.15	1.59
Forestry Pre	123,084	9.07	22.94	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 (section 3.4)	125,706	2.38	30.65	0
Alternative instrument (Appendix L, column 1)	123,084	54.26	79.40	11.56
Alternative instrument (Appendix L, column 2)	123,084	3.70	26.50	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.

Figure A9: African MNE affiliates and headquarters



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

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).

D Additional details on the setting

The framework described in section 3.1 enables us to analyze the impact of private investments on conflict, focusing on the dimensions of resource scarcity and the type, nature, and nationality of the firms involved. Two additional and important factors also warrant further consideration: the differential bargaining power of multinational versus local firms and the role of competition.

The two dimensions of the framework previously described (resource intensity and the effect on the opportunity cost of conflict, which depend on the nationality/type of firm) are not independent. For example, it is possible that a multinational firm has bargaining over a host country, potentially leading to a more intensive use of scarce resources. This can increase prices for locals (the *opportunity cost effect*, see, for instance, fixed-resources congestion models like Helpman, 1998), thereby elevating conflict probability.[68] Land-intensive MNEs, such as those involved in forestry and agriculture, can acquire land either through market purchases or government allocation (often as long-term leases). In the former case, increased market pressure can elevate land prices and conflict likelihood. Alternatively, MNEs may opt to acquire land with a transfer to the government, which then decides whether to share it with locals. This represents a forced reduction in the availability of the scarce resource, consequently decreasing the expected rents that can be extracted from it.

Both scenarios can be conceptualized within this framework. If the government chooses not to redistribute the transfer, leading to land expropriation, an increase in conflict probability is straightforward. Conversely, if the government redistributes the transfer received from the MNE, even in part, then conflict probability depends on various factors. For instance, if the government's compensation offer is incentive-compatible, informed by the locals' valuation of their land (such as expected agricultural production), and backed by fulfilment assurances, then conflict is generally avoided. However, conflict can still arise through channels such as asymmetric information or commitment problems (Fearon, 1995). For example, if the government cannot accurately assess the locals' attachment to the land, then the uncertainty may result in conflict. Similarly, if locals are unaware of the economic transfer amount from the MNE to the government and later discover its true value, then feelings of betrayal may incite conflict. This situation can also be viewed as a commitment problem in a multi-period framework, where conflict doesn't end the game but temporarily alters the transfer distribution, which is revisited in subsequent periods. For instance, the government might promise increased job opportunities in the future, and the locals' trust in the government's promise can play a role. For example, if people believe the

[68] In cases of expropriation, the price effectively becomes infinite due to the imposed quantity constraint.

promises there may be a temporary decrease in conflict. That trust is either confirmed or violated in the following period or reverted if promises are not kept.

Using the aforementioned framework, suppose there is an increase in MNE activity in a specific region. This may not alter the economic landscape significantly, in which case, the impact of MNE investment is ambiguous, hinging on the balance of forces characteristic of the framework. Conversely, the presence of domestic firms in the region or sector might mean that the entry of an MNE introduces additional competition. Notably, most local firms in developing countries are small and perform poorly (Tybout, 2000), unlike the highly productive and highly profitable "superstar firms" (Autor et al., 2020). These large and productive firms are more likely to withstand local competition, often leading to the exit of smaller local firms from the market(Melitz and Ottaviano, 2008). In this second scenario, the MNE effectively replaces the local firms. Given the same degree of resource intensity, the activities of both are identical, thus muting the rent channel. In this case, the effect of the MNE on conflict probability depends solely on the change in the opportunity cost of conflict, which is connected to the difference in job quantity and quality offered by domestic versus multinational firms, as described before.

E 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%).[69] 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.[70]

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.

[69] 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*.

[70] 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 $\times$ 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:

$$z_{k,c,t} = \sum_m s^m_{k,c,2007} \left(dep^m_{97-06} \times cre_{t-1} \right) \tag{6}$$

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 3.2.

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 3.2. 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 × size	0.0441***	0.0715***	0.0908***
	(0.0114)	(0.0180)	(0.0223)
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		34.04	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×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×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 E. The section *First stage* reports the coefficients of the first stage estimations. Kleibergen-Paap F-statistic are reported for columns 2 and 3.

F Quantification

In Section 3.3, we documented that the presence of MNEs' affiliates accounts for a significant 13.39% of conflicts during the analyzed period. The top graph in Figure A10, following the methodology outlined in footnote 37, further breaks down the proportion of conflicts explained in each African country. As anticipated, the figure reveals considerable heterogeneity: while the majority of countries have a share of explained events below 50%, there are 9 countries where this share notably exceeds this threshold.

