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Income Shocks and Linguistic Diversity: Determinants of the Number of Violent Actors.

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SUMMARY

I combine georeferenced information on violent actors with two different types of income shocks and a measure of linguistic diversity at the spatial resolution of 0.5 x 0.5 degree latitude and longitude for all the African continent during the period 1997-2007. I find that the effect of income shocks on the number of violent actors varies with different levels of linguistic diversity. Two shocks are used: an adverse economic shock, a rainfall variation, and a positive shock, a change in the price of minerals. A rainfall shock reduces the number of violent actors in high fractionalized cells. Instead, a shock on the mineral prices increases the number of violent actors in high fractionalized cells. I provide evidence of the importance of linguistic diversity on the relationship between income and conflict and the different relationships between linguistic diversity and two different types of shocks.

Keywords: Violent actors, linguistic diversity, conflict, income shocks.

1 Introduction

Conflict has been largely studied in the literature, pointing out his causes, consequences and his different types. The source of this interest is mainly due to the high number of conflicts around the world, above all civil wars. This attention is also understandable owing to the immense and undeniable suffering of human beings as a consequence of the wars.

The present work investigates the reasons why in some regions there are few armed groups and in others many of them. It has been used different definitions of violence to measure conflicts, such as the number of fatalities, number of violent events, or battles. However, to the best of my knowledge, no paper uses as a dependent variable the number of violent actors.

Particularly, I analyze whether the effect of an income shock on the number of violent actors is heterogeneous by the ethno-linguistic diversity computed in different levels of aggregation. I use two income shocks: a rainfall variation shock, and a shock on the prices of minerals. My results show that the effect of income shock on the number of violent actors varies across cells with different levels of ethno-linguistic diversity. Moreover, linguistic diversity has a different relationship with the two types of shocks. To measure ethno-linguistic diversity I use two indices: the ethno-linguistic fractionalizacion (ELF) and the ethno-linguistic polarization (ELP) at different levels of aggregation (Desmet, Ortuño-Ortín, and Wacziarg (2012)). Higher levels of aggregation implies coarse linguistic divisions (Desmet et al. (2012)).

My empirical analysis is based on the Armed Conflict Location Events Data (ACLED), which provides information on the actors involved in the conflict and the location, the data of ethno-linguistic diversity calculated by (Gomes (2020)) using the methodology of Desmet et al. (2012), the double standardized rainfall shock used in (Armand, Atwell, and Gomes (2020)) and proposed in (Hidalgo, Naidu, Nichter, and Richardson (2010)), and the data on mines on the paper of (Berman, Couttenier, Rohner, and Thoenig (2017)). I use a panel of disaggregated cells of 0.5 x 0.5 degree latitude and longitude covering all the African continent. Using the PRIO/UCDP grid cell, the geolocation of the conflict events and, the exogenous variation of the shocks, I am able to establish a causal identification. Furthermore, the inclusion of cell fixed effects and country-year fixed effects absorb fixed spatial characteristics and any common time-varying country trend which can bias the results, ensuring the identification of the interesting relationship.

In the first part of my study, I estimate whether a rainfall shock affects the number of armed groups depending on the ethno-linguistic diversity of the cell. I find that in high fractionalized cells, a rainfall shock reduces the number of armed groups. A possible explanation is the following: a rainfall shock reduces the opportunity cost of fight and the difficulty to form an armed group is higher in more fractionalized places. Hence, it is more difficult to form an armed group based on ethnicity when a rainfall shock occurs. I find significance at more disaggregated levels of ethnic diversity and the coefficients are greater when I consider the ethno-linguistic polarization (ELP). Several consistency tests are done to check the sensitivity of the results.

In the second part of this work, I study whether an increase in the price of minerals affects the number of armed groups in those cells producing them, depending on the linguistic diversity of the cell. I find that in more fractionalized cells, an increment in the mining activity raises the number of armed groups. A shock on the mineral price is a positive shock, that is, it arises the resources to fight, increasing the value of minerals. In more fractionalized places, there is a higher number of groups when there is a positive shock because more groups are fighting for the resources. I find significance at every level of aggregation of the linguistic diversity and the coefficients are greater when the ethno-linguistic polarization is used as a measure of linguistic diversity. These results are also robust when I do some consistency tests.

