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Globalization and Conflicts: The Good, the Bad and the Ugly of Corporations in Africa

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Abstract
Using georeferenced data on the affiliates and headquarters of multinational enterprises together with georeferenced conflict data, this work is the first to establish a causal link between the activities of multinational enterprises and violence. The results indicate that activities which increase local human capital, such as education and health, decrease the probability of civil conflict, while the activity of sectors intense in scarce resources, in particular forestry, increases conflict. The increase in the likelihood of conflict is amplified especially in areas where the leading ethnic groups can place the burden of land deals on unrepresented groups.

Key words: multinationals, civil conflict, FDI, ethnic minority
JEL Codes: C23; D74; F23; L70; O13

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1 Introduction

This paper investigates the impact of multinational enterprises (MNE) on civil conflict. Although this is a key determinant of underdevelopment, the role of multinationals in triggering conflicts has received surprisingly limited attention in the literature. I tackle this question by merging geolocalized information on conflict events with novel data on MNE affiliates, and their headquarters, for all African countries from 2007 onwards. MNE activity is found to have significant and heterogeneous effects on the probability of conflict. In particular, activities that increase local human capital (e.g. education and health) significantly decrease conflict probability, while affiliates in exploitative sectors (e.g. those intensive in scarce resources, such as forestry) have the opposite effect. The increase in conflict caused by the activities of multinationals in exploitative sectors appears to be amplified where there are politically unrepresented ethnic groups. Berman et al. (2017) analyse the impact of mining on conflict. Among their results, they provide evidence that in the mining sector a larger presence of foreign firms amplifies the impact that mineral price shocks have on conflicts, while they find no statistically significant effect for domestic firms.[1] My empirical analysis expands this framework, focusing on all sectors of production, not only mining, but finding the same dichotomy between national and foreign affiliates of MNE.

The empirical analysis involves an original ad hoc dataset which combines two Bureau van Dijk datasets, *Historical Ownership Dataset* and *Orbis*, on the worldwide location and activities of both MNE affiliates and their headquarters with the *Armed Conflict Location Events Data (ACLED)* on the location and type of conflict events and the actors involved. The units of analysis are cells of 0.5×0.5 degree latitude and longitude (approx. 55km $\times$ 55km at the equator) covering the entire African continent. The use of georeferenced information, together with an instrumental variables strategy, country$\times$year fixed effects, and cell fixed-effects, permits causal identification. The unique dataset on multinationals overcomes measurement and endogeneity problems, and makes it possible to instrument MNE activities in a specific cell-year with several measures of the headquarters worldwide performance over time.

The cases of Liberia and Mozambique help illustrate the magnitude of the phenomenon investigated. Mozambique gained its independence from Portugal in 1975, after centuries of resistance, establishing the ideal of "la liberté de l'homme et de la terre" (freedom of man and land). Yet in April 2011, in the Nacala Corridor, in the north, Mozambique signed an ambitious and highly controversial trilateral cooperation programme, the ProSavana project, to promote "sustainable and inclusive agricultural development" together with Japan and Brazil. The project in-

[1] The authors distinguish between firms from a foreign colonizer country and firms from a foreign country with no colonial ties to the country where the mine is located.

volved well-known multinational agribusiness and logging enterprises, including the Portuguese Espirito Santo Group. The program targets 19 districts in three provinces, covering a total of 10.7 million hectares, of which 930,000 are cultivated annually by 692,000 rural families.[2] Case studies have accused this project, like many others, of violating local people's rights (e.g. expropriation of villages, threats to food security, intensive use of water depriving people in the surrounding areas) with little if any compensation, and often producing conflict situations.[3] More in general, there is a growing literature that points to the behaviour of private logging firms as a cause of violence. For example, see the exhaustive analysis of the Liberian case by Global Witness in its report Holding the Line (2017), which documents in detail all the links between local government, multinationals and large logging contracts, with the emblematic case of the multinational Samling Global.[4] On the other hand, we observe also cases of multinationals creating positive spillovers (Dhingra and Thenreyro, 2017), such as technology transfers, higher labour standards, or investments in education, therefore raising the value of the outside option for the local population with respect to criminal activities, thus decreasing the probability of conflict. For a detailed discussion, see the analysis of FDI spillovers in Sub-Saharan Africa proposed by the World Bank (2012).

The first part of this paper documents the correlations between MNE activities and conflict. A first finding is that only some specific types of MNE affiliate activity are correlated with the probability of conflict. This is demonstrated by exploiting variations in MNE presence over time at the cell level. The second part of the paper argues for the causal nature of the correlations found using an instrumental variable approach. Relying on the internal capital market literature, and exploiting the headquarter-affiliate credit link (Boutin et al., 2013), I instrument MNE activities at the local level using historical financial data at headquarters level and credit availability. More specifically, I interact pre-period headquarters dependence on external credit with credit availability in the headquarters' home countries, in order to obtain an exogenous variation

[2] The population of the target area was estimated at 4.3 million in 2011, most of them in rural areas and depending on agriculture for their subsistence. More specifically, the average rural household in the region has 5 members, so close to 3.5 million people in the area (more than 80% of total) live in the countryside and are engaged in agriculture. Note that small-holder farming is practised by 99% of all rural households in the region, the typical farm averaging 1.34 hectares in size (MASA, 2015).

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

[4] On top of the NGOs like Global Witness, other actors and movements active in reporting these violations are think tanks like the Oakland Institute, research projects like Environmental Justice (former EJOLT - Environmental Justice Organizations, Liabilities and Trade), financed by the European Commission and the European Research Council, or research centres like the Environmental Science and Technology Institute of the Autonomous University of Barcelona (ICTA-UAB) or Business and Human Rights.

of MNE activities over time. The intuition is straightforward: some affiliates, in any given cell-year, are part of a relatively healthy and robust multinational, not dependent on external credit, while others haved weaker parent corporations. The latter are expected to be hit significantly harder by the 2008-2009 credit crisis, and therefore to reduce their activities substantially more sharply. In the third part of the paper I provide evidence of a potential mechanism underlying the results. Indeed, the impact of MNE activities in the exploitative sectors on the likelihood of conflict is shown to be amplified in areas characterized by the presence of powerless ethnic groups, i.e. groups not represented in the local government. Using the *Ethnic Power Relations (EPR) Core Dataset 2018*, which gives information on the geo-localization of ethnic groups and their access to power, one finds that MNE activities play an especially important role in the probability of civil conflict in areas where the leading ethnic group(s) can place the burden of land deals on unrepresented groups.

This paper makes three main empirical contributions. First, this is the first systematic study of the impact of multinational enterprises on civil conflict. Second, to my knowledge, it is the first paper that instruments MNE activities using the headquarter-affiliate ownership link. Third, it presents an original dataset mapping the worldwide population of MNE affiliates and headquarters in a panel framework. Moreover, it also provides a potentially generalizable rationalization for the different effects in different sectors, with a clear link with the literature on ethnic conflict.

The paper is organized as follows: section 2 discusses the existing evidence and the conceptual framework. Section 3 describes the data. Section 4 presents the empirical analysis. In section 5 a potential mechanism is examined. Section 6 concludes.

2 Existing evidence and conceptual framework

2.1 Evidence

In the last decade the literature has debated the complex link between trade and conflict. Examining both international and domestic conflicts, a first cluster of papers use country-level aggregate trade data (imports plus exports) as the measure of trade.[5] However, global value chains now represent the main mechanism of international trade, in which multinationals are the main players.

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

Despite this predominant role, significantly less attention has been paid to the relation between foreign direct investment (FDI) and conflict. Polachek et al. (2012) develop and empirically test a two-country, one-period model, with homogeneous multinationals, showing that FDI can improve international relations. This result is confirmed empirically by Bussmann (2010).[6] Morelli and Sonno (2017) show how country-level asymmetries in foreign value added,[7] a proxy for global value chains, can be relevant in conflict analysis.

Recent works use disaggregated data to study the determinants of intra-state conflicts. These works seek to avoid country-level aggregation so as to overcome the attenuation bias implicit in loss of within-country variations. Dube and Vargas (2013) exploit exogenous price shocks in international commodity markets to assess how different income shocks affect conflict, finding that a sharp fall in coffee prices lowers wages and increases violence more sharply in municipalities where more coffee is cultivated. On the other hand, a rise in oil prices increases both municipal revenue and violence differentially in the oil regions. Two works study the role of multinationals in violence, one on conflict and one on protest, but both on the mining sector alone. Berman et al. (2017) analyse the impact of mining on conflict. My own empirical analysis essentially expands their framework, in particular focusing on all industries, not only mining, and relying on a different identification strategy. The authors use exogenous variations in world prices to document a significant and sizeable positive impact of mining on conflict at the local level. Particularly interesting for this work, among their results the authors also provide evidence that in the mining sector a larger presence of foreign firms, defined as firms with headquarters not located in the former colonial power, amplifies the impact that mineral price shocks have on conflicts, while they find no statistically significant effect for domestic firms. Moreover, they show that the higher the share of foreign companies which are members of networks promoting Corporate Social Responsibility in the mining industry, the lower the probability of conflict. Christensen (2018) finds that the probability of protest is twice as great in the case of foreign mining investment. The intuition is that in a setting of asymmetrical information, when communities' expectations exceed what mining companies can pay, protests result.

To the best of my knowledge, the literature offers no systematic analysis studying the impact of MNE activity, in all industries, on conflict. This paper has the additional advantage of overcoming one of the main limitations of the proximity-concentration trade-off literature[8] by using

[6] FDI sales are used in these works as a proxy of MNE activities, owing to the lack of data on the actual location of MNE affiliates.

[7] Foreign value added indicates how much one country's exports depends on other countries' inputs.

[8] This strand of work focuses on the implications of the firm's choice between FDI sales and arm's-length trade in deterministic models. See Markusen (1984), Brainard (1997), Helpman et al. (2004).

actual MNE affiliate activity rather than FDI shares (used as a proxy in the past owing to the lack of a database of physical presence of affiliates).

2.2 Conceptual framework

A simple framework describing the individual decision to engage in conflict can help formalizing the possible mechanisms at work. I adapt Becker (1968) to individual choices between employment in either a productive sector or a violent sector, depending on whether wages exceed the return to violent activity. This framework can be applied to the civil war context if conflict is conceptualized as a tool for violently siphoning resources from the economy (civil war arises from theft, as in Grossman, 1999). The utility in case of conflict is equal to:

$$U_C = pr - (1-p)c - m$$

where p is the probability of winning the conflict; r is the appropriable rent; c is the absolute value of the cost of losing the conflict; m is the absolute value of the cost of conflict. On the other hand, the utility of working activity is equal to:

$$U_W = \alpha_l \, l + \alpha_\omega \, \omega$$

where l is the income from land; ω is the income from non-land activity (i.e. a proxy of education and/or human capital); α_l and α_ω are parameters in $[0, 1]$ reflecting how much the individual (i.e. the relevant ethnic group) is represented in the government.[9] Therefore, conflict occurs if and only if:

$$U_C \geq U_W$$

Without losing generality, we can assume U_C to be equal for all individuals in the same area,[10] and hence can be controlled by cell fixed effect. In Appendix A the framework presented above is represented graphically, and simple comparative statics are described. The following hypotheses arise:

Hypothesis 1: MNE activity in sectors that reduce land income (l) increases the probability of conflict; activities that increase the income from non-land-intensive activity (ω) decrease the probability of conflict.

[9] For example, in the case of land expropriation, you can think of α_l as $\alpha_l = 1 - e + k$, where e is the fraction expropriated by the government and $k \leq e$ is the government compensation. More generally, you can think of informal taxes (τ), e.g. $\alpha_\omega = 1 - \tau$.

[10] For example, p can indicate the pushback of the government, c the legal/physical strictness rebels are subjected to by local authorities; m the cost of buying weapons to trigger conflict; r the appropriable rent from the area and from gaining power. Allowing r to depend on either $(l, \omega, \alpha_l, \alpha_\omega)$, leaves the results qualitatively unchanged. See Appendix A.

Hypothesis 2: The less individuals are politically represented in the government, α_i with $i = \{l, \omega\}$, the higher the probability of conflict.

3 Data

3.1 Data description

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

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. The sample period is 2007-2015, 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. Information is also provided on the precision of the geo-referencing of the events, which is at least the municipality level in more than 96% of the cases and even finer (town or village) for more than 80%. Following Berman et al. (2017) the only events considered are those that are geolocalized with the finer precision level, and I drop duplicate events.[12] ACLED uses several sources, including press accounts from regional and local news, humanitarian agencies and research publications. I aggregate the data by year. A dummy variable is constructed which equals 1 if at least one conflict happened in the cell during the year. This represents the cell-specific conflict incidence. As in Berman et al. (2017) and previous works using the same methodology, this is my main dependent variable throughout the paper. 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.

Multinational enterprise data. To my knowledge this is the first systematic study of the actual decisions of multinationals to locate affiliates in foreign countries, covering all sectors and all

[11] See e.g. Berman et al. (2017), Besley and Reynal-Querol (2014), or Michalopoulos and Papaioannou (2016) for papers using similar grid-cell level data and combined with the same conflict data.