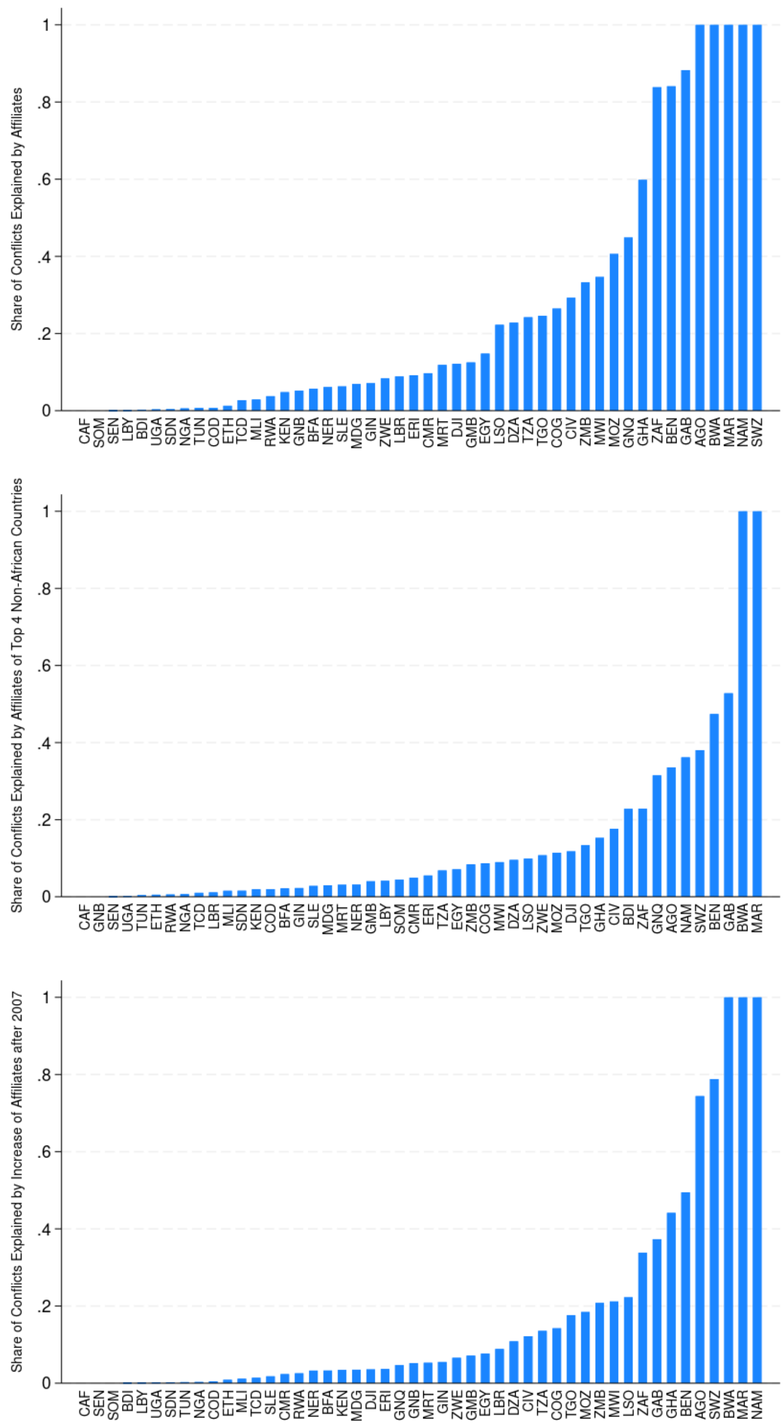
To gain a deeper understanding of this phenomenon, we analyze the influence of the parent company's nationality. As detailed in Section 2, the most common non-African headquarters are British, comprising 10% of affiliate-year observations, followed by American and French, each at around 8%, and German at 5%. The central graph in Figure A10 replicates the previous analysis, but focuses on affiliates with headquarters in these four countries.[71] The results indicate that affiliates from these top four non-African home countries account for 6.75% of the conflicts observed during 2007-2018.

Lastly, we aim to contextualize the previously obtained figure. The third graph in Figure A10 illustrates a country-level counterfactual scenario, assuming the number of affiliates remained unchanged throughout the period. Given the significant rise in affiliates reported in this study, it's pertinent to speculate on the predicted number of violent events if the count of multinational affiliates had stayed constant at the 2007 level.[72] In this hypothetical scenario, the proportion of events accounted for would be 6.30% of the total number of events, a figure similar to that of the previous counterfactual analysis.

[71] Technically, with respect to the steps detailed in footnote 37, we change the third step and use the observed number of affiliates minus the number of affiliates whose headquarters are located in these four countries to predict conflicts.

[72] Technically, with respect to the steps detailed in footnote 37, we change the third step and use the number of affiliates in 2007 to predict conflicts in all years.

Figure A10: Quantification



Notes: The figures depict the proportion of conflicts attributable to MNEs' affiliates by country. The top panel includes all multinationals; the central panel focuses solely on affiliates of British, American, French, and German parent companies; and the third panel is based on the assumption that the number of affiliates remained constant at their 2007 values throughout the entire period.

G 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 ($dep^{m}_{97-06} \times cre_{t-1}$) 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.[73]

Second, I address omitted variable concerns. As discussed in Section 3.2, 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.

[73] 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 3.2). *Average Simulated Instrument* indicates the average of 1,000 simulated (randomized) instruments, detailed in Appendix G. Kleibergen-Paap F-statistic is reported.

H Instrument validity

The 2SLS strategy presented in section 3.2 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 I, 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.

H.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).

H.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.

I Cell-level commodity import values and remoteness

In this section, I check the robustness of the main result with respect to import value shocks at the cell level. This is a particularly important test in order to check the validity of the exclusion restriction presented in section 3.2. 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.[74] 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.[75] 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:

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

where $\alpha_{p,k}$ is the share of agricultural commodity *p* in cell *k* and $M^{W}_{c,p,t} = \sum_{j \neq c} M^{W}_{j,p,t}$ 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-

[74] 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.

[75] 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.[76] 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.[77]

Table A11: Commodity import values 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 I) 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 3.2). Kleibergen-Paap F-statistic is reported.

[76] 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.

[77] 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.

J Alternative estimations

In this section, I test the robustness of the main result outlined in section 3.3 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.[78] As we can see, the coefficients are almost unchanged not only among each other, but also to the one in our main specification in 3.3, 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.

[78]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 3.2 together with a second instrument described in Appendix J in columns 1 and 2, with an instrument constructed by substituting the credit component of the instrument described in 3.2 with a measure of credit given to private firms specifically by the financial sector in column 3. Kleibergen-Paap F-statistic is reported.