The two income shocks considered affect conflict in two different ways: through the opportunity cost channel and through a rapacity effect (Dube and Vargas (2013)). I find the linguistic diversity has a different relationship with both shocks. In more fractionalized places, when a rainfall shock occurs, the number of armed groups is lower; when a price-mineral shock comes, the number of armed groups is greater. Another important conclusion of the study is the existence of heterogeneity by linguistic diversity when the relationship between income and conflict is studied. This result has not been found before (Miguel, Satyanath, and Sergenti (2004); Hegre and Sambanis (2006); Laitin, Watkins IV, et al. (2007)). Hence, my results go in the same direction as (Alesina and Ferrara (2005); Easterly and Levine (1997)), which finds that social divisions have an effect on economic outcomes.

My work contributes to the literature in various ways. First, it studies the relationship between income shocks and conflict, considering two types of channels: rapacity and opportunity cost channel. Second, it provides how linguistic diversity can affect conflict and possible channels to do it: through income shocks. Third, to the best of my knowledge, it is the first work that tries to explain the disparity of the number of violent actors in different regions.

This work is organized as follows: Section 2 describes the conceptual framework of this work and the existing literature. Section 3 presents the data and some descriptive analysis. Section 4 discusses the empirical methodology and the identification strategy. Section 5 provides the results and different sensitivity tests. The last section concludes.

2 Conceptual Framework

The use of weather variation to identify the impact of income shock on different outcomes has been widely used in the literature. The main reason is that temperature or precipitation varies randomly over time, isolating an exogenous variation in income. Using these kinds of weather shocks in economies highly dependent on them gives strong identification properties. In the literature, two approaches are used: using a weather variation as an instrument for economic growth or focusing directly on the effect of a weather variation on an outcome of interest (reduced form approach). This work uses the latter approach: identify the direct effect of a weather shock on the number of violent actors.

The literature which analyzes the relationship between weather shock and economic outcomes is quite extensive, see the excellent review of (Dell, Jones, and Olken (2014)). I focus here on the relationship between weather shocks and conflict. One of the earliest contributions to the literature was (Miguel et al. (2004)). They analyzed the relationship between rainfall and civil conflict, finding that a rainfall shock led to an increase in civil conflict. After that, numerous works have found that a negative rainfall shocks increase conflict (Fjelde and von Uexkull (2012); Maystadt, Ecker, and Mabiso (2013); Bohlken and Sergenti (2010)) and increase political instability (Burke and Leigh, 2010; Hidalgo et al. (2010)). Although there have been some studies arguing that the relationship between rainfall and conflict is weaker (Brückner and Ciccone (2011)), a meta-analysis done by (Hsiang, Meng, and Cane (2011)), in which reanalyzed all empirical studies of weather, find that irregular precipitation raises conflict.

The mechanism that explains the relationship between precipitation and conflict is called in the literature opportunity cost effect. (Dal Bó and Dal Bó (2011)) shows theoretically that any income shock which increases prices in labor-intensive goods will reduce conflict owing to an increment in the opportunity cost. This result is corroborated empirically by (Dube and Vargas (2013)). More explicitly, when a rainfall shock occurs, the return in economies highly dependent on the level of precipitation will see their outcome reduced, with the consequences of lower wages and hence a lower opportunity cost.

On the other hand, their theoretical model (Dal Bó and Dal Bó (2011)) also show that an increment in prices of non-labour intensive goods will increase conflict because there are more resources to capture. (Dube and Vargas (2013)) also prove this result empirically, namely the rapacity channel. Hence, depending on the type of shock, the effect on conflict will be different. If the income shock increases the resources to appropriate, more people are willing to fight in order to capture resources. In other words, a positive income shock increases the rents of the resources, and the prize of "winning" is greater, encouraging people to fight.

Due to the fact that in Africa, (above all Sub-Saharan Africa), most of the cropland is not irrigated, the dependence of the rain is high. As shown in (Miguel et al. (2004)), the link between a rainfall shock and economic growth is elevated. Thus, a rainfall shock is a good measure to the variation in income growth, triggering the opportunity cost channel developed theoretically by (Dal Bó and Dal Bó (2011)) and showed empirically in (Dube and Vargas (2013)). An anomalous change in the level of precipitation (flooding or drought), decreases the agricultural output and make the opportunity cost lower.