[12] This cleaning choice does not affect the dependent variable, which is conflict incidence.

countries of the world, in a panel setting. The main constraint of any analysis studying the trade-off between exports and opening an in-country affiliate has been the "dearth of internationally comparable measures of the extent of FDI across both industries and countries" (Helpman et al., 2004, pp. 306). In this paper I overcome this limitation using a novel algorithm. Two different sorts of data are combined: worldwide ownership connections (provided by the *Historical Ownership Database* by Bureau Van Dijk) and firm-level financial accounts (from *Orbis* by Bureau van Dijk). The first dataset provides daily information on ownership of all firms connected through an ownership link, for the entire world, from 2007 onwards.[13] The second dataset provides full financial statement information, the industry (to 4 digits), and additional data such as the location of the firm (latitude and longitude, or zip code). Having defined a multinational as a combination of firms with autonomous legal status under some form of hierarchical control, I define control according to international standards for multinational corporations (OECD, 2005; UNCTAD, 2009b; Eurostat, 2007), i.e. a parent-company holding (directly or indirectly, i.e. via another subsidiary) of the majority (50.01%) of voting rights of the affiliate, making it the ultimate controlling institution or beneficial owner. This methodology allows the key distinction between domestic and foreign affiliates. Domestic affiliates are defined as those located in the same country as their headquarters; foreign affiliates are located in a different country. I validate panel dataset obtained for this paper with the cross-sections available in the literature (UNCTAD, 2011; Altomonte and Rungi, 2013; Rungi et al., 2018; Altomonte et al., 2018). The correlations are on average above 97%. See Appendix B for a detailed description of the MNE data and its validation. I focus on the subset of affiliates located in Africa and their relative headquarters around the world. The final sample covers 52 countries and the MNE affiliates operating in these countries, with information on location and sector of activity. Knowing the geolocation of each affiliate, I aggregate them at the cell-year level. A limitation of the data is the poor coverage of affiliates' financial information. That is, I have full balance-sheet data for the headquarters, but for the affiliates I cannot deduce useful information - even, say, their size. I record only where and when they are active. Presence thus serves as a proxy for MNE activity.[14]

Ethnic groups data. I use the *Ethnic Power Relations (EPR) Core Dataset 2018* (Vogt et al.,

[13] For example, it will report that, from a give date onward, firm A is owned (directly or indirectly, see details in Appendix B) by firm B, for 60%.

[14] The low coverage of affiliates' balance sheet information might decrease the estimations' precision. However, the majority of MNE sectors which will be key in the analysis (i.e. forestry) will have an impact on conflict through their presence in a specific area. In other words, land-grabbing activity can be independent of the number of employees in the local affiliate. Future research could integrate balance sheet information to verify whether the intensive margin of affiliates' activity (e.g. size) has a role on determining conflict likelihood, and also if this effect is heterogeneous depending on MNE sectors, as just discussed.

2015). It contains information about all politically relevant ethnic groups and their access to state power in every country of the world from 1946 to 2017. The data comprise politically relevant ethnic groups for each country, their relative size as a share of the total population, and their access to executive state power. Furthermore, I have geo-localized these data merging the EPR group-year data with the spatial information contained in the *GeoEPR 2018 dataset*. Finally, using a geographic model of intersection algorithms in Qgis, I have constructed a dataset cell-year-group in which all main information about each ethnic group in one cell-year is contained.

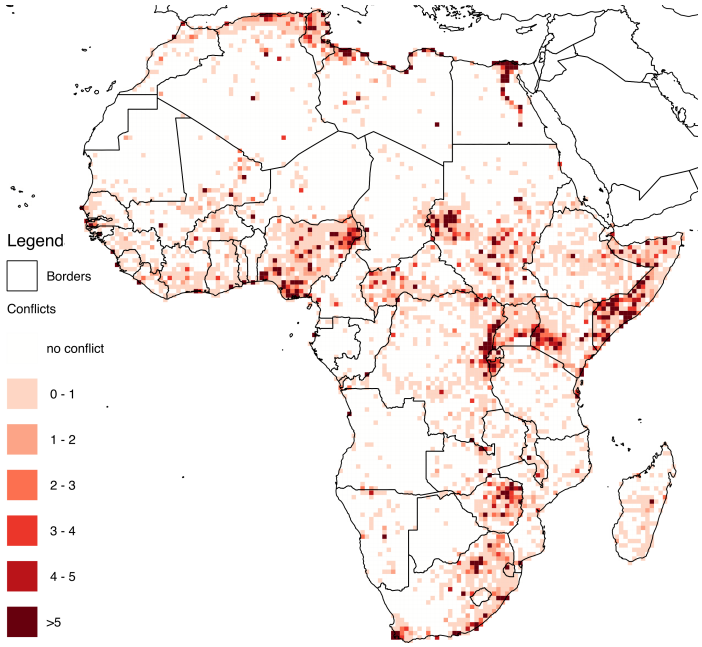
Other data. For population data I use data from *LandScan*.[15] This dataset has information about the population living in 30-arc second cells (that is approximately 1 km^2 near the equator). Clearly, the dimension in km^2 of these cells is not constant, as cell width varies with latitude of the cell. 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. 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 certain rasters inside certain zones, defined as polygon layers, in this case, PRIO-GRID cells. Finally, a number of cell-specific data are added, including climate (rainfall and temperature), distance from the border, and whether the cell is in a capital city.

3.2 Descriptive statistics

Table 1 reports some descriptive statistics. Figure 1 and Figure 2 show maps with averages over the period. We observe over 10,000 cells in 9 years. A few elements are worth mentioning. First, the unconditional probability of finding a conflict in a given cell and a given year is low, around 10%. In most cells no conflict event occurs during the entire period. The probability of observing a foreign MNE affiliate is also very low, at 2%, and domestic MNE affiliates are even rarer, at the cell-year level of 1%. Second, affiliates tend to be spatially clustered: conditional on observing at least one affiliate in a cell, the average number of affiliates is 12.95 and 15.71, respectively, for foreign

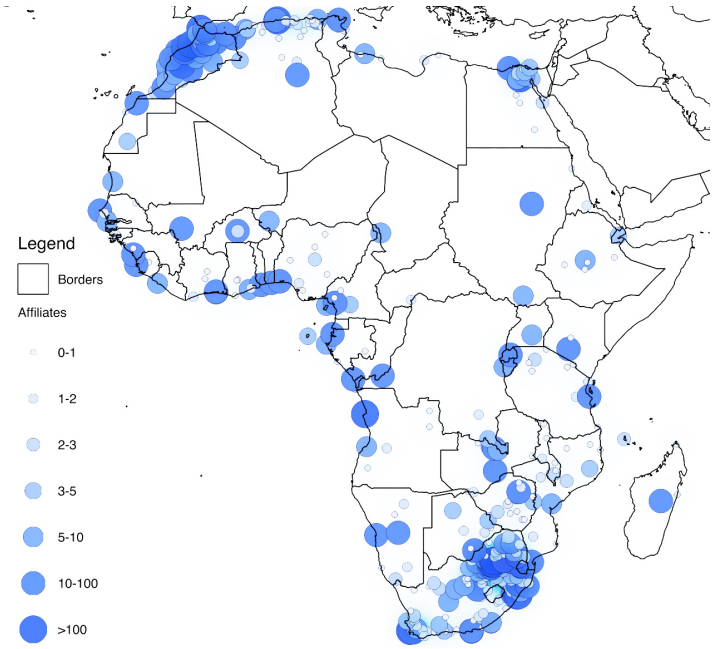
[15] This product was made utilizing the LandScan (2006-2015)™ High Resolution global Population Data Set copyrighted by UT-Battelle, LLC, operator of Oak Ridge National Laboratory under Contract No. DE-AC05-00OR22725 with the United States Department of Energy. The United States Government has certain rights in this Data Set.

Figure 1: Conflict events



Notes: The map shows the average number of conflicts (ACLED) in each cell over the years 2007-2015.

Figure 2: MNE affiliates



Notes: The map shows the average number of MNE affiliates in each cell over the years 2007-2015.

and domestic. Finally, conflict probability is much higher in cells with at least one MNE affiliate, around 51%.[16] Of course, these descriptive statistics do not take into account key variables at the cell-year level, such as population, something which is dealt with in detail in the empirical analysis. Appendix C presents additional statistics for the conflict and the MNE data. In the

Table 1: Descriptive statistics

		Obs.	Mean	S.D.	Median
Conflict					
	Prob. conflict > 0, all cells	92,995	0.10	0.30	0
	Prob. conflict > 0, if affiliates $= 0$	90,501	0.09	0.28	0
	Prob. conflict > 0, if affiliates > 0	2,494	0.51	0.50	1
	# conflict, all cells	92,995	0.66	9.02	0
	# conflict, if conflict > 0	9,166	6.70	28.03	2
MNE					
	Prob. foreig affiliate > 0, all cells	92,995	0.02	0.15	0
	# foreign affiliate > 0, all cells	92,995	0.28	4.81	0
	# foreign affiliate > 0, if affiliate > 0	2,030	12.95	29.93	2
	Prob. domestic affiliate > 0, all cells	92,995	0.01	0.12	0
	# domestic affiliate > 0, all cells	92,995	0.21	5.45	0
	# domestic affiliate > 0, if affiliate > 0	1,247	15.71	44.38	2

Notes: Author's computation from ACLED and the MNE dataset elaborated for this work. There dataset is composed of 10,333 cells in a panel from 2007 to 2015. Affiliates with headquarter in their same country are defined domestics affiliates, otherwise foreign affiliates.

sample period the ACLED dataset records 61,626 conflict events. Table A3 shows descriptive statistics at the event-day level, and then aggregates the data at the cell-year level.[17] As we can see, more than 85% of cells where at least one conflict was reported show at least one violent event. As stated by the ACLED's codebook itself, "a politically violent event is a single altercation where often force is used by one or more groups for a political end, although some instances - including protests and non-violent activity - are included in the dataset to capture the potential pre-cursors or critical junctures of a conflict". Even if the preferred specification includes all events in order to capture key developments leading to conflicts, the sensitivity analysis shows that all results are robust to dropping non-violent events and that there is no specific type of event driving the results. Figure A5 shows annual aggregates of the number of MNE affiliates and headquarters in the African sample. The rate of growth of the number of affiliates drops sharply owing to the

[16] And 53% for cells with at least one foreign MNE affiliate (obs. 2494).

[17] Conditioning on observing a conflict event (9,166 cell-year observations), the median number of conflicts is 2, as shown in Table 1, while at the 25^{th} and 75^{th} percentiles the number of conflicts events are respectively 5 and 23. Among all cell-years (92,995 observations), the percentage of cells with always peace is 69% (standard deviation 0.46), while that with always conflict is 1% (standard deviation 0.10).

crisis. Before 2009, the average rate of growth of African affiliates was 19%,[18] but it halves after 2009. The 31% jump in 2015, after years of growth below 10%, is subject to robustness checks, to make sure that the overall results are not driven by this single sharp increase.

4 Impact of multinationals on conflict

In this section the heterogeneous effects that MNE activity has on the probability of conflict are examined. The correlations between the variables are presented and an instrumental variable approach is proposed to overcome endogeneity problems and to demonstrate causality.

4.1 Correlations

First, following Berman et al. (2017), let us estimate a specification of the following form:

$$CONFLICT_{k,t} = \sum_{s \in S} \beta_s \times Affiliates^s_{k,t} + FE_k + FE_{c,t} + \gamma X_{k,t} + \epsilon_{k,t} \quad (1)$$

where (k, t, r) denote respectively cell, year, country (or region), s indicates the sector, FE_k are cell fixed-effects, $FE_{c,t}$ is an additional battery of fixed effects that can vary at different levels depending on the specification (e.g. country×year, region×year),[19] X_{kt} are time-varying controls that always include the number of affiliates of domestic headquarters. The dependent variable, $CONFLICT_{kt}$, is violent events at cell-year level, violence being measured in terms of incidence, i.e. a binary variable coding events in the ACLED dataset as non-zero. The main explanatory variables, namely the vector of covariates $Affiliates^s_{kt}$, are the number of foreign MNE affiliates in each sector in 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 HAC correction allowing for both cross-sectional spatial correlation and location-specific serial correlation, applying the method developed by Colella et al. (2019), who elaborating on Conley (1999) 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.[20] The first column of Table 2 shows the

[18] 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).

[19] Border cells are assigned to the country or region that represents the largest share of their territory.

[20] 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 500km is set for the spatial kernel - close to the median internal distance in my sample of African countries according to the CEPII geodist dataset, and following other works in the literature (Berman et al., 2017).

correlations between sectoral MNE activity (number of affiliates) and conflict probability in the full sample.[21] Exploiting the within-cell variation of affiliates, we observe that: activity in the *Forestry* and *Professional, scientific, technical, administration and support service activities* sectors is positively and significantly correlated with conflicts;[22] while activities in *Education, human health and social work activities*, *Public administration and defence*, and *Other services* are negatively and significantly correlated. In line with the literature (Berman et al., 2017), the presence of affiliates of corporations headquartered within the country do not have a positive significant effect on conflict.[23] For this reason, hereafter, the number of domestic affiliates is controlled for in all specifications, and foreign affiliates are simply called affiliates. As the aim of this paper is to precisely and causally identify the effect of MNE activities on conflict probability, in the following columns I exclude areas characterized by particularly high conflict levels, independently from multinationals. In particular, critique to this approach relates to the possibility of reverse causality in cells with affiliates in the resource sectors (mining and quarrying, oil, gas, etc). Some recent literature (Caselli et al., 2015; Berman et al., 2017) finds a causal link between the presence of resources and violence. Guidolin and La Ferrara (2007) find evidence that conflicts increase the value of exploitative firms.[24] For these reasons, column (2) restricts the sample to cells without resources (gold, diamonds, oil, etc). Do Quoc et al. (2019), studying the links between capital cities, conflict, and the quality of governance, find that conflict is more likely to emerge (and dislodge incumbents) closer to the capital. Moreover, 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.[25] For

[21] This specification uses mainly the High-level SNA/ISIC sector aggregation, but the results are robust to different aggregations, such as NACE Revision 2. See Appendix D for the replication of Table 2 with NACE Revision 2 aggregation.

[22] The latter include, for example, leasing of agricultural and forestry machinery.

[23] For readability, in Table 2 domestic affiliates are grouped in a single indicator. However, as appendix E shows in Table A5, if we replicate Table 2 by splitting domestic affiliates by sector, and grouping in a single indicator foreign affiliates, no sector shows a positive correlation with conflicts, while the domestic affiliates in *Education - Health* remain with a negative and significant sign. This is in line with the exploitative behaviour of foreign MNE described in works such as Just Business (Ruggie, 2013): "Multinational corporations became the central focus of business and human rights concerns because their scope and power expanded beyond the reach of effective public governance systems, thereby creating permissive environments for wrongful acts by companies without adequate sanctions or reparations." Interestingly, in Table A5, the aggregate index *Foreign affiliates* is positive and significant in any specification.