K Event study

In this section, we present an event study analysis using the estimation procedure proposed by de Chaisemartin and D'Haultfoeuille (2022). This method is particularly suitable in our context as our treatment is both staggered and repeated.[79]

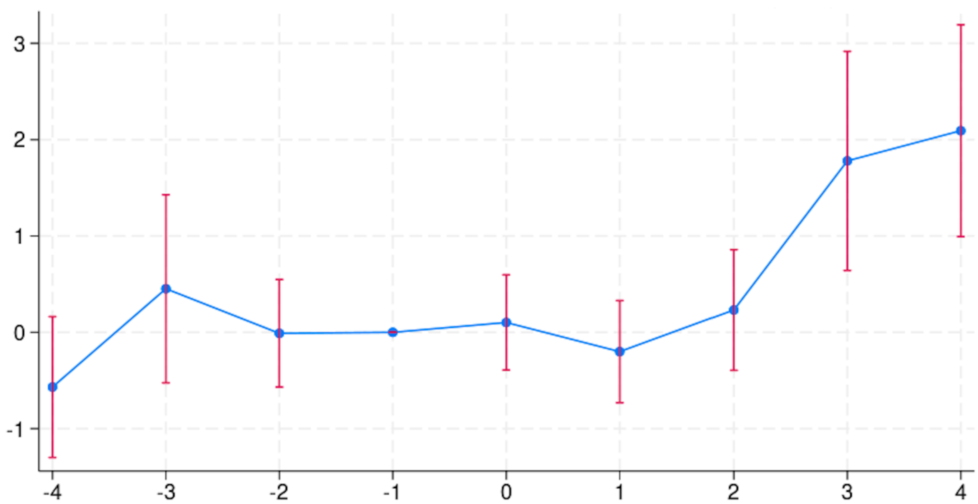
The treatment in our study is defined as the entry of at least one new affiliate into a cell within a given year. It's important to highlight that this analysis diverges from the one in the paper; there, we examined the effect of the *number* of affiliates in a cell-year. In contrast, in this context, we redefine the treatment as a binary variable indicating an *increase* in the number of affiliates for a specific cell-year.

The diagnostic test for negative weights, as outlined in de Chaisemartin and D'Haultfoeuille (2020), indicates potential issues with negative weights in this setting. Notably, negative weights are present in 13.56% of cases, and have a sum of -0.0855. Consequently, in the case of treatment effect heterogeneity, the estimate could be biased. Consequently, we employ the robust estimator from de Chaisemartin and D'Haultfoeuille (2022), i.e. Difference-in-Differences Estimators of Intertemporal Treatment Effects. I compute the treatment effect in three periods previous to the treatment (as a placebo) and five periods following the treatment (to allow for delays in treatment effect). Standard errors are determined through 500 bootstrap iterations.

Results are displayed in Figure A11. Reassuringly, this analysis reveals no pre-trends in affiliate presence before the treatment period, and it confirms a significant increase in conflicts following a rise in the number of affiliates in a cell. The main analysis in section 3.3 focuses on the contemporaneous effects and the intensive margin of affiliates' presence (the number of affiliates per cell-year). In contrast, the approach in this appendix uses a different treatment definition, specifically the *increase* in the number of affiliates. This difference may explain why, unlike the baseline results where a simultaneous effect is observed, here the escalation in conflicts occurs a few years after the increase in the number of multinational affiliates in a cell.

[79] Other estimators, like those from Callaway and Sant'Anna (2021) and Sun and Abraham (2021), are effective for staggered treatments but lack robustness in scenarios involving repeated treatments.

Figure A11: Event Study



Notes: The graph shows the estimated treatment effect and 95% confidence intervals using the robust estimators in de Chaisemartin and D'Haultfoeuille (2022). Events are defined as the entry of at least one new subsidiary in the cell. Difference-in-difference estimates from last period before treatment changes ($t = -1$) to t. Horizontal axis indicates time relative to time period where treatment first changes ($t = 0$).

L Alternative IV strategy

This section introduces an alternative approach to define the share for the shift-share design used in the IV strategy. This alternative method, detailed below, does not depend on data regarding the presence of specific business groups in a cell at the beginning of the period, thus potentially reducing bias in the shares for the 2SLS analysis. It estimates the likelihood of certain industries being active in each cell based on pre-period cell characteristics. However, it's limited in applicability to only a subset of industries due to reliance on geographical cell-specific characteristics. Therefore, while this method provides an important robustness test to the analysis, the preferred specification remains the one outlined in Section 3.2.

The analysis is limited to the industries of agriculture, forestry, and mining. This limitation is necessary as these sectors permit the determination of cell-specific suitability based on pre-period geographical cell characteristics. The weights for each cell are constructed as follows: the percentage of arable land (ISAM-HYDE) is used as the weight for the agriculture industry, tree coverage percentage (ISAM-HYDE) for the forestry industry, and a dummy indicating the presence of valuable resources (such as diamonds, gold, gems, petroleum, sourced from PRIO GRID) for the mining industry. All weights are defined in the year 2000, prior to the sample period.

In terms of shocks, I use a variant of the main instrument's shock, aggregated at the sector-year level. Specifically, the agriculture-year shock is constructed as a weighted mean of the group-year shocks (pre-period parent company vulnerability multiplied by the credit shock) for all groups with at least one African subsidiary in agriculture. The weight used is the number of subsidiaries each parent company has in the industry. A similar approach is applied to forestry and mining. To illustrate, consider Group A with two agriculture subsidiaries and one forestry subsidiary in Africa in 2010. The group-year shock for Group A in 2010 is counted twice in the weighted mean for agriculture and once for forestry, but not at all for mining.

Finally, by multiplying the cell-sector weights by the corresponding sector-year shock and averaging the three results, I derive cell-year instruments. The underlying idea is that credit shocks impacting groups specialized in agriculture are likely to influence the number of subsidiaries in cells well-suited for agriculture. A similar rationale applies to forestry and mining sectors.

Keeping all the remaining details of the empirical strategy equal to those of the baseline, column 1 of Table A13 presents the result of the 2SLS estimation using the approach described above. The result confirms the sign and the significance of the coefficient of interest. It is worth noting that the shares of this estimation strategy rely only upon geographical cell-specific pre-period characteristics. Therefore, the power of this instrument might be limited. For example, assuming two identical cells (as far as agriculture, forestry and mining characteristics are concerned) one next to a city and another one significantly far away, this strategy allocates the same likelihood of observing affiliates in both cells, while it is known that multinational firms are more likely to be active close to cities.