The other side of the coin is a positive shock on the resources: a shock that increases the gains of appropriation. For example, (Dube and Vargas (2013))) exploits international price changes in oil prices to show that an increase in the prices of oil leads to an increase in conflict in those municipalities which produce it; Berman et al. (2017) linking natural resources and conflict find that an increase in prices of minerals raise conflict in areas where the mineral is produced. A positive shock on the mining activity increases conflict because the extraction of revenue from mines is greater as the price of mineral increases: more revenue means there is more to fight.

The effect of ethnic fractionalization on conflict has been controversial. For example, (Fearon and Laitin (2003)) argues that ethnic fractionalization has no effect on the onset of civil wars. In contrast, (Montalvo and Reynal-Querol (2005)) maintain that polarization affects civil conflict. The effect of linguistic diversity on different outcomes, such as, public goods, growth or redistribution has also been studied (Easterly and Levine (1997); Alesina, Baqir, and Easterly (1999); Fearon and Laitin (2003)). Desmet et al. (2012) reviews all these papers using a new proxy of ethnic diversity, the ethno-linguistic fractionalization or polarization (see Section 3.3 for more details). They found that the effect on conflict, growth, and redistribution depends on the level of aggregation of ethno-linguistic diversity. For outcomes related to coordination problems, more disaggregated levels are more significant. However, to explain outcomes related to a conflict of interest, more aggregated levels are more important.

I use all this literature to analyze whether the effect of income shock on the number of violent actors varies depending on the ethno-linguistic diversity. The literature has been unable to corroborate the heterogeneity by linguistic diversity when it has studied the effect of an income shock on the level of conflict. I show that the number of violent actors depends on linguistic diversity when an income shock comes. I use two shocks: a rainfall shock (for more details, see Section 3.2), affecting the opportunity cost channel, and a price-mineral shock, using the specification and data of (Berman et al. (2017)), which can be considered as a triggering of a rapacity effect. To measure linguistic diversity, I use the methodology of Desmet et al. (2012), see Section 3.3.

3 Data

My main objective is to study the determinants of why in some regions there are a few armed actors, while others have many. I, therefore, need data on the location of conflicts events and the actors who are responsible for them. To guarantee that the unit of observation is not endogenous to the number of armed actors, I use a grid cell of Africa divided in 0.5 x 0.5 degrees (around 55 x 55 kilometers). Hence, my unit of observation is a cell-year. Then, I study whether the effect of an income shock on the quantify of armed depends on the linguistic diversity of the cells. In this section, I explain how the variables were constructed and provide information about the datasets.

3.1 Conflict Data

I use the Armed Conflict Location and Event dataset (ACLED). This dataset records information on conflict events in all the African continent, starting in 1997. I focus in two periods: 1997-2017 when the income shock is the rainfall and 1997-2010 when the income shock is over the price of minerals. The difference in the periods is due to the availability of rainfall shocks and mines.

The unit of observation in ACLED is the event. For each event, ACLED contains information of the type of event, the location, the date, the actors of both sides of the conflict, and the result of the outcome. Moreover, it provides geographical information, latitude and longitude, and the geoprecision of which the event is recorded. For this work, I restrict the sample to the events recorded with the highest precision, that is, events for which the precise coordinates are available.

I use this geographical information to match the events in ACLED database to the grid of 0.5 x 0.5 degree-cell of PRIO/UCDP using the spatial join of QGIS. Spatial join is useful to join or transfer attributes of two layers. The tool I use in QGIS is called: Join Attribute by Location. I use this tool to match the events of ACLED with the cell of PRIO/GRID in which the event is produced (see Figure (1)). I do the match with the goal to join the grid cells the rainfall data and the information about the minerals. Hence, I construct the main dependent variable of this work summing the number of armed actors of each grid in a given year. In my sample, at least one actor is in each grid. I do not consider cells in which there is no actors. The main focus of this work is to determine the reasons why there are regions with a few actors and others with many, not why some regions have conflict and others do not. As an alternative measure of violence, I create another dependent variable with the number of fatalities in a cell-year. My results are robust to this new variable.

ACLED classifies the type of groups according to the their goals and the organization of each group. They do the following classification: State Forces, Rebel Groups, Political Militias, Identity Militias, Rioters, Protesters, Civilians, and External/Other Forces. In this work, I consider the armed actors belong to each ACLED group with the exception of Rioters, Protesters, and Civilians [1]. Hence, in my sample, it is considered as an armed group any state forces, the main reason of this inclusion is because according to ACLED "state forces does not imply legitimacy". It is reasonable to consider a state forced as any other armed group. The inclusion of external forces is due to the fact that the boundaries in Africa were made arbitrary after the Berlin Conference in 1884-1885, producing long-run effects (Michalopoulos and Papaioannou (2016)). Hence, it could be that some state forces act violently outside of their country because of an ethnic reason. In the robustness check, I remove from the sample the State and the External forces. On the other hand, in Appendix A I give a definition of each group of actors according to the definition of ACLED.