[24] They give several explanations: during conflict, (i) entry barriers might be higher; (ii) the bargaining power of governments might be lower and hence licensing cheaper; (iii) lower transparency leads to more unofficial deals which are profitable to the firms; (iv) the manufacturing sector leaves the country, forcing it to specialize in natural resources.

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

Table 2: MNE and conflict

	(1)	(2)	(3)	(4)	(5)
Estimator			LPM		
Dependent variable			Conflict incidence		
Agriculture	0.00581	0.0121	0.00391	0.0114	0.0117
	(0.0111)	(0.0125)	(0.0124)	(0.0129)	(0.0140)
Forestry	0.163***	0.179***	0.157***	0.155**	0.175**
	(0.0558)	(0.0666)	(0.0579)	(0.0701)	(0.0689)
Fishing	-0.0983	-0.128	-0.150	-0.194	-0.205
	(0.112)	(0.152)	(0.118)	(0.181)	(0.175)
Mining and Quarrying	0.0143	0.0315	0.0129	0.0292	0.0270
	(0.0139)	(0.0245)	(0.0159)	(0.0242)	(0.0238)
Other Resources	-0.00569	-0.00255	0.0148	0.0193	0.0157
	(0.0108)	(0.0149)	(0.0153)	(0.0184)	(0.0189)
Manifacturing - Industries	-0.00184	-0.00356	-0.00178	-0.00204	-0.00208
	(0.00573)	(0.00886)	(0.00601)	(0.00900)	(0.00904)
Construction	-0.00394	0.0226	-0.00110	0.0175	0.0109
	(0.0141)	(0.0166)	(0.0142)	(0.0164)	(0.0169)
Wholesale - Accomodation	-0.00164	-0.00726	0.00115	-0.00575	-0.00928
	(0.00548)	(0.00660)	(0.00627)	(0.00689)	(0.00828)
Information - Communication	0.0129	0.0356*	0.0364*	0.0517**	0.0475
	(0.0160)	(0.0207)	(0.0214)	(0.0258)	(0.0307)
Finance - Insurance	0.00353	0.00281	-0.00137	-0.00324	-0.0115
	(0.00382)	(0.00955)	(0.00449)	(0.00943)	(0.00989)
Real estate	-0.0105	-0.0164	-0.0174	-0.0141	-0.0127
	(0.0211)	(0.0266)	(0.0219)	(0.0266)	(0.0279)
Support Service Activities	0.0162**	0.0293**	0.0188**	0.0271*	0.0282*
	(0.00699)	(0.0136)	(0.00825)	(0.0152)	(0.0152)
Education - Health	-0.0863**	-0.108**	-0.146***	-0.132***	-0.156***
	(0.0340)	(0.0473)	(0.0438)	(0.0489)	(0.0544)
Public Administration - Defence	-0.142	-0.141	-0.158**	-0.157**	-0.167**
	(0.0883)	(0.0920)	(0.0778)	(0.0780)	(0.0823)
Other Services	-0.0345**	-0.0479**	-0.0389**	-0.0452**	-0.0411*
	(0.0154)	(0.0188)	(0.0169)	(0.0201)	(0.0231)
Domestic affiliates	0.0004	0.0003	0.0003	0.0002	0.0003
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Country × year FE	Yes	Yes	Yes	Yes	Yes
Cell FE	Yes	Yes	Yes	Yes	Yes
Excluding resources		Yes		Yes	Yes
Excluding capitals			Yes	Yes	Yes
Controls					Yes
Observations	92,995	92,357	89,585	89,000	89,000

Notes: LPM estimation. Dependent variable: conflict incidence (ACLED). ***,**,* = indicate significance at the 1, 5, and 10% level, respectively. Conley (1999) standard errors in parenthesis, allowing for spatial correlation within a 500km radius and for infinite serial correlation. Each variable indicates the number of MNE foreign affiliates in its specific sector. *Domestic affiliates* indicates the number of affiliates with a headquarter located in their same country. In column (2) cells with natural resources are excluded. In column (3) cells in capital cities are excluded. Column (3) excludes both cells with natural resources or in capital cities. Column (5) adds the lag of population ad the cell-level (LandScan) and cell-specific time trends.

these reasons, column (3) excludes cells in capital cities. Column (4) excludes both resource areas and capital cities, while column (5) adds the lag of population at the cell level and cell-specific time trends.[26] Considering the final aim of this work, this last column represents our favourite specification.

4.2 IV strategy

In the specifications proposed above, but also more generally, assessing the impact of MNE activities on violence poses a series of methodological difficulties, chief among them being the potential reverse causality from local violence to MNE activity. Excluding resource-intense areas, 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 instrument multinational activities in each cell-year.

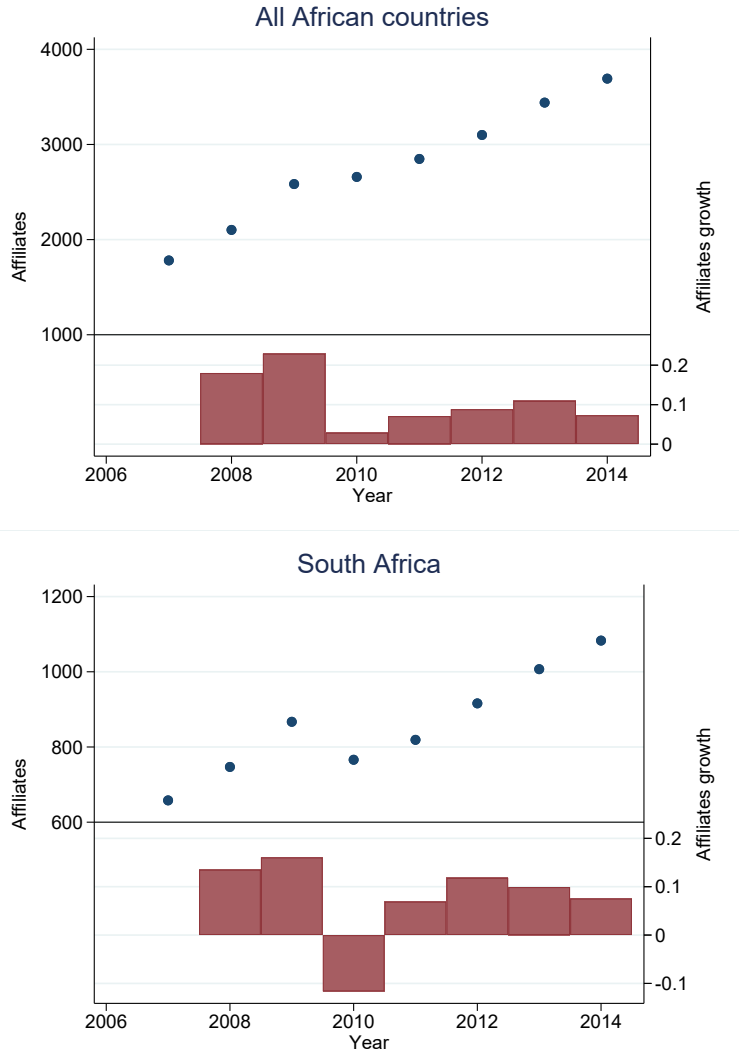
4.2.1 Methodology

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 only on number of affiliates; the coverage of size variables, like number of employees, is particularly poor. So we instrument multinational activities with only one dimension of its realizations, i.e. number of affiliates. The basic empirical strategy exploits the fact that some affiliates within a cell-year were part of relatively healthy and robust multinationals, whereas others belonged to less healthy groups, which were affected more severely by the crisis. More specifically, pre-period data on the parent corporation's exposure to external credit is used, together with the amount of credit given in the headquarters country. I use this within-cell-year variation to identify how the probability of conflict changes with the (exogenous) change in multinational activity. The idea is that when a shock hits the parent company, especially a credit shock like that of 2008-2009, if some constraint on the amount of borrowing or any general financial help is imposed on affiliates by the parent, this will have 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 shortage had a clear impact on multinational activities in Africa. Figure 3 shows the aggregate number of affiliates in Africa and its rate

[26] Clearly, population is a key determinant of conflict. However, the lag of population could be considered a *bad control*, but at the same time omitting it could cause an omitted variable bias. Results are robust including these control variables or not; see the robustness Section 4.2.3.

of increase. Note the sharp drop in the growth rate following the crisis, from 20% previously to an average of 7% in the first few years after 2009.[27] In several countries, such as South Africa, the number of affiliates actually declined, as the second panel of Figure 3 shows.

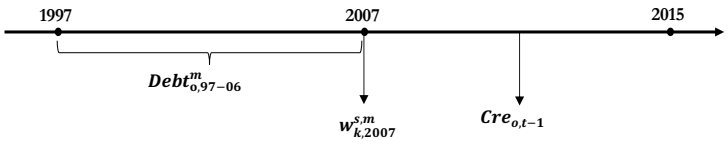
Figure 3: African affiliates



Notes: The graphs show aggregate numbers of affiliates by year, for all African countries and focusing only on South Africa respectively. The histograms below show changes in number of affiliates.

[27] The dataset elaborated for this work only covers two years before the crisis due to data availability difficulties. However UNCTAD's data on FDI flows confirm that before 2009 there was stable and rapid growth of FDI worldwide and in Africa (UNCTAD, 2009a; UNCTAD, 2009b), and this growth diminished sharply with the 2008-2009 crisis.

Figure 4: IV data timeline



Notes: The graph shows the time coverage of the data used for the IV strategy.

Given the credit mechanism behind the 2008-2009 crisis, I follow Autor et al. (2013) in exploiting parent corporations' heterogeneity in dependence on external finance in the decade before my analysis.[28] I interact this with a year-country variable for the level of credit the parent company receives in its home country. The intuition is that the crisis hits parent firms differently depending on their reliance on credit. To avoid endogeneity I compute a headquarters-level measure of access to credit from the previous decade. Considering that the analysis is performed at the cell-year level, I need one instrument (at least) for each sector, for each cell-year. 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 each sectors in the cell. Specifically, $w^{s,m}_{k,2007}$ represents the parent m's share of affiliates in cell k year 2007 in sector s.[29] Second, I estimate the parent corporation's dependence on external credit in the previous decade (1997-2006),[30] in the headquarters home country, o, denoted by $Debt^{m}_{o,97-06}$. Third, I then interact this firm-specific (time-invariant) variable with measures of credit availability at the home country-year level, $Cre_{o,t-1}$.[31] Figure 4 is a visual representation of the IV approach. For each cell-year, therefore, we obtain an instrument z for each sector s:

$$z^{s}_{k,t} = \sum_{m \in s} w^{s,m}_{k,2007} \left(Debt^{m}_{o,97-06} \times Cre_{o,t-1} \right) \tag{2}$$

where I keep as constant the initial share of multinationals, in each sector and in each cell, as weighting strategy ($w^{s,m}_{k,2007}$) for exogeneity. This methodology presents the main limitation that the instrument is not informative on *where* a headquarters might increase/decrease its activity,

[28] They instrument the exposure to import competition from China with the exposure to import competition from developed countries in the previous decade.

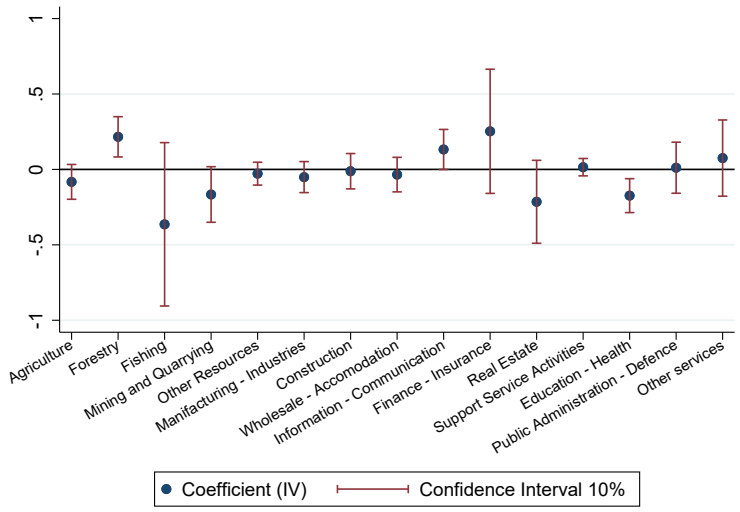
[29] This is measured as the ratio between the number of m's affiliates in sector s in cell k year 2007, or in it's first year of activity in that sector-cell, and the total number of affiliates in sector s in this cell-year.

[30] Measured as debt over equity, see Rajan and Zingales (1998) and Manova (2013).

[31] World Band data: (i) Domestic credit provided by financial sector (% of GDP), (ii) Domestic credit to private sector (% of GDP). The first is used in the main specification, i.e. $Cre_{o,t-1}$, the second is an alternative measure of credit in the robustness checks.

while it is exogenously describing the level of multinational activities in cells where there was already a headquarters' affiliate at the beginning of the analysis. However, this might represent a problem of power of the instrument. Indeed, this limitation does not allow to instrument all sectors simultaneously, due to a problem of power. In Figure 5 I plot the IV sector-specific coefficients of 15 different regressions. Each dot represents the IV coefficient of the corresponding sector, controlling for all the other sectors (not instrumented). In other words, each regression replicates column (5) of Table 2 instrumenting one single sector at the time. For example, the first dot represents the coefficient of the instrumented variable (number of affiliates in) *Agriculture*, namely -0.0826 with a standard error of 0.0704, in a regression in which all the other (number of affiliates in the other) sectors are controlled for, but not instrumented. As it is possible to note, the only two sectors which remain significant are *Forestry* and *Education, human health and social work activities*, with positive and negative signs respectively (0.126*** and -0.174**).[32]

Figure 5: IV all sectors



Notes: Each point represent the IV coefficient for a specific sector in a LPM estimation which follows the specification of column (5) of Table 2, in which the dependent variable is conflict incidence (ACLED) and all the other sectors (not instrumented) are controlled for, but not showed in the graph. The brackets represent the 10% confidence interval.