To improve the power of the IV strategy, the shares of cells where we never observe a multinational affiliate over the sample period are set to zero. It is worth underlying that, also with this modification, this alternative shift-share instrumental strategy is based on shares constructed without making any use of any multinational-specific allocation of affiliates, while it relies on similar shifters (despite being aggregated at the industry level) described in section 3.2. Column 2 of Table A13 reports the results of the second approach described above. As expected, the power of the instrument increased by almost 40%, and the sign and significance of the coefficient are confirmed. In terms of magnitude, the latter is roughly comparable with a replication of the main specification using the same set of affiliates used in this analysis. Indeed, replicating the 2SLS results of column 2 of Table 2 only for affiliates in agriculture, forestry, and mining, we would obtain a beta coefficient of 0.716, with a standard deviation equal to 0.318.

Table A13: Alternative IV Strategy Specification

	(1)	(2)
Estimator	2SLS	
Dep. Var.	Conflicts	
Affiliates	2.069**	1.000***
	(0.970)	(0.384)
Cell FE	Yes	Yes
Country×year FE	Yes	No
Instr = 0 cells with never MNE	No	Yes
KP F	4.26	5.92
Obs	123,084	123,084
First stage	0.00343***	0.0383***
	(0.00165)	(0.0157)

Notes: 2SLS estimations. Dependent variable: number of violent conflicts (ACLED). ***,**,* = indicate significance at the 1, 5, and 10% level, respectively. Controlling for: cell FE 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 Appendix L, using industry-specific shocks and shares defined from pre-period geographic characteristics of the cells. In column 2, the instrument is set to zero in cells where affiliates are never observed during the period. The section *First stage* reports the coefficients of the first stage estimations. Kleibergen-Paap F-statistic are reported at the bottom of the table.

M Local firms

This appendix is dedicated to the data and analysis with local firms. The main analysis is replicated using (different forms and lags of) local firms as control variables. Then, the main channel studied in the paper (use of land) is tested also with and for local firms.

Local firms 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).

M.1 The role of local firms

In section 3.4, the number of local firms (lagged by 1, 2, and 3 years) are used as additional controls in the main specification (rows 17, 18, and 19). In columns 1-3 of Table A14, we replicate these results but report 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 E, 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 4-6 of Table A14, I control for the number of affiliates in each cell-year multiplied by their size (see Appendix E for details on this procedure), lagged by 1, 2, and 3 years, respectively. As we can see, the results are confirmed. In columns 7-9, instead, I include as controls four variables counting the number of local firms in each of the four size categories. 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 on any causal interpretation of their estimating coefficients.

M.2 Local firms and land acquisition

As outlined in the theoretical framework in Section 3.1, both multinational affiliates and local firms might impact conflict in the context of land acquisitions. This section replicates the mechanism studied in Section 4, focusing on the role of local firms. Specifically, Figure A12 mirrors

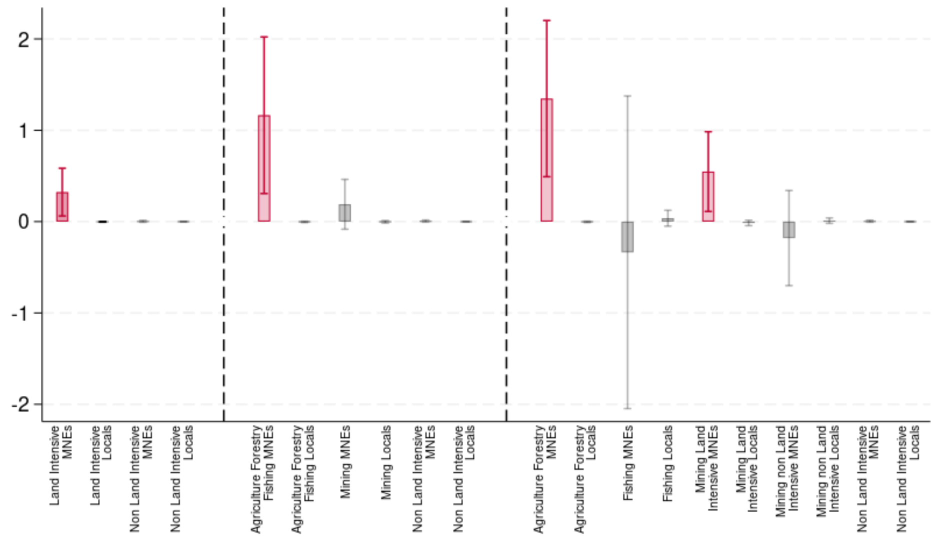
Table A14: Local firms

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Estimator					2SLS				
Dep. Var.					Conflicts				
Affiliates	0.188***	0.196***	0.191***	0.194***	0.197***	0.192***	0.197***	0.200***	0.201***
	(0.0422)	(0.0465)	(0.0450)	(0.0441)	(0.0464)	(0.0449)	(0.0454)	(0.0455)	(0.0454)
Local firms (lag 1)	-0.000201**								
	(0.0000969)								
Local firms (lag 2)		-0.000422***							
		(0.000117)							
Local firms (lag 3)			-0.000377***						
			(0.000112)						
Local firms $\times$ size (lag 1)				-0.000103**					
				(0.0000477)					
Local firms $\times$ size (lag 2)					-0.000160***				
					(0.0000419)				
Local firms $\times$ size (lag 3)						-0.000145***			
						(0.0000404)			
Local firm size 1 (lag 1)							-0.000605***		
							(0.000210)		
Local firm size 2 (lag 1)							-0.000157**		
							(6.32e-05)		
Local firm size 3 (lag 1)							0.00302		
							(0.00199)		
Local firm size 4 (lag 1)							-0.00306**		
							(0.00144)		
Local firm size 1 (lag 2)								-0.000185	
								(0.000464)	
Local firm size 2 (lag 2)								-0.00156*	
								(0.000818)	
Local firm size 3 (lag 2)								0.00239	
								(0.00160)	
Local firm size 4 (lag 2)								-0.00258**	
								(0.00108)	
Local firm size 1 (lag 3)									0.000632*
									(0.000373)
Local firm size 2 (lag 3)									-0.00209***
									(0.000739)
Local firm size 3 (lag 3)									0.000322
									(0.00126)
Local firm size 4 (lag 3)									-0.00144*
									(0.000863)
Cell FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country$\times$year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FP F	25.70	22.67	23.80	23.20	24.82	24.78	23.49	22.75	23.85
Obs	125,076	125,076	125,076	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$\times$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. This variable is instrumented in all specifications, details are explained in section 3.2. *Local firms* indicate the number of local firms (not belonging to a multinational company) in each cell-year. *Local firms $\times$ 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 about the size categories are explained in Appendix E. *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 all columns.