In ACLED database when an armed group is not identified due to a lack of information, it is considered as Unidentified Armed Group (Country)', where the country reflects the territory in which the group perpetrates the violence. In the baseline result (subsections 5.1 and 5.2) I consider an unidentified group as another armed group. In the robustness section (Section 5.3), I remove all the unidentified groups from the sample.

It is possible that the recorded conflict by ACLED can be biased due to different media coverage of the regions. To alleviate this, I include cell and country-year fixed effects in order to control for possible structural differences in the reporting of events.

[1] The exclusion of these groups is because most of the times does not have an associated armed group

Figure 1

Example QGIS

3.2 Climate Variables

I use the double-standardized rainfall deviations constructed by (Armand et al. (2020)). The data are provided by Climate Hazards Groups InfraRed Precipitation with Station data (CHIRPS) based on daily precipitations. Due to the broad range of climate variation, rainfall totals would be unsuitable because a 20-centimeter drop in annual rainfall can have a different effect depending on the region. I am analyzing all the African continent, so I need to ensure the comparability of the rainfall data across cells. I use the double-standardized rainfall deviations proposed by (Hidalgo et al. (2010)) and I take the data from (Armand et al. (2020)). The rainfall data is constructed as follows: the monthly rain total data are standardized by station and month and then are summed up by year for each cell. After that, the annual-totals of each cell are standardized again but in this occasion by station-year. The measure of rainfall used is the absolute value of standardized rainfall because the association between rainfall and income changes is non monotonic. This is the rainfall shock used during this work.

Some crops do not just need a normal average of rainfall, but also not extreme temperature. I control for it in the regressions using the standardized temperature deviations ensuring the comparability of the temperature across cells. I take the data from (Armand et al. (2020)).

3.3 Ethnolinguistic diversity

In order to measure ethnic diversity, I use as a proxy two indices: the ethno-linguistic fractionalization (ELF) (Alesina, Devleeschauwer, Easterly, Kurlat, and Wacziarg (2003)) and the ethno-linguistic polarization (Esteban and Ray (1994); Montalvo and Reynal-Querol (2005)). My measure ELF gives the probability that two randomly picked individuals from a given cell speak two different languages. Instead, ELP captures how far the distribution of the linguistic groups in a given cell is from the bipolar distribution (1/2, 0, 0,...0, 1/2), which symbolizes the highest level of polarization (Montalvo and Reynal-Querol (2005)).

To obtain the ELF and ELP of the grid cell in the African Continent, I use the data from (Gomes (2020)). The methodology follows to get the ELF and ELP is the one proposed by Desmet et al. (2012). The linguistic diversity is computed at different levels of aggregation of the Ethnologue language trees. Levels of aggregation more aggregated reveal deeper cleaves, developed farther away in the history Desmet et al. (2012). Hence, more aggregated classification keep groups more distant from each other. The levels of aggregation go from (1) to (15), for this work I focus on levels (1), (5), (10), and (15)

To clarify what I am saying, I use the example of Desmet et al. (2012). Figure (1) represents a hypothetical language tree with three levels of aggregation, (1), (2), and (3). Level (1) is a more aggregated level than Level (2). A, B and C can be considered the mother languages of a1, a2, a3, b1, b2, c1, and c2, respectively. The small number in parenthesis at the end of each line represents the shares of population speaking the language. Note that the level of aggregation adds a historical dimension to linguistic diversity.

Figure 2

Exam of Language Tree (Desmet et al. 2012)

K. Desmet et al. / Journal of Development Economics 97 (2012) 322–338

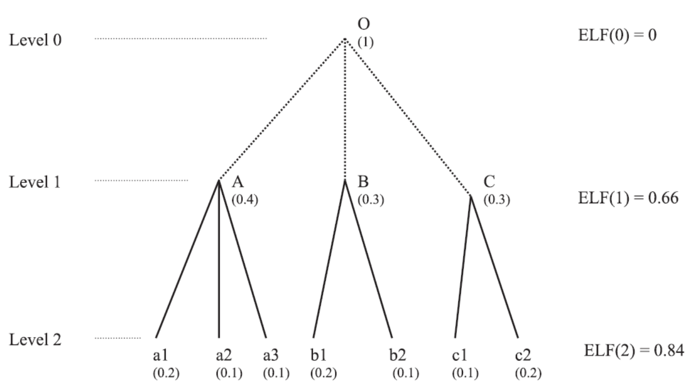

Fig. 2. Hypothetical language tree.