[32]Because the other sectors' MNE affiliates could be considered endogenous, in Appendix F I replicate Figure 5, without including the other sectors as controls. However, the specifications in F suffer omitted variables bias, so the preferred specification is the one with the controls included. In particular, note that the only two sectors which are significant in both figures (so both controlling and not controlling for the other sectors) are the two mentioned above, *Forestry* and *Education - Health*.

4.2.2 Baseline results

Table 3 reports the baseline results. The estimation is the same as for equation 1, but here both variables *Forestry affiliates* and *Health - Education affiliates* are instrumented at the cell-year level. The dependent variable is the incidence of conflict. We can see that in every column, the coefficients of interest are significant at the 1% level. In particular, an increase in MNE activity in the exploitative sectors increases conflict probability, while in sectors that enhance local human capital it decreases it. 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). All specifications also control for the number of foreign affiliates in other sectors, and for the domestic multinationals' number of affiliates. Column (1) of Table 3 replicates column (5) of Table 2 to facilitate comparison of the instrumented and non-instrumented results. Column (2) presents the instrumented results. A few points are worth understanding. First, the IV approach confirms the downward bias of the linear probability model (LPM), which underestimates the effect of MNE activity on violence, because of the lower probability of observing MNE activities in cells where there is violence. Second, the magnitude of the effects is very substantial. The mean (and standard deviation) of the two explanatory variables *in cells with some MNE activity* are 0.083 (0.335) for *Forestry* affiliates and 0.093 (0.445) for *Education - Health* affiliates; and the probability of a conflict in these cells is 0.53. Therefore, given the results of Table 3, column (2), a 1-standard-deviation increase in MNE activity in the *Forestry* sector increases conflict probability by 14% of the mean. And a 1-standard-deviation increase in MNE activity in *Education - Health* affiliates decreases conflict probability by more than 15% of the mean.

4.2.3 Sensitivity analysis

The baseline estimates of Table 3 prove to be robust to a large battery of checks. Table 4 presents these results.

Sample and dependent variable. First let us 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 4 we first restrict the sample to cells

Table 3: Baseline results

	(1)	(2)
Estimator	LPM	IV
Dep. Var.	Conflict incidence	
Forestry	0.175**	0.221***
	(0.0689)	(0.0804)
Education - Health	-0.156***	-0.184**
	(0.0544)	(0.0722)
Country × year FE	Yes	Yes
Cell FE	Yes	Yes
Kleibergen-Paap Wald F statistic		15.19
Observations	89,000	89,000
First stages		
Forestry affiliates		
Instrument for Forestry affiliates		5.672***
		(1.3849)
Instrument for Education - Health affiliates		0.314
		(0.2701)
Education - Health affiliates		
Instrument for Forestry affiliates		0.835
		(0.8455)
Instrument for Education - Health affiliates		3.903***
		(0.8455)

Notes: LPM estimation in column (1), IV estimation in columns (2). Dependent variable: conflict incidence (ACLED). ***,**,* = indicate significance at the 1, 5, and 10% level, respectively. Controlling for: cell FE, country×year FE, cell×year trends, other sectors affiliates (different than *Forestry* and *Education - Health*), domestic affiliates (with a headquarter located in their same country). Excluding resources areas and capital cities. Conley (1999) standard errors in parenthesis, allowing for spatial correlation within a 500km radius and for infinite serial correlation. *Forestry affiliates* indicates the number of foreign affiliates operating in the Forestry sector in the cell. *Education - Health affiliates* indicates the number of foreign affiliates operating in the sector Education and Human Health. The last two variables are instrumented, details are explained in Section 4.2.1. The section *First stages* reports coefficients of the first stage estimations formalized in equation (2).

with some MNE activity during the period (row 1). 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 in the two sectors. With this very demanding restriction, the Kleibergen-Paap rk Wald F statistic is still high, above 19, indicating that the instrument is not weak even excluding all cells with no affiliates initially. Alternatively, in row 2, I implement a neighbour-pair fixed effects estimation, similar to Acemoglu et al. (2012) and Buonanno et al. (2015). Starting from the full sample, I replicate the main specification in the subsample of mining cells and their immediate

neighbouring cells without MNE affiliates.[33] I define a neighbourhood fixed effect that is specific to each (MNE affiliate + neighbours) group. The instrument of the MNE affiliate in the cell is also assigned to its neighbours. By contrast, the number of affiliates can differ as it is set to zero in neighbouring cells with no affiliates. Identification hence 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. Next, we exclude 2015 (row 3) as a sort of outlier, given the sharp rise (26%) in number of affiliates that year (see Figure A5). 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. In row 4 I exclude from the sample all border cells for which the distance between the cell's centroid and the closest international border is smaller than 39 kilometers. In Appendix G the thesis is tested for an alternative dependent variable, e.g. violent events only and events with some fatalities only. Finally I explore robustness to using the alternative Uppsala Conflict Data Program Georeferenced Event Dataset (UPCDP-GED), which follows a different coding strategy.

Additional controls. 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 (Miguel et al., 2004; Hendrix and Salehyan, 2012). For this reason, the results are checked after controlling for (the log of) rainfall and (the log of) temperature (row 5). Further, to control for possible indirect effects of the crisis on specific areas within a country (if the textile industry, say, was particularly hard-hit, this might be expected to impact on specific African areas), I substitute country×year fixed effects with region×year fixed effects (row 6). In row 7 I add the lagged and lead values of the dependent variable (conflict incidence) at the cell level. In row 8 I exclude the lag of population and cell-specific time trends from the specification. In order to proxy the level of development, or a disaggregated measure of GDP, I then control for nightlights at the cell level (row 9).[34]

Different instruments. I also replicate the IV results using different instrumental variables. First, we use of two instruments for each variable, instead of one (row 10). Specifically:

$$z_{k,t}^{Debt,s} = \sum_{m \in s} w_{k,2007}^{s,m} \left(Debt_{o,97-06}^{m} \times Cre_{o,t-1} \right)$$

[33] This estimation confirms also that the results are robust to the inclusion of capital cities and resources areas.

[34] Image and Data processing by NOAA's National Geophysical Data Center, then aggregated at the cell-level. DMSP data collected by the US Air Force Weather Agency. Data are limited to 2013, hence the drop in the number of observations.

$$z_{k,t}^{IFP,s} = \sum_{m \in s} w_{k,2007}^{s,m} \left(IFP_{o,97-06}^{m} \times Cre_{o,t-1}^{'} \right)$$

where the first is the same as in equation 2, while IFP is an Index of Financial Pressure (Nickell and Nicolitsas, 1999) measured as

$$IFP = \frac{Interest\ Payments}{Profit\ Before\ Tax + Depreciation + Interest\ Payments}$$

$Cre_{o,t-1}^{'}$ is domestic credit (provided by financial sector) as a % of GDP, and $Cre_{o,t-1}$ measures domestic credit to private sector also as % of GDP. These two different credit aggregates serve to reduce multicollinearity. The results are robust to this procedure. In addition, the use of two instruments allows us to perform the Hansen-J test, which yields a non-significant p-value (0.332), confirming the exogeneity of the instruments. The IV procedure is also applied using a different measure of credit (row 11): in the IV strategy presented in equation 2, the variable $Cre_{o,t-1}$ is replaced by $Cre_{o,t-1}^{'}$ (described above). And the results also hold using a modified version of the instrument, in which both the values of the independent variables of interest and the instruments of the cells without affiliates are replaced by the corresponding values of the closest cell with some MNE activity, divided by the distance between the two cells (row 12).[35] This methodology also enables us to test once again the strength of the IV strategy again, not assigning zero to all cells without affiliates.

Test of the identification assumption. A potential concern is the instrument's ability to actually predict the probability of the parent company's closing affiliates in a given cell-year. For this reason, to test the identification assumption we can regress the probability of each parent (m), in each cell-year (k, t), closing at least one of its affiliates ($CloseAff_{kt}^{m}$) on the instrument, controlling for cell fixed effects (FE_k), country×year FE (FE_{ct}), and other headquarters-specific fixed effects. More specifically, I estimate the following equation:

$$CloseAff_{kt}^{m} = \beta \left(Debt_{o,97-06}^{m} \times Cre_{o,t-1} \right) + FE_k + FE_{ct} + \gamma X_m + u_{mkt} \tag{3}$$

Table 5 shows that an increase in credit in the home country does in fact decrease the probability of closing affiliates (column 1), and this result is robust to headquarters-sector fixed effects (column 2) and headquarters-location fixed effects (column 3).[36]

[35] In cases where a cell with no affiliates is equidistant from more than one cell with affiliates, the average of the variables of interest in these cells is taken.

[36] Specifically, following the international ISO-3166 classifications, the aggregate locations used as fixed effects are: Australia and New Zealand, Caribbean, Central America, Eastern Africa, Eastern Asia, Eastern Europe, Northern Africa, Northern America, Northern Europe, South America, South-Eastern Asia, Southern Africa, Southern Asia, Southern Europe, Western Africa, Western Asia, Western Europe.

Table 4: IV - Sensitivity analysis

	Forestry		Education - Health			
	Coeff	Std. Err.	Coeff	Std. Err.	K-P F stat	Obs.
Sample						
(1) Only cells with some affiliates	0.232***	(0.0711)	-0.261***	(0.0823)	17.36	2,186
(2) Neighbor-pair fixed effects	0.133**	(0.0561)	-0.235***	(0.0631)	11.62	35,986
(3) Excluding year 2015	0.187***	(0.0690)	-0.187***	(0.0692)	29.91	79,112
(4) Excluding border cells	0.227***	(0.0826)	-0.187**	(0.0742)	14.70	73,178
Controls						
(5) Precipitation and temperature	0.188***	(0.0681)	-0.187***	(0.0678)	29.90	79,092
(6) Region×Year FE	0.194**	(0.0893)	-0.136**	(0.0616)	13.14	89,000
(7) Conflict (t-1) and (t+1)	0.217**	(0.0960)	-0.202***	(0.0781)	14.60	69,222
(8) Excluding lag population and cell-trends	0.230***	(0.0854)	-0.146**	(0.0719)	14.60	89,000
(9) Nightlights	0.185**	(0.0723)	-0.199***	(0.0650)	38.35	69,223
Estimation and IV						
(10) Two instr.: Debt & IFP (H-J p-value=0.332)	0.166**	(0.0693)	-0.141*	(0.0730)	23.76	89,000
(11) Diff. measure of credit (to all from finance)	0.217***	(0.0731)	-0.170**	(0.0693)	12.65	89,000
(12) Intr. of closest cell with aff. >0 / distance	0.237***	(0.0832)	-0.239***	(0.0763)	18.17	89,000

Notes: The table reports IV estimation results from 11 different specifications described in Section 4.2.3. Dependent variable: conflict incidence (ACLED). ***,**,* = indicate significance at the 1, 5, and 10% level, respectively. Only coefficients of the variables *Exploitative affiliates* are and *Human capital affiliates* reported. The first indicates the number of foreign affiliates operating in an the *Forestry* sector in the cell. The second indicates the number of foreign affiliates operating in the sectors *Education - Health*. *K-P F stat* stands for the Kleibergen-Paap Wald F statistic.

Selection. Despite the IV approach, another potential problem with this methodology is that the parent multinational may selectively decide, in crisis periods, to close specific affiliates, presumably those that are more costly or problematic (e.g. those in conflict areas). Figure 6, however, which compares the number of affiliates in cells where conflict was always absent with that in cells with some conflict (>0) during the period, shows that this does not happen to be the case, as the trends in cells with and without conflicts are parallel. A more formal test can be performed by replicating equation 3 controlling for whether a conflict event in the cell has a significant role per se in the corporation's decision to close affiliates, or whether such a role emerges when the effect is interacted with the instrument. Formally, the following specification addresses this concern:

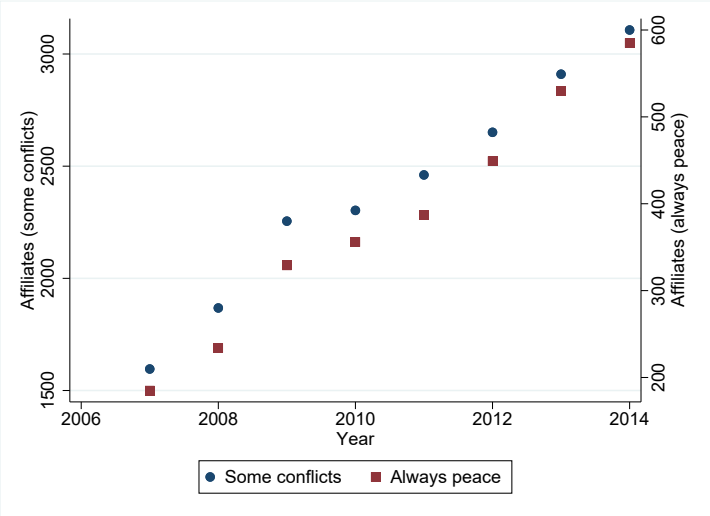
$$\begin{aligned} CloseAff_{kt}^{m} = & \beta \left(Debt_{o,97-06}^{m} \times Cre_{o,t-1} \right) \\ & + \gamma \, Conflict_{k,t} + \omega \, Debt_{o,97-06}^{m} \times Cre_{o,t-1} \times Conflict_{k,t} \\ & + FE_k + \gamma X_m + u_{mkt} \end{aligned}$$

As we can see from the last three columns of Table 5, the relevant coefficients, namely γ and ω, are never significant.[37] In other words, Figure 6 and Table 5 confirm that there are no signs of

[37]Note that they remain non-significant even if the variable $Conflict_{k,t}$ is replaced by its lagged version

selection in the parent company's decision to close affiliates.

Figure 6: Conflict cells and the crisis



Notes: The graph shows the aggregate number of affiliates by year, for all Africa, comparing cells always in peace with cells in which at least one conflict takes place during the period analysed.