Figure 5 but includes local firms categorized similarly to multinational affiliates. The results, as shown in Figure A12, reveal significant effects only from multinational affiliates active in land-intensive industries, as previously identified in Section 4. T-tests confirm significant differences between coefficients for affiliates and local firms in various specifications. For instance, the p-value for the difference between *Land Intensive MNEs* and *Land Intensive Locals* is 0.04 in the first specification. In the third and final specification, the p-values for differences between *Agriculture Forestry MNEs* and *Agriculture Forestry Locals*, and between *Mining Land Intensive MNE* and *Mining Land Intensive Locals*, are 0.009 and 0.036, respectively. For clearer presentation, Figure A13 focuses solely on local firms, replicating the analysis from Figure 5, and reaffirms the same conclusions.

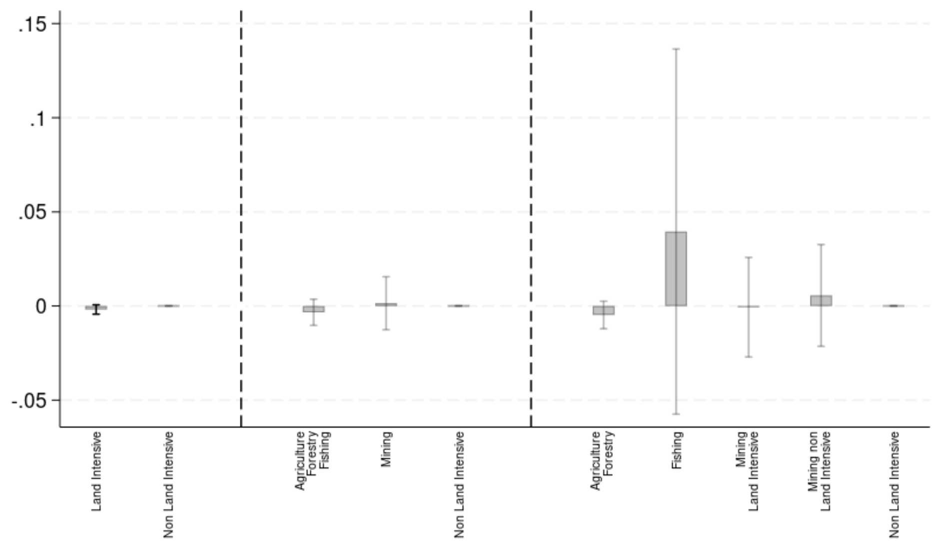
Figure A12: Industry heterogeneity - Multinational Affiliates and Local firms



Notes: The figure replicates the three OLS estimations described in section 4.1, including both multinational affiliates and for local firms. 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 local firms indicated below represents the number of affiliates or local firms belonging to that specific group in a cell-year (e.g. *Land intensive MNEs* represent the number of multinational affiliates belonging to land intensive industries - for details see Section 4.1 and Appendix Q). In each specification cell and country×year fixed effects are included.

Lastly, Table A15 replicates the main analysis for local firms, mirroring the mechanism studied for affiliates. Column 1, paralleling column 1 of Table 4, Panel A, examines the interaction between local firms and land deals, showing no significant correlation between the number of local firms, their interaction with land deals, and conflicts. Column 2, reflecting column 1 of Table 4, Panel B, finds no differential conflict effects in cells where agriculture was significant in 2000. Columns 3-6 extend this analysis using Afrobarometer data (detailed in Section 4.3), again finding no parallels to the positive relations observed with multinational affiliates and land management complaints. However, given potential endogeneity issues with local firm data, these findings should be interpreted cautiously.

Figure A13: Industry heterogeneity - Local firms



Notes: The figure replicates the three OLS estimations described in section 4.1, but for local firms. 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 local firms indicated below represents the number of local firms belonging to that specific group in a cell-year (e.g. *Land intensive* represent the number of local firms belonging to land intensive industries - for details see Section 4.1 and Appendix Q). In each specification cell and country×year fixed effects are included.

Table A15: Land deals and locals' complaints - Local firms

	(1)	(2)	(3)	(4)	(5)	(6)
Estimator	2SLS		2SLS		OLS	
			Issue:	Issue:	Issue:	Issue:
Dep. Var.	Conflicts		Land	Farm./Agric.	Land	Farm./Agric.
Local Firms	0.0000546	0.0000782	-0.000156	-0.000263**		
	(0.0000489)	(0.0000726)	(0.0000981)	(0.000129)		
Local Firms×Land Deals	0.0173					
	(0.0111)					
Land Deals	-0.798**					
	(0.355)					
Local Firms×Agr. Land Pre		0.0000512				
		(0.0000955)				
Land intensive local firms					-0.0251	-0.00245
					(0.0158)	(0.0121)
Non land intensive local firms					0.000343	-0.000220
					(0.000305)	(0.000326)
Cell FE	Yes	Yes	Yes	Yes	Yes	Yes
Country×year FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	No	Yes	Yes	Yes	Yes
FP F						
Obs	125,076	123,084	127,794	127,794	127,794	127,794