The two measures of ELF and ELP, in cell k and at aggregation level j are defined as:

$$ELF(j)_k = 1 - \sum_{i=1}^{N} \left[s(j)_{i(k)}\right]^2 \qquad (1)$$

$$ELP(j)_k = 4 \sum_{i=1}^{N} \left[s(j)_{i(k)}\right]^2 \left[1 - s(j)_{i(k)}\right] \tag{2}$$

where $s(j)_{i(k)}$ is the share of population speaking language i at level of aggregation (j) in cell k. N is the number of languages in cell k.

3.4 Mines

The other shock considered in this work is based on the price on minerals. I take advantage of the methodology of (Berman et al. (2017)). They construct a dataset in which they collect if an mine is active in a given cell and in a given year as well as data about the type of mineral produced by the mine. They also collect information about the world price of the main mineral produced in the cell. I match their data set with my dataset of ACLED using the grid of PRIO. I use their data to interact a mineral shock with the measure of ethnic diversity and see a possible heterogeneity in the effect of the shock on the number of armed groups. More details about the empirical methodology used in the paper is commented in Section 4.2, in the empirical part of this work.

3.5 Descriptive Statistics

In this section, I provide descriptive statistics following the analysis of Desmet et al. (2012). In Tables (2) and (3), I display a summary statistic of the ethno-linguistic fractionalization and polarization of the levels of aggregation used in this work, as well as a correlation table. In table (4), I show the different number of violent actors and his frequency as well as some other relevant information.

In Table 1, I show means and standard deviations. Note that for ELF, the mean growth as the level of aggregation falls. It makes sense, when the level of aggregation falls, there are more linguistic groups and hence the probability that two randomly picked individuals from a given cell speak two different languages is greater. The same happens with the polarization index.

More interesting information can be found in Table 2. The correlation between ELF1 and ELF15 is 0.598, meaning that the level of aggregation influences the measures of diversity. Higher the level of aggregation, lower the correlation between ELF and ELP: at the level of aggregation 15, the correlation between ELF and ELP is 0.820; while when the level of aggregation is 1, the correlation between both is 0.992. The intuition is that when a few groups remains (higher aggregation levels), it is more difficult to distinguish ELF from ELP. One last observation is the correlation between ELF1 and ELP15: it is just 0.469. Hence, aggregation is not the same as changing from ELF to ELP. All these results go in the same line than Desmet et al. (2012)).

In general, the correlation between ethno-linguistic fractionalization and ethno-linguistic polarization is high at the same level of aggregation: it goes from 0.820 (between ELF15 and ELP15) to 0.992 (between ELF1 and ELP15). Hence, differences in the results between ELF and ELP should take into account with caution due to the high level of correlation between them.

Table 1

Summary Statistics

Variable	**Mean**	**Std. Dev.**	**Min.**	**Max.**
ELF1	0.114	0.169	0	0.66
ELF5	0.226	0.25	0	0.865
ELF10	0.324	0.298	0	0.914
ELF15	0.353	0.308	0	0.936
ELP1	0.052	0.075	0	0.25
ELP5	0.082	0.083	0	0.25
ELP10	0.098	0.082	0	0.25
ELP15	0.101	0.079	0	0.25

Table 2

Correlations

Variables	ELF1	ELF5	ELF10	ELF15	ELP1	ELP5	ELP10	ELP15
ELF1	1.000							
ELF5	0.664	1.000						
ELF10	0.618	0.816	1.000					
ELF15	0.598	0.801	0.961	1.000				
ELP1	0.992	0.660	0.616	0.598	1.000			
ELP5	0.643	0.930	0.789	0.778	0.658	1.000		
ELP10	0.499	0.721	0.860	0.834	0.518	0.800	1.000	
ELP15	0.469	0.648	0.778	0.820	0.489	0.741	0.941	1.000

The period considered for the analysis is the one from 1997-2007. My sample covers 49 countries. Table (3) shows the different quantities of violent actors by cell and year. For example, during the 20 years, cells with one actor has appeared 8577 times. This contrast with the last row of the table, only one time has been a cell-year observation which has registered 28 violent actors. The big disparity between the number of actors is the main reason I have considered as a dependent variable the log-transformation of the number of violent actors in order to reduce the skewness of the data.