5 Mechanism

The first part of the paper tests the first hypothesis presented in the theoretical framework. This section studies the second hypothesis, concerning the role of political representation of ethnic groups. We study the channels whereby ethnic political representation can be linked with conflict probability. Considering the key role of ethnic groups in developing countries,[38] what happens to the effects just described in areas characterized by the presence of politically excluded minorities, i.e. ethnic groups without any representation in the national government? Unrepresented minorities could increase conflict probability owing to their exclusion from the benefits generated by MNE activities. Assume the government decides to redistribute the transfer received from the multinational; if representatives of the local communities sit in the government, the relation between the two agents (government and locals) will resemble a repeated game.[39] In this case

$Conflict_{k,t-1}$. Moreover, results remain unchanged if we substitute the headquarters' aggregate location fixed effect (17 groups, listed in footnote 36) with a specific headquarter-country fixed effect.

[38] See for example Walter (2006) on the importance of group concentration; Cederman and Girardin (2007), Reynal-Querol (2002), Saideman et al. (2002) on the relevance of ethnic discrimination; and Morelli and Rohner (2015) on the he importance of natural resource concentration and regional ethnic concentration for ethnic conflict.

[39] In other words, the more locals are represented, the better informed the government is on their beliefs concerning their land (e.g. the value of expected agricultural output), and no worries of unfulfilled promises will induce

Table 5: The impact of conflict on affiliates' closing

	(1)	(2)	(3)	(4)	(4)	(6)
Estimator	LPM					
Dep. Var.	HQ closing affiliate					
$Debt^{m}_{o,97-06} \times Cre_{o,t-1}$	-0.0627**	-0.0772***	-0.0628**	-0.0599***	-0.0717**	-0.0602**
	(0.0275)	(0.0289)	(0.0278)	(0.0232)	(0.0300)	(0.0234)
$Conflict_{k,t}$				0.00434	0.00571	0.00524
				(0.00953)	(0.0106)	(0.00988)
$Debt^{m}_{o,97-06} \times Cre_{o,t-1} \times Conflict_{k,t}$				-0.00385	-0.00749	-0.00353
				(0.0379)	(0.0430)	(0.0385)
Country×Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Cell FE	Yes	Yes	Yes	Yes	Yes	Yes
Headquarter sector FE	No	Yes	No	No	Yes	No
Headquarter location FE	No	No	Yes	No	No	Yes
Observations	4,277	3,907	4,276	4,277	3,907	4,276

Notes: LPM estimation. Dependent variable: headquarter closing at least one affiliate in cell k year t. ***,**,* = indicate significance at the 1, 5, and 10% level, respectively. Standard error clustered at the headquarter level. $Debt^{m}_{o,97-06} \times Cre_{o,t-1}$ indicates the instrument used in the main specification, at the headquarter level. It is computed as the interaction between the headquarters level of dependence on external credit in the decade before the analysis (Bureau Van Djik), $Debt^{m}_{o,97-06}$, and an index of credit provided to firms in the headquarters country (World Bank), $Cre_{o,t-1}$. $Conflict_{k,t}$ is a dummy variable taking value 1 when in cell k at year t at least a conflict event is recorded in the ACLED dataset.

the government makes a compensation offer that is incentive-compatible, so we always observe civil peace. Instead, when the local population is poorly represented, several channels could lead to conflict: for example, asymmetric information or commitment problems (Fearon, 1995). To illustrate information problems, the government can be assumed not to know how strongly the ethnic groups are attached to their land, and therefore how much compensation they need to be given. Differently from the previous case, here the government faces uncertainty, so conflict takes place with more than zero probability.[40] Or this situation can be seen as a commitment problem. In this multi-period framework, conflict is not game-ending but establishes a temporary distribution of the transfer payment, which will be reviewed at the start of the next period. For example, the government might offer the locals a certain transfer today and promise to increase the number of jobs tomorrow. Locals can believe this promise or not, in any case increasing the probability of conflict to more than zero.

In the *Ethnic Power Relations (EPR) Core Dataset* (Vogt et al., 2015) for 2018, ethnic groups

the group to start a conflict because their members in the government will ensure their fulfilment.

[40] Another example of asymmetric information can be a more behavioural explanation. Assume the locals do not have information on the transfer the multinational gives to the government, because they are not represented. They are only able to observe what they are offered, using this to estimate the original transfer to the government. If, after accepting the offer, they learn the original value of the transfer, they may feel betrayed and start a conflict. In real life you can think of this signal as the locals seeing the machinery and the magnitude of the investments targeted on what was their land.

are included following a two-step process. First, a time-variant list of countries worldwide is defined. Then, ethnic groups are coded.[41] Data collection is performed with an online expert survey under the label Expert Survey of Ethnic Groups (ESEG). Then each country coding is reviewed and evaluated by the EPR Management Committee. I have constructed a dataset in which per each cell-year, there is information about the ethnic group contained in that cell in that year. To do so, I have used a geographic model of intersection algorithms.[42] The final database gives information on each group in power in each country, with 7 classifications (monopoly, dominance, senior partner, junior partner, powerless, discrimination, self-exclusion).[43] A group is considered to be in power if it belongs to one of the first four classes. To test the possible channels, assume that in each country c year t there are $EthGroupsPower^{c}_{kt}$ ethnic groups in the power coalition, and hence $TotEthGroups^{c}_{kt} - EthGroupsPower^{c}_{kt}$ groups out of power. Now consider that each country c is divided into cells, and that exploiting the foregoing data we can determine, for each cell-year, which subsample of groups $EthGroupsPower^{c}_{kt}$ and groups $TotEthGroups^{c}_{kt} - EthGroupsPower^{c}_{kt}$ are present. Hence, the following index is computed for each cell k year t:

$$EthnicMinorities^{c}_{kt} = \frac{TotEthGroups^{c}_{kt} - EthGroupsPower^{c}_{kt}}{TotEthGroups^{c}_{kt}} \times 100 \tag{4}$$

Considering that this channel could change significantly depending on population of each ethnic minority area, I also propose an analysis concerning the population of each ethnic group. In particular, I use the variable containing information about each ethnic group as a fraction of the country's total population. The index of ethnic minorities that takes into consideration the

[41] In this sense, EPR defines ethnicity as "any subjectively experienced sense of commonality based on the belief in common ancestry and shared culture". However, these are included in the dataset only if politically relevant. In other words, groups are included "if at least one political organization claims to represent it in national politics or if its members are subject to state-led political discrimination".

[42] This algorithm creates a dataset containing the geographical intersection of the other two. The *GeoEPR* dataset provides information about ethnic groups as polygons in the space. Thus, the intersection algorithm creates, in this case, the new dataset formed by the intersection of cells with these polygons. Through the use of a graphic modeller, I have run one single model containing all year-specific intersection algorithm such that Qgis perform these algorithms in succession automatically.

[43] Each ethnic group is assigned, according to the degree of access to central state power, to one of the seven categories. *Monopoly*: the group holds monopoly power in the executive and it is able to exclude all other ethnic groups. *Dominance*: the group holds a dominant power in the executive but there is some limited inclusion of members of other ethnicities who however do not have a real influence on decision making. *Senior Partner*: representatives of the group participate as senior partners in the executive and have a real influence on political decisions. *Junior Partner*: representatives participate as junior partners in government. *Powerless*: no political power in the executive although without being explicitly discriminated. *Discrimination*: group members are subject to active, intentional and targeted discrimination with the intent of excluding them from political power. *Self-excluded*: group members control a particular territory and have declared it independent from central government.

population of each ethnic group is constructed in the following way for each cell k, year t, and country c:

$$EthnicMinoritiesPop^{c}_{kt} = \frac{TotPop^{c}_{kt} - PopPower^{c}_{kt}}{TotPop^{c}_{kt}} \times 100 \quad (5)$$

where $TotPop^{c}_{kt}$ is the sum of the population of all ethnic groups in a given cell k of a given country j in a given year t; $PopPower^{c}_{kt}$ is the sum of the population of all ethnic groups in power in a given cell k of a given country c in a given year t. As a consequence, $TotPop^{c}_{kt} - PopPower^{c}_{kt}$ is the total population of all ethnic groups in a given cell-year that are not in power. Thus, this index is the proportion of the population of ethnic groups not in power over the total in a given cell in a given year. $EthnicMinorities^{c}_{kt}$ has a mean of 33.85 and a standard deviation of 43.30 in the full sample, and 12.32 and 26.53 respectively in the sample with some affiliates. On the other hand, $EthnicMinoritiesPop^{c}_{kt}$ has a mean of 31.58 and a standard deviation of 43.49 in the full sample, and 10.57 and 25.66 respectively in the sample with some affiliates. The hypothesis is that activity in exploitative sectors is more likely to induce conflict in cells with a high $EthnicMinorities^{c}_{kt}$. Intuitively, in those cells land grabs are more likely to be to the detriment of the powerless groups. Table 6 shows the estimations of the following IV specification:

$$\begin{aligned} CONFLICT_{k,t} = {} & \sigma\ Forestry_{k,t} + \tau\ EducationHealth_{k,t} + \theta\ EthnicMinorities_{k,t} \\ & + \eta\ Forestry_{k,t} \times EthnicMinorities_{k,t} \\ & + \rho\ EducationHealth_{k,t} \times EthnicMinorities_{k,t} \\ & + FE_k + FE_{c,t} + \Gamma X'_{k,t} + u_{k,t} \end{aligned}$$

where $Forestry_{k,t}$ and $EducationHealth_{k,t}$ are instrumented as in the baseline specification (column 2, Table 3); $EthnicMinorities_{k,t}$ is the index described above in column (1), and replaced by $EthnicMinoritiesPop_{k,t}$ in column (2); the interaction terms are instrumented interacting the instruments of $Forestry_{k,t}$ and $EducationHealth_{k,t}$ together with the index of $EthnicMinorities_{k,t}$ in column (1) and with $EthnicMinoritiesPop_{k,t}$ in column (2); FE_k and $FE_{c,t}$ are cell and country×year fixed effects; and $X'_{k,t}$ contains the same controls as in the baseline specification. In the first column of Table 6 the IV results using the $EthnicMinorities_{k,t}$ index are shown, while the second column uses $EthnicMinoritiesPop_{k,t}$. Table 6 shows that the coefficient η is always positive and significant while, interestingly, the coefficient σ loses its significance when we introduce the interaction with the ethnic minority share. This suggests that the main channel through which MNEs in the *Forestry* sector increase conflict is the presence of politically unrepresented ethnic groups. In other words, this result shows that MNE activities play an especially important role in the probability of civil conflict in areas where the leading ethnic groups can place the burden of land deals on unrepresented groups. The magnitude of

this effect is large: a 1-standard-deviation increase in the number of *Forestry* affiliates *in cells with some affiliates* (0.335), together with a 1-standard-deviation in the share of *Ethnic Minorities in cells with some affiliates* (26.53) increases the probability of conflict by 6 percentage points, or more than 11% of the sample mean in these cells. The magnitude of the effect is very robust if we consider the $EthnicMinoritiesPop_{k,t}$, as in column (2). One could argue that this result

Table 6: MNE and Ethnic Minorities

	(1)	(2)
Estimator	IV	
Dep. Var.	Conflict incidence	
Forestry	0.124	0.131
	(0.0945)	(0.0938)
Education - Health	-0.197**	-0.202**
	(0.0937)	(0.0933)
Ethnic Minority	0.000327**	0.000335**
	(0.000157)	(0.000142)
Forestry × Ethnic Minority	0.00596***	0.00713***
	(0.00152)	(0.00191)
Education - Health × Ethnic Minority	0.00134	0.00140
	(0.00125)	(0.00126)
Country × year FE	Yes	Yes
Cell FE	Yes	Yes
Kleibergen-Paap Wald F statistic	9.352	12.41
Observations	69,348	68,962

Notes: IV estimation. Dependent variable: conflict incidence (ACLED). ***,**,* = indicate significance at the 1, 5, and 10% level, respectively. Controlling for: cell FE, country×year FE, cell×year trends, other sectors affiliates (different than *Forestry* and *Education - Health*), domestic affiliates (with a headquarter located in their same country). Excluding resources areas and capital cities. Conley (1999) standard errors in parenthesis, allowing for spatial correlation within a 500km radius and for infinite serial correlation. *Forestry affiliates* indicates the number of foreign affiliates operating in the Forestry sector in the cell. *Education - Health affiliates* indicates the number of foreign affiliates operating in the sector Education and Human Health. The last two variables are instrumented, details are explained in Section 4.2.1. *Ethnic Minority* indicates the share of politically unrepresented ethnic groups present in the cell-year in column (1), computed as in equation (4), while in column (2) it is the is the proportion of the population of ethnic groups non in power over the total in a given cell in a given year, computed as in equation (5).

is driven not by the share of excluded ethnic groups, but by ethnic fragmentation. In Appendix H Table 6 is replicated, but substituting $EthnicFragmentation_k$ for $EthnicMinorities_{k,t}$, confirming that ethnic fragmentation is not driving the results.

Finally, studying the nature of conflict provides additional anecdotal evidence to further corroborate the mechanism described. ACLED codes three categories of violent events. First, battles, defined as "violent interactions between two politically organized armed groups (...) typically within the context of a civil war". Second, violence against civilians, "deliberate violent acts (...) against unarmed non-combatants". Third, riots, "demonstrations against a (typically) political entity, such as a government institution, although they may also include demonstrations against

businesses or other private institutions". The channel described in the paper is characterised by local violence, not escalating to the level of a civil war (thus, no battles), in which locals react and fight to protect their lands (thus, no violence against civilians). Table A8 in Appendix I replicates our baseline specifications (Table 3, column 2) for each of the three categories of violent events covered by the ACLED dataset. Interestingly, Table A8 confirms that the only type of event which allows the detection of a significant role of MNE activity, also unconditionally with respect to other events, is riots.[44] Despite the aim of this paper being to study the probability of conflict events in general, not the unconditional probability of specific types, this is an important confirmation of the theory presented. Considering the events coded as riots are explicitly defined as violent demonstrations against either *political institutions* or *business*, this strongly relates with the possibility that locals react to either the ethnic groups in power (i.e. the government) or against the multinationals directly.