Notes: OLS estimation. Dependent variables: number of violent conflicts (columns 1 and 2); binary variable taking value 100 if the respondent declares land to be one of the three main problems the government should address (columns 3 and 5); binary variable taking value 100 if the respondent declares farming/agriculture to be one of the three main problems the government should address (columns 4 and 6). ***, **, * = indicate significance at the 1, 5, and 10% level, respectively. Controlling for: cell and country×year FE. Additional *Controls* include a set of individual-level variables (age, age squared, educational dummies, dummy for urban residence, dummies for religion, and 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. *Local Firms* indicates the number of firms affiliates in the cell that are not MNE affiliates. *Land Deals* indicates the percentage of the cell covered by a large-scale land acquisition. *Agr. Land Pre* is a dummy variable assuming value one if the share of the cell devoted to agriculture in 2000 is above the mean of cells with some agricultural activity. *Land intensive Local Firms* and *Non Land Intensive Local Firms* indicate number of local firms in land intensive (primarily industries) and non land intensive industries (secondary and tertiary industries), respectively.

N 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 A16, 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.

Given the count nature of the dependent variable, Table A17 presents IV Poisson estimation results. Due to computing power limitations, this estimation cannot include a large number of fixed effects. Column 1 displays results without any fixed effects. Country and year fixed effects are incorporated in columns 2 and 3, respectively. Column 4 includes both country and year fixed effects. The effect is confirmed as both positive and significant. Although these results cannot replicate the extensive fixed effects of the main specification, they, alongside other checks such as row 20 of Table 3 (where the main variable is replaced with a dummy), are reassuring about the robustness of the main finding.

Table A16: 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	Excl. Johan., Pret., Capet., Casablanca
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 3.2. 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.

Table A17: IV Poisson

	(1)	(2)	(3)	(4)
Estimator	IV Poisson			
Dep. Var.	Conflicts			
Affiliates	0.0169***	0.0489***	0.0164***	0.0461***
	(0.00117)	(0.00337)	(0.00114)	(0.00330)
Country FE	No	Yes	No	Yes
Year FE	No	No	Yes	Yes
Obs	125,076	125,076	125,076	125,076

Notes: IV Poisson estimation. Dependent variable: number of violent conflict (ACLED). ***,**,* = indicate significance at the 1, 5, and 10% level, respectively. Controlling for: country FE in columns 2 and 4, and year FE in columns 3 and 4. *Affiliates* indicates the number of MNE affiliates in the cell. The latter is instrumented with the instrument described in 3.2. Standard errors are clustered at the cell level.

O 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 A18, 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 A18: 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	

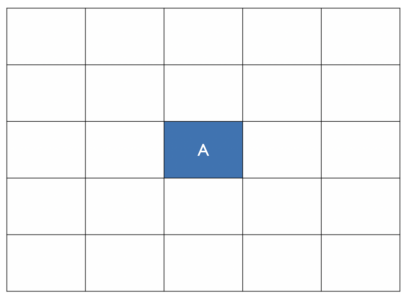
Notes: The table shows different standard errors of 2SLS estimations. Dependent variable: number of violent conflict (ACLED). ***,**,* = indicate significance at the 1, 5, and 10% level, respectively. Controlling for: cell and country × year FE. Conley (1999) standard errors in parenthesis at different 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 3.2. Kleibergen-Paap F-statistic are reported for each specification.

P Moran's I statistics

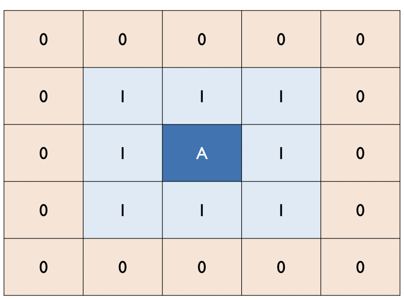
In this section, I first briefly review the methods used to perform spatial correlations, and then I present Moran's statistics for multinationals and conflicts data.

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:

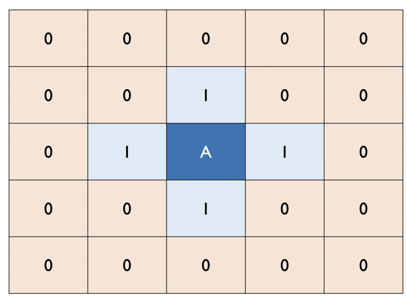
Figure A14: Spatial weight matrices



Base Map



Queen-distance band 1

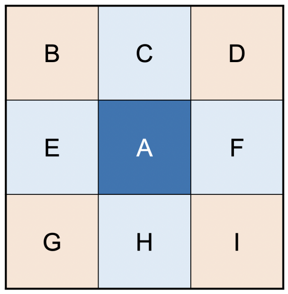


Rook-distance band 1

Hence, considering a smaller set of cells, the Rook 1 weights matrix is presented in Figure A15. 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 A15: 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

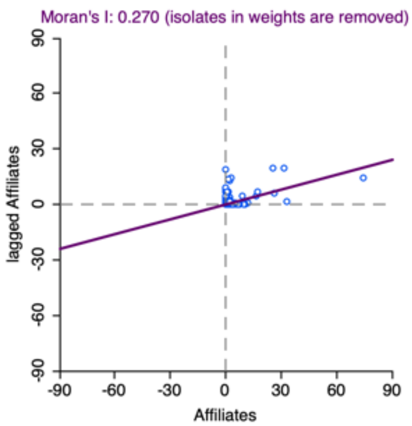
Moran's I Moran (1950):

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

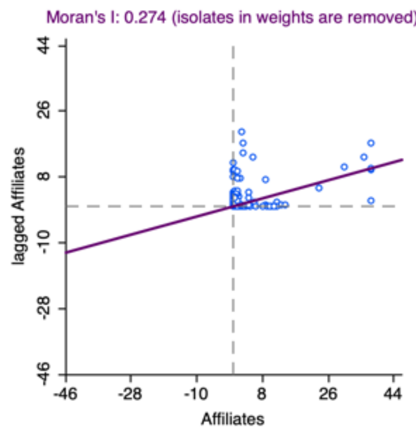
where $\bar{x}$ is the average, and w_{ij} is the element of the weight matrix for the couple (x_i, x_j). This index compares the value of the variable at any location with the value at all other locations. By construction $-1 < I < 1$. When I is close to 1 (-1) there is evidence of a strong positive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

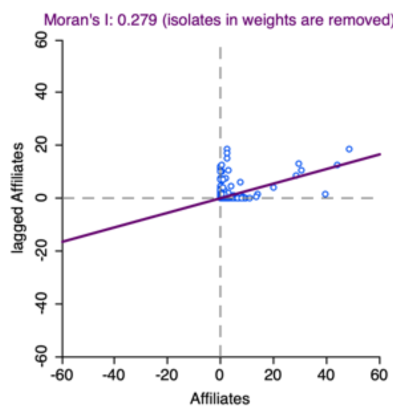
Figure A16: Rook 1 Moran's MNE



Year 2007

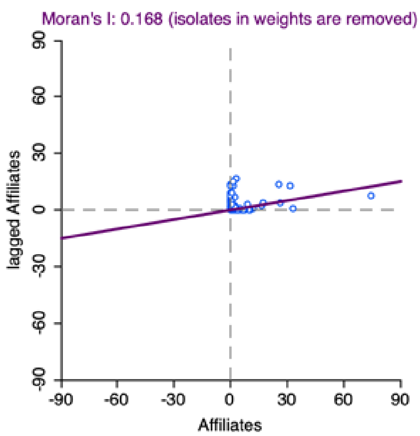


Year 2018

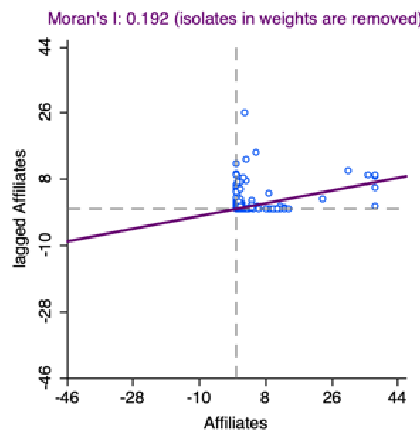


Average years 2007-2018

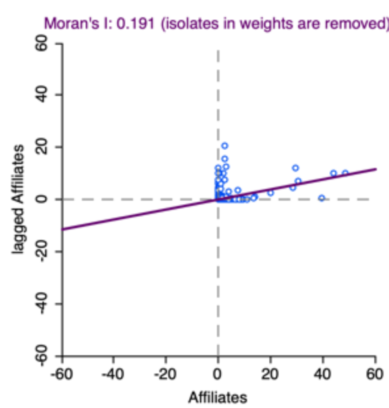
Figure A17: Queen 1 Moran's MNE



Year 2007

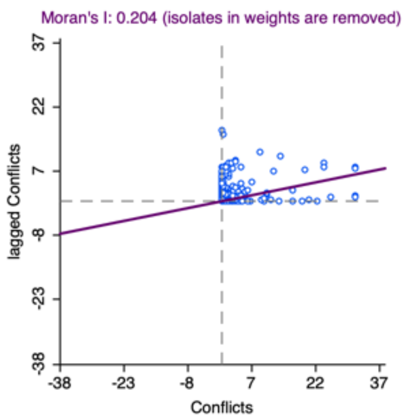


Year 2018

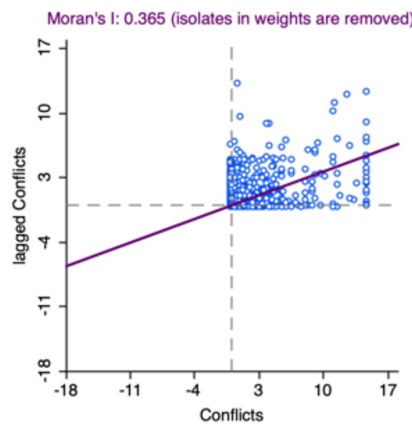


Average years 2007-2018

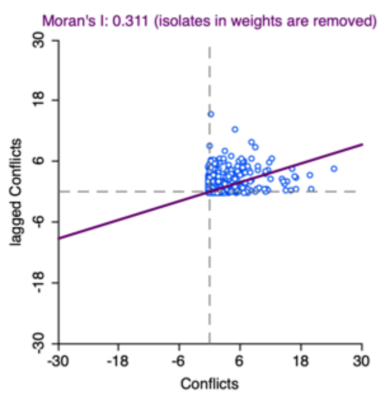
Figure A18: Rook 1 Moran’s Conflicts



Year 2007

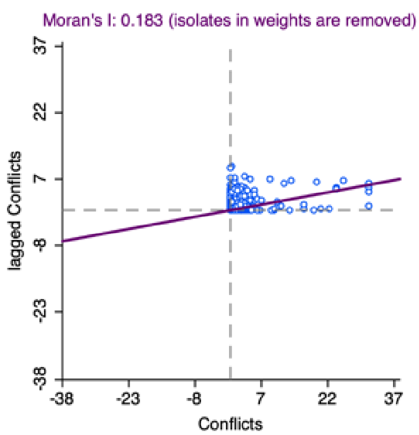


Year 2018

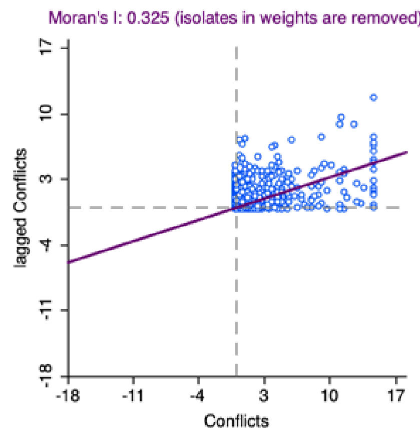


Average years 2007-2018

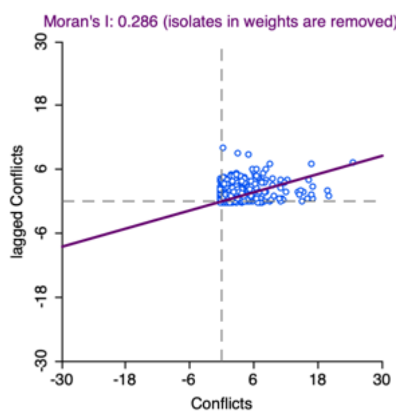
Figure A19: Queen 1 Moran's Conflicts



Year 2007



Year 2018



Average years 2007-2018

Q 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, A20, and A21.