6 Conclusion

This paper offers a systematic analysis of the activity of multinational enterprises on the likelihood of civil conflict in Africa, using novel and fine-grained panel data. I document a significant and quantitatively important impact of multinationals' activity on the likelihood of conflict, the nature of the effect depending on the sector of activity. Exploitative sectors, i.e. forestry, increase conflict probability, while activity in local human-capital-enhancing sectors, such as education and health, decreases it. A battery of sensitivity tests confirms that the results are robust to a variety of alternative specifications and additional controls. This disaggregated study of the causal impact of multinational corporations' activities on conflict also illuminates a potential mechanism through which these activities can lead to the escalation of violence. In particular, the increase in the likelihood of conflict is magnified in areas characterized by a high share of politically unrepresented ethnic groups.

[44] Note 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 3. In fact, *Battle* and *Violence against civilians* show the correct signs, but there is not enough power to detect their role unconditionally with respect to other events. However, *Riots* show a positive and significant role for *Forestry* and negative and significant for *Education - Health*.

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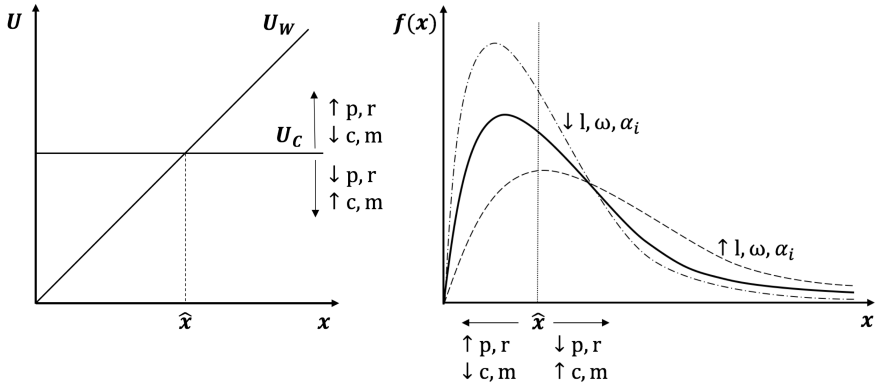
Appendix

A Conceptual framework - graphical representation

The simple framework presented in section 2.2 can be summarized graphically as in Figure A1. On the vertical axis we plot the utilities, while on the horizontal axis we represent the unidimensional index $x = \alpha_l \ l + \alpha_\omega \ \omega$. Intuitively, U_W is represented by a 45 degree lines, while U_C is a horizontal straight line with positive intercept.[45] The intercept between U_W and U_C characterises the cutoff value of x, namely $\hat{x}$, which represents the income that makes individuals indifferent between working and triggering conflict. Individuals at the left of $\hat{x}$ (characterized by either low l, or low r, or low α_i with $i = \{l, \omega\}$, or any combination of them) prefer conflict, because for them $U_C > U_W$. The opposite applies for people on the right of $\hat{x}$. Decreasing the cost of triggering conflict, m, and/or the potential cost of losing the conflict, c, shifts the U_C line up, therefore increasing $\hat{x}$. In other words, if the conflict option is less costly, the cutoff income has to be higher in order to keep people indifferent between U_W and U_C. The opposite happens with an increase in p and/or in r.

Figure A1: Conflict cutoff and probability



Assuming that $x \sim f(x)$, from the right panel of Figure A1 we can see how these changes shift the cutoff $\hat{x}$, thereby increasing the share of people preferring conflict, namely $F(\hat{x})$. On the other hand, any decrease in either l, ω, or α_i with $i = \{l, \omega\}$, will shift $f(x)$ to the left, thereby increasing conflict likelihood, $F(\hat{x})$; while any increase in either l, ω, or α_i with $i = \{l, \omega\}$, will shift $f(x)$ to the right, hence increasing the probability of peace, $1 - F(\hat{x})$.

[45] Assuming $pr \geq (1-p)c + m$. If r depends on any of $(l, \omega, \alpha_l, \alpha_\omega)$, U_C will have a positive slope. For example, assuming $r = x + g$, where g represents the gain in power in case of winning the conflict, the two utilities will always cross simply assuming that $pg \geq (1-p)c + m$.

B Multinational enterprise dataset

In this appendix I provide additional information on the MNE dataset, which geolocalizes the worldwide population of affiliates and headquarters, from 2007 onward.

One of the main challenges for the literature has been the absence of a global source of firm-level data on the basis of which to document the activities of MNEs. In the past, the data used has been mainly multinational corporation activity at the industry level or aggregate FDI flows from balance-of-payments statistics as a proxy for foreign firm activity. The first detailed characterization of global, firm-level multinational activity is provided by Alfaro and Charlton (2009), using data from Dun & Bradstreet. The authors elaborate a cross-section for the year 2005, covering 650,000 multinational subsidiaries in 400 industries and 90 countries. UNCTAD, with its World Investment Report, compiles yearly a list of the biggest corporations operating worldwide. In particular, UNCTAD (2011) also reports the number of parents and affiliates involved in FDI activities hosted by each country, for the year 2009.[46] The first dataset covering control chains of corporate activities both domestically and abroad for all countries of the world is offered by Altomonte and Rungi (2013).[47] The authors map at the firm-level 1,519,588 affiliates of 270,374 headquarters in 2010, across more than 200 countries and all industries. Rungi et al. (2018) propose an algorithm to derive the boundaries of business groups after simulating a voting rule in the presence of interlocking assemblies of shareholders. The authors elaborate a cross-section for the year 2015.[48] In a recent work with coauthors (Altomonte et al., 2018), we use both data obtained with the approach proposed in this paper and with that of Rungi et al. (2018). Moreover, we compare the two approaches in detail, documenting that both produce similar results. Other works focus on subsamples of countries or only large groups. For example, Belenzon et al. (2019) elaborate a dataset of 53,944 groups in 15 West European countries,[49] dropping those that hold less than 10 million dollars in total assets, or have no more than two subsidiaries.

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 busi-

[46] They use information from the Financial Times Ltd (fDi Markets).

[47] The correlations between the number of headquarters controlling foreign affiliates abroad and the number of foreign affiliates located in each country, as retrieved from Altomonte and Rungi (2013) and matched against the corresponding data from UNCTAD (2011) are 0.94 and 0.93. Potential differences might arise from the fact that the survey of UNCTAD (2011) refers to data in 2009, while Altomonte and Rungi (2013) cover 2010.

[48] A particularity of this approach is that it is able to capture particularly complicated cases of cross-holdings, ownership cycles and consolidation of voting rights across fragmented networks of equity stakes.

[49] United Kindim, France, Germany, Spain, Italy, Norway, Sweden, Finland, Denmark, Ireland, Belgium, Netherlands, Switzerland, Portugal and Greece.

ness group, relying on the definition of direct or indirect majority ($\geqslant 50.01\%$) of voting rights provided by Bureau Van Djik. This definition of control follows the international standards for multinational corporations (OECD, 2005; UNCTAD, 2009b; Eurostat, 2007). I elaborate on a routine prepared by Bureau Van Djik for the identification of a corporate ultimate owner and then implement an algorithm based on the ownership links that provides the hierarchical structure accordingly, by climbing up the ownership structure. With this approach, I construct the network of business groups for more than 200 countries, from 2007 to 2015, and then geolocate them using zipcodes. To my knowledge, this is the first global, firm-level dataset documenting multinational activities in a panel setting. More details on this procedure can be found in the Appendix of a subsequent more technical paper with coauthors, Altomonte et al. (2018), where we use the approach proposed in this paper and explain the steps used to construct the networks of groups more in details, in particular comparing it with other approaches in the literature.

I can validate my data with three different datasets. First, following Alfaro and Charlton (2009), I compare my data with the data from UNCTAD (2011), for the year 2009. Figure A2 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 number of MNE headquarters in that specific country in my dataset. A perfect correlation would be visualized by a straight 45° line. In this case 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 he correlation is 0.95.[50]

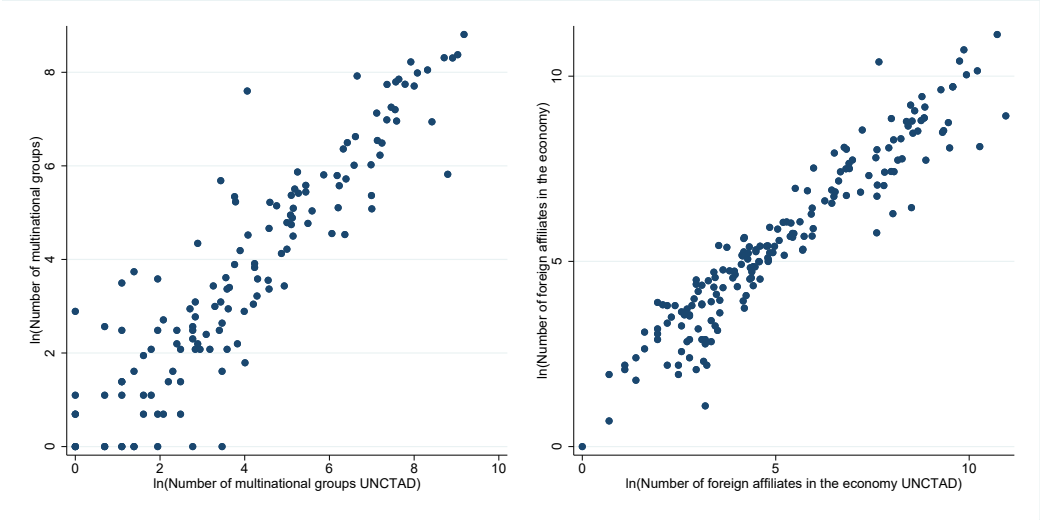
Second, I can validate my dataset with the data for the year 2010 by Altomonte and Rungi (2013). Following the logic described above, the correlation for the (log of) number of MNE headquarters in each country is 0.97, while for the (log of) number of foreign affiliates it is 0.99, as shown in Figure A3.

Third, I validate the geographic coverage of the dataset proposed in this paper for the year 2015, Table A1, with the same table proposed by Rungi et al. (2018). "Parent companies - All" is the number of parent companies by host economy; "Parent companies - Multinational" is the number of multinational companies by host economy;[51] "Subsidiaries - All" is the number of subsidiaries located in a given host economy; "Subsidiaries - Foreign" is the number of foreign subsidiaries located in a given host economy. The correlations between these four variables and the

[50] 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 2016, 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*, where all the changes in covered are documented by year and by country.

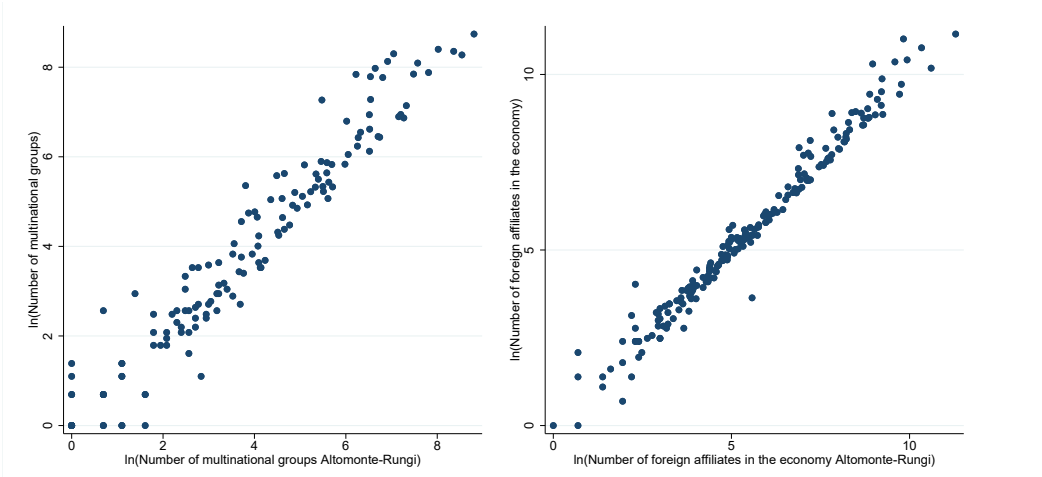
[51] A multinational company is defined as a Global Ultimate Owner controlling at least one foreign subsidiary.

Figure A2: 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.

Figure A3: 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.

corresponding table shown in Rungi et al. (2018) are (excluding the observations in the "Unassigned Country" category and taking into account also the breakdown by country, i.e. 21 data points), 0.997, 0.998, 0.995, 0.990, respectively. For a more detailed comparison of this data with Rungi et al. (2018), see the Appendix of Altomonte et al. (2018).

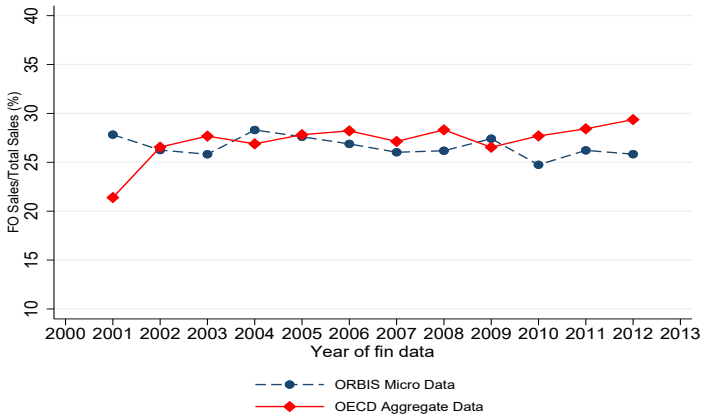
Table A1: Geographic coverage year 2015

	Parent companies				Subsidiaries			
Host economy	All	%	Multinational	%	All	%	Multinational	%
Africa	6,592	0.27	4,52	2.09	42,242	0.82	26,209	2.43
Asia	1004,666	4.30	25,688	11.86	407,614	7.94	172,21	15.97
Australia	77,048	3.16	2,963	1.37	173,045	3.37	31,923	2.96
EU	629,104	28.42	119,362	55.11	1,865,582	36.36	561.503	52.06
Latin America	28,527	1.17	17,871	8.25	93,383	1.82	68,308	6.33
Other Europe	64,691	2.66	16,239	7.50	149,614	2.92	35.543	3.30
Rest of the World	48,81	2.00	7,031	3.25	102,729	2.00	28,607	2.65
Russia	45,01	1.85	1,029	0.48	141,493	2.76	54,071	5.01
USA	1,368,195	56.17	21,873	10.10	2,155,012	42.00	100,281	9.30
Unassigned country	149,902	-	149,769	-	26,366	-	25,871	-
Total	2,585,545	100.00	366,345	100.00	5,157,080	100.00	1,104,526	100.00

Notes: The table considers data of 2015. The regional aggregation follows the online version of the United Nations publication "Standard Country or Area Codes for Statistical Use". In "Unassigned country" there are the observations for which we cannot assign a country, namely those with alpha-2 country ISO codes II, KV, YY and ZZ. The percentages are computed excluding these countries.

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 this 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 the 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 A4. Table A2 shows the distribution of MNE affiliates by African countries.

Figure A4: 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.

Table A2: Affiliates country-year

Country	2007	2008	2009	2010	2011	2012	2013	2014	2015
Algeria	137	181	234	275	297	298	286	294	321
Angola	65	73	98	114	113	125	136	166	175
Benin	13	14	17	17	19	21	20	22	26
Botswana	25	21	30	32	32	40	35	60	70
Burkina Faso	8	10	13	13	13	17	16	18	23
Burundi	1	2	4	6	6	6	6	7	7
Cameroon	46	46	54	54	52	49	57	65	68
Cape Verde Is.	16	19	22	22	25	24	26	32	33
Central African R	0	0	1	2	2	2	2	2	3
Chad Republic	5	6	6	6	7	5	8	10	11
Comoros	0	1	2	1	1	2	4	4	4
Congo	13	13	14	19	22	23	29	28	38
DR Congo	10	10	13	20	13	17	20	24	32
Djibouti	1	3	4	4	5	5	6	6	7
Egypt	74	89	98	105	119	138	149	145	173
Equatorial Guinea	6	6	6	6	6	6	7	7	8
Eritrea	0	1	1	1	1	2	2	2	2
Ethiopia	2	2	1	3	6	7	9	15	19
Gabon R	10	15	19	22	29	31	32	31	37
Gambia	4	6	7	7	8	8	8	10	12
Ghana	7	8	8	10	13	12	13	13	15
Guinea	6	8	11	12	15	21	23	22	21
Guinea-Bissau	1	1	1	3	2	2	1	1	3
Ivory Coast	55	59	71	74	76	79	78	82	106
Kenya	12	18	15	14	15	15	22	25	30
Liberia	2	5	4	5	8	5	7	7	11
Libya	0	0	0	0	1	3	4	5	8
Madagascar	9	11	13	14	15	19	24	28	33
Malawi	5	4	6	5	5	4	5	4	6
Mali R	10	13	17	13	13	14	16	16	23
Mauritania	6	6	7	7	7	8	9	8	7
Mauritius	117	150	224	239	272	320	386	425	478
Morocco	401	502	605	683	734	754	867	932	1127
Mozambique	48	49	69	78	79	88	102	116	131
Namibia	38	42	60	58	63	70	71	77	95
Niger R	4	7	5	6	5	8	6	7	11
Nigeria	9	10	14	12	14	18	20	21	23
Principe	0	2	2	2	4	5	5	7	6
Rwanda	6	9	10	8	8	7	9	16	18
Senegal R	42	54	71	81	94	85	93	89	100
Seychelles	3	4	4	3	3	4	6	11	10
Sierra Leone	7	9	10	10	9	11	12	12	11
South Africa	1493	1700	1997	1829	1937	2126	2353	2466	3666
South Sudan	2	1	3	3	3	3	5	6	7
Sudan	12	12	17	20	21	23	27	24	29
Swaziland	28	32	40	42	42	46	55	53	56
Tanzania	25	28	31	34	31	32	45	58	69
Togo	6	7	11	14	15	13	20	16	24
Tunisia	11	11	12	11	10	10	11	12	13
Uganda	5	8	8	8	8	8	7	7	8
Zambia	62	68	91	98	99	111	130	126	160
Zimbabwe	18	23	23	28	31	39	39	39	66
Total	2886	3379	4104	4153	4428	4789	5329	5679	7440

Notes: The table presents the number of foreign affiliates by country and year.

C Additional descriptive statistics

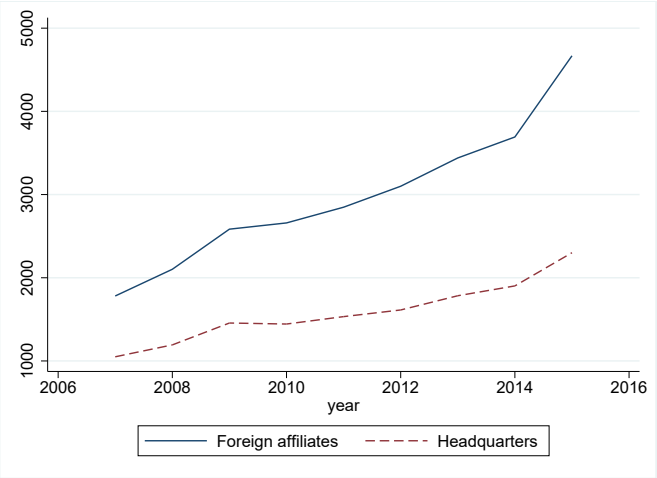
In this section we provide additional information on the conflict and multinationals data. Table A3 disaggregates the ACLED at the event-date level, and then at the cell-year level. On the other hand, Figure A5 shows the evolution of African foreign affiliates and their headquarters around the world.

Table A3: Conflict statistics

Type of event	Frequency	Percent
Event-date level		
Battle	16,096	26.12
Riots	7,761	12.59
Violence against civilians	15,360	24.92
Remote violence	4,233	6.87
Headquarter or base establishment	165	0.27
Non-violent transfer of territory	457	0.74
Protest	13,891	22.54
Strategic development	3,663	5.94
Total	61,626	100
Cell-year level		
Only violent	4,941	53.90
Violent and non-violent	2,921	31.87
Only non-violent	1,304	14.22
Total	9,166	100

Notes: In the first panel (*Event-date level*), the unit of observation is a single event recorded in the ACLED dataset. The first four types of events are classified as violent. In the second panel (*Cell-year level*), the unit of observation is a cell-year. The sample is limited to cell-year showing at least one event recorded in the ACLED dataset.

Figure A5: MNE affiliates and headquarters



Notes: Author's computation from the MNE dataset obtained from Orbis Historical Ownership Database, Bureau Van Djik. The sample is limited to African affiliates, with their headquarters worldwide.

D Different sectors aggregation

In Table A4 I replicate the correlations presented in Table 2, but applying the Nace sectors aggregation. As we can see, the results are confirmed.

Table A4: MNE and conflict - Nace aggregation

	(1)	(2)	(3)	(4)	(5)
Estimator			LPM		
Dependent variable			Conflict incidence		
Agriculture	5.71e-07	0.00753	0.000587	0.00551	0.00784
	(0.0128)	(0.0142)	(0.0136)	(0.0150)	(0.0156)
Forestry	0.169***	0.172**	0.166***	0.149**	0.169**
	(0.0544)	(0.0675)	(0.0573)	(0.0715)	(0.0696)
Fishing	-0.125	-0.137	-0.169	-0.200	-0.209
	(0.114)	(0.166)	(0.119)	(0.190)	(0.183)
Mining and quarrying	-0.00230	0.00587	0.0121	0.0198	0.0165
	(0.00908)	(0.0118)	(0.0123)	(0.0143)	(0.0144)
Manufacturing	-0.00316	-0.00485	-0.00331	-0.00376	-0.00153
	(0.00589)	(0.00874)	(0.00624)	(0.00913)	(0.00944)
Electricity, gas, steam and air conditioning supply	0.00896	0.00652	0.00561	0.0222	-0.0155
	(0.0399)	(0.0781)	(0.0460)	(0.0851)	(0.0851)
Water supply; sewerage, waste management and remediation activities	0.0570	0.0290	0.0537	0.0574	0.0391
	(0.0478)	(0.0615)	(0.0502)	(0.0740)	(0.0834)
Construction	-0.00229	0.0153	0.000377	0.0106	0.00409
	(0.0138)	(0.0168)	(0.0151)	(0.0167)	(0.0170)
Wholesale and retail trade; repair of motor vehicles and motorcycles	0.00490	-0.00156	0.00889	-0.000623	-0.00933
	(0.00747)	(0.00794)	(0.00884)	(0.00809)	(0.00981)
Transportation and storage	-0.00720	0.00481	-0.0130	0.00602	-0.00250
	(0.0137)	(0.0195)	(0.0162)	(0.0222)	(0.0229)
Accommodation and food service activities	-0.0152	-0.0130	-0.0155	-0.00803	0.00436
	(0.0124)	(0.0151)	(0.0134)	(0.0168)	(0.0171)
Information and communication	0.0148	0.0315	0.0339	0.0477*	0.0410
	(0.0158)	(0.0193)	(0.0207)	(0.0261)	(0.0328)
Financial and insurance activities	0.00191	-0.000716	-0.00315	-0.00610	-0.0133
	(0.00420)	(0.0101)	(0.00489)	(0.00985)	(0.0104)
Real estate activities	-0.0126	-0.0147	-0.0177	-0.0112	-0.00677
	(0.0207)	(0.0271)	(0.0222)	(0.0279)	(0.0284)
Professional, scientific and technical activities	-0.00524	-0.00289	0.00444	-0.00229	-0.00172
	(0.0104)	(0.0182)	(0.0127)	(0.0182)	(0.0187)
Administrative and support service activities	0.0358***	0.0656***	0.0322**	0.0617**	0.0592**
	(0.0124)	(0.0182)	(0.0140)	(0.0246)	(0.0235)
Public administration and defence; compulsory social security	-0.170**	-0.172**	-0.183**	-0.181*	-0.212**
	(0.0732)	(0.0865)	(0.0719)	(0.0943)	(0.105)
Education	-0.108**	-0.0955	-0.169***	-0.152***	-0.184***
	(0.0525)	(0.0591)	(0.0561)	(0.0535)	(0.0649)
Human health and social work activities	-0.0593*	-0.111*	-0.116**	-0.111*	-0.151*
	(0.0346)	(0.0630)	(0.0463)	(0.0652)	(0.0770)
Arts, entertainment and recreation	-0.0199	0.0231	-0.0114	0.0194	0.0332
	(0.0429)	(0.0319)	(0.0390)	(0.0354)	(0.0345)
Other service activities	0.0228	0.0908**	0.0192	0.0735*	0.107***
	(0.0513)	(0.0443)	(0.0685)	(0.0395)	(0.0247)
Activities of households as employers	-0.0306*	-0.0421*	-0.0395*	-0.0397*	-0.0436*
	(0.0173)	(0.0219)	(0.0210)	(0.0213)	(0.0251)
Activities of extraterritorial organisations and bodies	-0.0619	0	-0.0828	0	0
	(0.0879)	(0)	(0.0962)	(0)	(0)
Domestic affiliates	0.000518*	0.000366	0.000366	0.000259	0.000283
	(0.000294)	(0.000241)	(0.000279)	(0.000228)	(0.000265)
Country × year FE	Yes	Yes	Yes	Yes	Yes
Cell FE	Yes	Yes	Yes	Yes	Yes
Excluding resources		Yes		Yes	Yes
Excluding capitals			Yes	Yes	Yes
Controls					Yes
Observations	92,995	92,357	89,585	89,000	89,000

Notes: LPM estimation. Dependent variable: conflict incidence (ACLED). ***,**,* = indicate significance at the 1, 5, and 10% level, respectively. Conley (1999) standard errors in parenthesis, allowing for spatial correlation within a 500km radius and for infinite serial correlation. Each variable indicates the number of MNE foreign affiliates in its specific sector. *Domestic affiliates* indicates the number of affiliates with a headquarter located in their same country. In column (2) cells with natural resources are excluded. In column (3) cells in capital cities are excluded. Column (3) excludes both cells with natural resources or in capital cities. Column (5) adds the lag of population ad the cell-level (LandScan) and cell-specific time trends.

E Role of domestic affiliates

Table A5 replicates Table 2, but focusing on domestic affiliates, namely those affiliates having the headquarter in the same country where they are located.