Q.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 A19: Industry aggregation

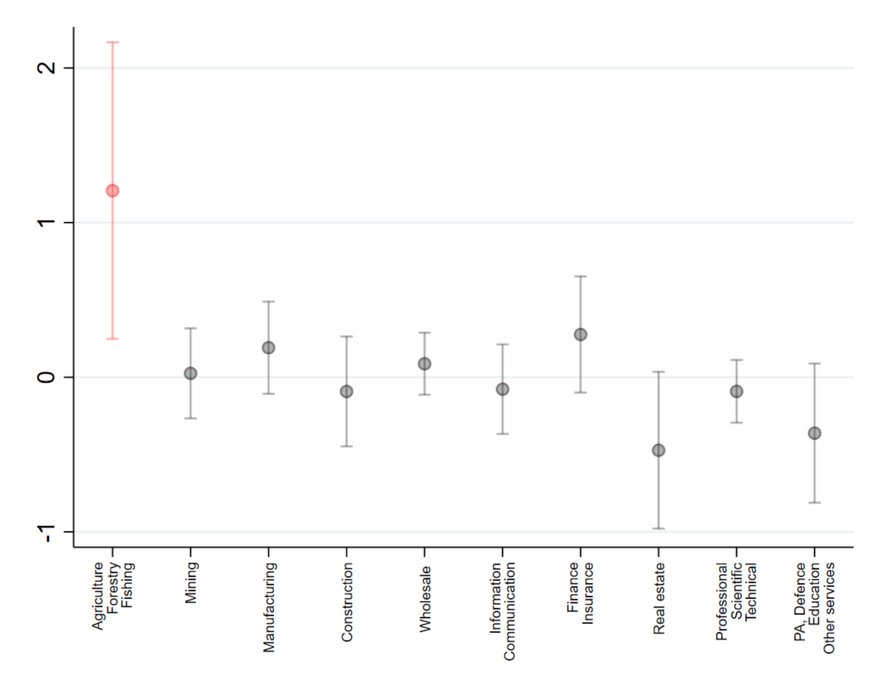
Industry
Agriculture, forestry and fishing
Mining and quarrying
Manufacturing and other industries
Construction
Wholesale and retail trade, transportation and storage, accommodation and food service activities
Information and communication
Financial and insurance activities
Real estate activities
Professional, 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).

Q.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 A20 shows that following the aggregation described above in Section Q.1, once again, the result on conflict is driven by the most land intensive industries.[80]

Figure A20: Alternative industries aggregation: 10 categories

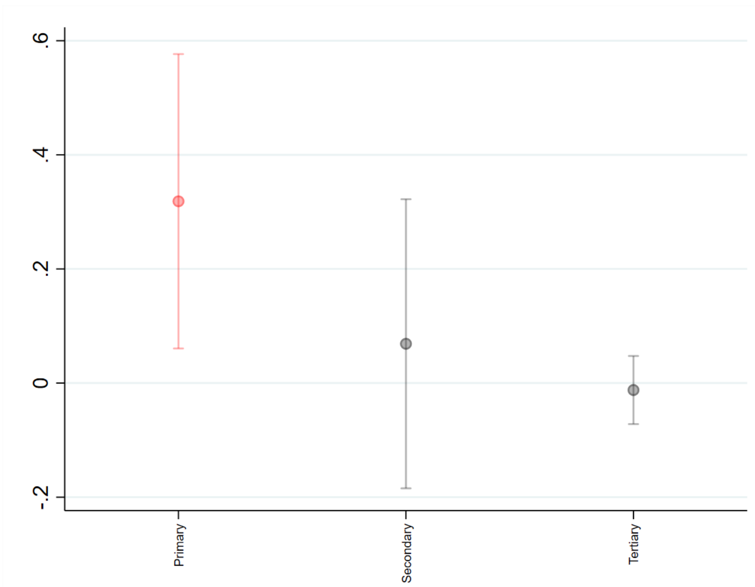


Notes: The figure reports the coefficients of an OLS estimation. Dependent variable: number of violent conflicts (ACLED). Controlling for: cell and country×year FE. Conley (1999) standard errors, allowing for spatial correlation within a 200km radius and for infinite serial correlation. Each group of 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 Q). In each specification cell and country×year fixed effects are included. The regressions' table of this Figure can be found in Appendix Q, Table A21.

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 A21 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).

[80]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 A21: Alternative industries aggregation: 3 categories



Notes: The figure reports the coefficients of an OLS estimation. Dependent variable: number of violent conflicts (ACLED). Conley (1999) standard errors, 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 Q). In each specification cell and country$\times$year fixed effects are included. The regressions' table of this Figure can be found in Appendix Q, Table A22.

Q.3 Additional tables

In this Section I include the regressions' tables which correspond to Figures 5, A20, and A21.

Table A20: 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 primary sector. *Non land intensive affiliates* indicates the number of MNE affiliates in the secondary and tertiary industries. The *Primary* 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 A21: Regressions' table for Figure A20

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 A22: Regressions' table for Figure A21

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.

R 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 A22: 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.