Table A5: Domestic MNE and conflict

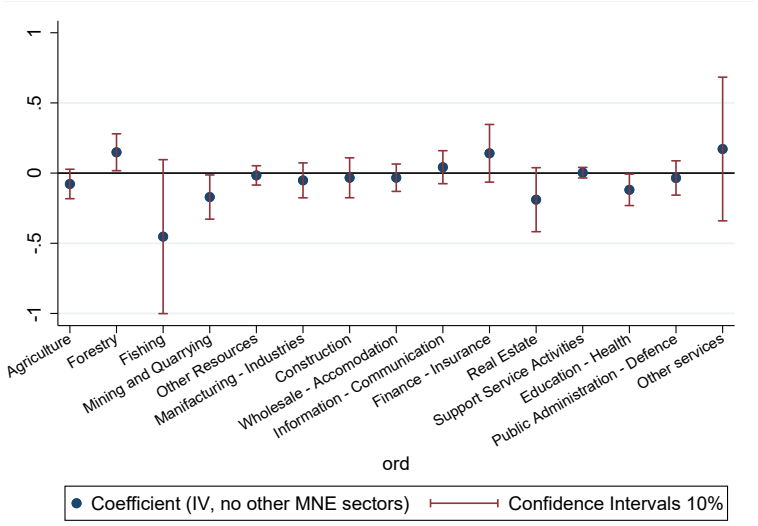
	(1)	(2)	(3)	(4)	(5)
Estimator			LPM		
Dependent variable			Conflict incidence		
Agriculture	0.00376	0.0137	0.00687	0.0169	0.0125
	(0.00772)	(0.0161)	(0.00861)	(0.0158)	(0.0170)
Forestry	0.00230	0.00677	-0.00107	0.0153	0.0190
	(0.0310)	(0.0352)	(0.0286)	(0.0336)	(0.0370)
Fishing	-0.0528	-0.0815*	-0.0585	-0.0822*	-0.0798
	(0.0326)	(0.0431)	(0.0367)	(0.0430)	(0.0486)
Mining and Quarrying	-0.0233	-0.0128	-0.0164	-0.00225	-0.00282
	(0.0205)	(0.0252)	(0.0213)	(0.0250)	(0.0246)
Other Resources	0.0118	-0.00210	0.0128	-0.00321	-5.15e-05
	(0.0126)	(0.0214)	(0.0156)	(0.0208)	(0.0220)
Manifacturing - Industries	0.00544	0.0119	0.00511	0.0113	0.0112
	(0.00544)	(0.00805)	(0.00565)	(0.00793)	(0.00830)
Construction	-0.000394	-0.0105	-0.00161	-0.0114	-0.00953
	(0.00705)	(0.0107)	(0.00785)	(0.0109)	(0.0108)
Wholesale - Accomodation	0.00151	0.00242	0.00151	0.00241	0.00243
	(0.00214)	(0.00210)	(0.00217)	(0.00212)	(0.00212)
Information - Communication	0.0104	0.0119	0.0104	0.0103	0.00934
	(0.00890)	(0.00896)	(0.00927)	(0.00889)	(0.0116)
Finance - Insurance	-0.00430	-0.00389	-0.00387	-0.00205	-0.00246
	(0.00414)	(0.00676)	(0.00448)	(0.00669)	(0.00718)
Real estate	-0.0131	-0.0376**	-0.0179*	-0.0400***	-0.0311*
	(0.00871)	(0.0154)	(0.00994)	(0.0154)	(0.0184)
Support Service Activities	-0.000182	-0.00333	0.00251	-0.00365	-0.00501
	(0.00770)	(0.0114)	(0.00853)	(0.0120)	(0.0122)
Education - Health	-0.0341***	-0.0403***	-0.0370***	-0.0383***	-0.0360***
	(0.00858)	(0.00688)	(0.00889)	(0.00640)	(0.00815)
Public Administration - Defence	-0.0181	-0.0442	-0.0261	-0.0421	-0.0380
	(0.0318)	(0.0350)	(0.0344)	(0.0342)	(0.0348)
Other Services	0.00153	-0.000520	-0.00223	-0.00417	-0.00422
	(0.00664)	(0.00955)	(0.00763)	(0.00934)	(0.00957)
Foreign affiliates	0.00185**	0.00467***	0.00255**	0.00468***	0.00426**
	(0.000941)	(0.00172)	(0.00119)	(0.00174)	(0.00209)
Country × year FE	Yes	Yes	Yes	Yes	Yes
Cell FE	Yes	Yes	Yes	Yes	Yes
Excluding resources		Yes		Yes	Yes
Excluding capitals			Yes	Yes	Yes
Controls					Yes
Observations	93,003	92,364	89,592	89,007	89,007

Notes: LPM estimation. Dependent variable: conflict incidence (ACLED). ***,**,* = indicate significance at the 1, 5, and 10% level, respectively. Conley (1999) standard errors in parenthesis, allowing for spatial correlation within a 500km radius and for infinite serial correlation. Each variable indicates the number of MNE foreign affiliates in its specific sector. *Domestic affiliates* indicates the number of affiliates with a headquarter located in their same country. In column (2) cells with natural resources are excluded. In column (3) cells in capital cities are excluded. Column (3) excludes both cells with natural resources or in capital cities. Column (5) adds the lag of population ad the cell-level (LandScan) and cell-specific time trends.

F IV without controls

In this section we replicate some of the main results without including (potential endogenous) other sectors as covariates in the estimations. We replicate Figure 5 without controlling for the other MNE sectors. In other words, Figure A6 plots the IV sector-specific coefficients of 15 different regressions. Each dot represents the IV coefficient of the corresponding sector, not controlling for all the other sectors. Each regression replicates column (5) of Table 2 instrumenting one single sector at the time. As it is possible to note, the only two sectors which remain significant in this figure and in Figure 5 are *Forestry* and *Education - Health*, with positive and negative signs respectively (0.148* and -0.119*).

Figure A6: IV all sectors (no controls)



Notes: Each point represent the IV coefficient for a specific sector in a LPM estimation which follows the specification of column (5) of Table 2, in which the dependent variable is conflict incidence (ACLED) and all the other sectors are not controlled for. The brackets represent the 10% confidence interval.

G Sensitivity conflict variable

In this section we present robustness of our dependent variable. Table A6 replicates our main specification (Table 3, column 2) focusing first only on violent events (according with the ACLED definition), and then only on events with at least one fatality. Interestingly, as the results show, the activity of *Forestry* affiliates increases both the incidence of violent events and events with fatalities, as expected. On the other hand, the affiliates in *Education - Health* sectors only reduce violent events, while losing its significance with respect to fatalities. The size of the coefficients in column (2) is smaller than the baseline results, reflecting the fact that the unconditional probability of observing specific types of events is smaller than the probability of observing any type of event. The latter being the primary focus of this paper, as shown in Table 3. We complement the sensitivity analysis on violence measurement using an alternative conflict database with geocoded information, the Uppsala Conflict Data Program Georeferenced Event Dataset (UCDP GED) Version 19.1 (Sundberg and Melander, 2013). It is more restrictive than ACLED, defining incidents as "where armed force was used by an organized actor against another organized actor, or against civilians, resulting in at least 1 direct death at a specific location and a specific date". Moreover, such events are only recorded for conflicts that reach at least 25 battle-related deaths, according to the standard PRIO threshold.[52] Due to these features, only the countries experiencing more than 25 conflict-related casualties are included in the UCDP GED sample. In our case, this would imply a dramatic sample size reduction, almost a half.[53] To alleviate this problem, I combine the two datasets in columns (3) of Table A6. To be precise, I code violent events with UCDP GED for country-year cells that are covered by this dataset, and for other country-year cells, I use a dummy assuming value 1 when in the cell/year the ACLED dataset registers at least one fatality. This procedure restores the initial sample size and confirms the results obtained in column (2). Column (3) shows that the results on fatal conflicts are confirmed jointly using the UCDP GED and ACLED datasets, however it is important to underline that the type of events described in this paper are characterised by localised conflict events, and not escalating into larger and more intense conflicts (e.g. battles or civil wars), see Appendix I. Therefore, the only dataset able to capture these events and currently available is that of ACLED.

[52] UCDP GED differs from ACLED also in it's data collection process. UCDP GED events are coded following two-steps. First, global newswire sources are consulted. Secondly, they are confirmed consulting local or specialized sources, such as translations of local news performed by the BBC, local media, NGO reports, and field reports.

[53] If we replicate the estimation on the sub-sample of country-years covered in UCDP GED, with a measure of conflict incidence based on UCDP GED events, the coefficient of interest looses its statistical significance. For comparison, we replicate the estimation on the same sub-sample using the incidence of events with fatalities from ACLED. We observe again a loss of significance, confirming that it relates to the drastic sample size reduction.

Table A6: Violence and fatalities

	(1)	(2)	(3)
Estimator		IV	
Dep. Var.		Conflict incidence	
		ACLED	UCDP-GED
	Violent events	Events with fatalities	Events with fatalities
Forestry	0.247**	0.173**	0.208***
	(0.0992)	(0.0778)	(0.0715)
Education - Health	-0.259*	-0.0903	-0.0441
	(0.139)	(0.103)	(0.0925)
Country × year FE	Yes	Yes	Yes
Cell FE	Yes	Yes	Yes
Kleibergen-Paap Wald F statistic	15.19	15.19	15.19
Observations	89,000	89,000	89,000

Notes: IV estimation. Dependent variable: violent conflict event incidence from ACLED in column (1), event with some fatalities incidence from ACLED in column (2), event with some fatalities incidence from UCDP-GED for the countries covered by this dataset and conflict incidence with fatalities from ACLED for the rest of the sample in column (3). ***,**,* = indicate significance at the 1, 5, and 10% level, respectively. Controlling for: cell FE, country×year FE, cell×year trends, other sectors affiliates (different than *Forestry* and *Education - Health*), domestic affiliates (with a headquarter located in their same country). Excluding resources areas and capital cities. Conley (1999) standard errors in parenthesis, allowing for spatial correlation within a 500km radius and for infinite serial correlation. *Forestry affiliates* indicates the number of foreign affiliates operating in the Forestry sector in the cell. *Education - Health affiliates* indicates the number of foreign affiliates operating in the sector Education and Human Health. The last two variables are instrumented, details are explained in Section 4.2.1.

H Ethnic groups fragmentation

In this section we analyse whether the result obtained in section 5 is driven by the ethnic group fragmentation characterizing each cell, instead of the share of politically non-represented ethnic groups. To test this hypothesis, we replicate the analysis presented in section 5, but substituting the variable $EthnicMinorities_{k,t}$ with $EthnicFragmentation_k$, a variable assuming value one if the number of ethnic groups in a cell at the beginning of the period is above the 75^{th} percentile of the distribution of ethnic groups in the sample.[54] The sample distribution of ethnic groups has mean = 1.55, s.d. = 0.77, 25^{th} and 50^{th} percentile = 1, 75^{th} percentile = 2, 99^{th} percentile = 4, min = 1, max = 6. Formally, we estimate the following equation:

$$\begin{aligned} CONFLICT_{k,t} = \sigma\ Forestry_{k,t} + \tau\ Education_h ealth_k \\ + \eta\ Forestry_{k,t} \times EthnicFragmentation_k \\ + \phi\ EducationHealth_{k,t} \times EthnicFragmentation_k \\ + FE_k + FE_{r,t} + \Gamma X'_{k,t} + u_{k,t} \end{aligned}$$

We do not include the $EthnicFragmentation_k$ alone because it would be absorbed by the cell fixed-effects (being evaluated at the beginning of the period to reduce endogeneity), while we want to test whether the ethnic fragmentation has a role when interacted with the number of *Forestry* affiliates (η), and/or with the number of *Education - Health* affiliates (ϕ). Table A7 confirms that both effects are not statistically significant.

[54] Results are qualitatively the same if we use as more stringent threshold, e.g. the 99^{th} percentile.

Table A7: Ethnic groups fragmentation

Estimator	IV
Dep. Var.	Conflict incidence
Forestry	0.267**
	(0.133)
Education - Health	-0.233**
	(0.0994)
Forestry × Ethnic Fragmentation	-0.0647
	(0.163)
Education - Health × Ethnic Fragmentation	0.126
	(0.159)
Country × year FE	Yes
Cell FE	Yes
Kleibergen-Paap Wald F statistic	8.498
Observations	69,348

Notes: IV estimation. Dependent variable: conflict incidence (ACLED). ***,**,* = indicate significance at the 1, 5, and 10% level, respectively. Controlling for: cell FE, country×year FE, cell×year trends, other sectors affiliates (different than *Forestry* and *Education - Health*), domestic affiliates (with a headquarter located in their same country). Excluding resources areas and capital cities. Conley (1999) standard errors in parenthesis, allowing for spatial correlation within a 500km radius and for infinite serial correlation. *Forestry affiliates* indicates the number of foreign affiliates operating in the Forestry sector in the cell. *Education - Health affiliates* indicates the number of foreign affiliates operating in the sector Education and Human Health. The last two variables are instrumented, details are explained in Section 4.2.1. *Ethnic Fragmentation* is a dummy variable assuming value one if the cell at the beginning of the period has a number of ethnic groups above the 75^{th} percentile of the sample mean.

I MNE activity and nature of conflict

Table A8 replicates column 2 of Table 3 for each violent category covered by the ACLED dataset: battles between fighting groups, violence against civilians, and riots. The dummy *Battle* in column (1) equals 1 when a cell/year has experienced a battle of any kind, regardless of whether control of the contested location changes.[55] In column, the dummy (2) *Violence against civilians* captures instances where any armed group attacks unarmed civilians within a larger conflict.[56] In column (3), the dependent variable *Riots* indicates instances of "violent demonstrations against a (typically) political entity, such as a government institution, although this may also include some demonstrations against businesses or other private institutions". The fact that the unconditional probability of observing specifically *Battles* or *Violence against civilians* is not statistically significant does not mean that these events are not relevant in the probability of observing any type of event, which is the main aim of this paper. On the other hand, it is particularly striking the fact that the only unconditional probability which turns out to be significant is the one of observing *Riots*, independently of other types of events. This, indeed, can be considered as an anecdotal evidence of the fact that the channels described in Sections 4 and 5 are the actual mechanisms in place, in particular relying on the definition of *Riots*, which underlines violent actions against *political institutions* (ethic groups sitting in the government) or *business* (MNEs).

[55] Formally, the ACLED definition of *Battle* is "a violent interaction between two politically organized armed groups at a particular time and location. Typically these interactions occur between government militaries/militias and rebel groups/factions within the context of a civil war."

[56] From ACLED, "although the victims can be combatants in a different context, during acts of violence against civilians, they are unarmed and not able to defend themselves or engage in violence".

Table A8: MNE and types of conflict events

	(1)	(2)	(3)
Estimator		IV	
Dep. Var.	Conflict incidence, including only		
	Battles	Violence against civilians	Riots
Forestry	0.0375	0.286	0.194*
	(0.101)	(0.219)	(0.117)
Education - Health	-0.141	-0.00234	-0.328**
	(0.0955)	(0.112)	(0.157)
Country × year FE	Yes	Yes	Yes
Cell FE	Yes	Yes	Yes
Kleibergen-Paap Wald F statistic	15.19	15.19	15.19
Observations	89,000	89,000	89,000

Notes: IV estimation. Dependent variable: Battle incidence in column (1), Riots incidence in column (2), Violence against civilians incidence in column (3), all from ACLED. ***,**,* = indicate significance at the 1, 5, and 10% level, respectively. Controlling for: cell FE, country × year FE, cell × year trends, other sectors affiliates (different than *Forestry* and *Education - Health*), domestic affiliates (with a headquarter located in their same country). Excluding resources areas and capital cities. Conley (1999) standard errors in parenthesis, allowing for spatial correlation within a 500km radius and for infinite serial correlation. *Forestry affiliates* indicates the number of foreign affiliates operating in the Forestry sector in the cell. *Education - Health affiliates* indicates the number of foreign affiliates operating in the sector Education and Human Health. The last two variables are instrumented, details are explained in Section 4.2.1.

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