Table (3) also displays the mean of the ELF and ELP to the levels of aggregation used in this work. For example, the mean of the ethno-linguistic fractionalization at level of aggregation 1 (ELF1) for the 8577 cells in which 1 violent actor is present is 0.109. In the descriptive results, I do not observe any tendency which indicates that when the number of violent actors is greater, the linguistic diversity is also greater.

Table 3

Descriptive Statistics

Number of Violent Actors	Frequency	ELF1	ELF5	ELF10	ELF15	ELP1	ELP5	ELP10	ELP15
1	8577	0.109	0.225	0.330	0.361	0.050	0.083	0.101	0.104
2	2815	0.114	0.227	0.320	0.346	0.052	0.083	0.097	0.100
3	1238	0.123	0.243	0.327	0.354	0.056	0.086	0.096	0.098
4	647	0.137	0.234	0.321	0.349	0.062	0.084	0.095	0.100
5	367	0.127	0.213	0.284	0.306	0.057	0.074	0.080	0.083
6	214	0.139	0.230	0.301	0.326	0.062	0.080	0.084	0.090
7	137	0.115	0.189	0.265	0.284	0.052	0.071	0.074	0.077
8	79	0.157	0.226	0.292	0.311	0.067	0.072	0.066	0.072
9	54	0.140	0.224	0.292	0.309	0.062	0.077	0.069	0.073
10	23	0.045	0.135	0.167	0.200	0.022	0.057	0.055	0.065
11	19	0.109	0.199	0.289	0.304	0.048	0.080	0.078	0.083
12	15	0.106	0.175	0.195	0.270	0.048	0.060	0.052	0.076
13	13	0.042	0.087	0.100	0.165	0.020	0.036	0.031	0.054
14	7	0.151	0.164	0.275	0.492	0.071	0.074	0.081	0.154
15	6	0.111	0.203	0.342	0.381	0.051	0.077	0.084	0.092
16	3	0.046	0.046	0.046	0.072	0.023	0.023	0.022	0.033
17	3	0.010	0.018	0.018	0.059	0.005	0.009	0.009	0.029
18	3	0.137	0.152	0.283	0.341	0.064	0.067	0.075	0.100
20	3	0.096	0.206	0.262	0.322	0.043	0.072	0.050	0.064
21	4	0.076	0.164	0.206	0.251	0.035	0.059	0.042	0.053
22	2	0.012	0.023	0.023	0.031	0.006	0.011	0.011	0.015
23	1	0.273	0.603	0.771	0.824	0.122	0.208	0.143	0.124
24	2	0.012	0.022	0.022	0.077	0.006	0.011	0.011	0.038
25	2	0.012	0.023	0.023	0.031	0.006	0.011	0.011	0.015
28	1	0.016	0.038	0.038	0.038	0.008	0.019	0.019	0.018

4 Empirical Methodology

Now, I turn on to my empirical analysis. I discuss my identification strategy for the two main baseline specifications. I examine whether the effect of an income shock on the number of armed groups varies across the level of ethno-linguistic diversity of the grid cell. I use two shocks: a rainfall shock and a shock on the price of minerals. Section 4.1 shows the specification for the rainfall shock; Section 4.2 show the specification for the mineral shock.

4.1 Methodological Issues: Rainfall shock

To evaluate whether there is a heterogeneity effect of a rainfall shock on the number of armed groups depending on the ethnolinguistic diversity I estimate the baseline speficication:

$$\text{Log(Nactors)}_{kt} = \alpha_1 Prep_{kt} + \alpha_2 Temp_{kt} + \alpha_3 \left(Prep_{kt} \times EL()(j)_k\right) + \mathbf{FE}_k + \mathbf{FE}_{it} + \varepsilon_{kt} \tag{3}$$

where (k,t,i) denote respective cell, time (year) and country. The dependent variable Log(Nactors)_{kt} corresponds to the logarithm of the number of actors by grid and year. The dependent variable is in logarithm to reduce the skewness of the data. I also show the results without taking the log-transformation. The explanatory variables are $Prep_{kt}$, which corresponds to the double-standardized rainfall deviations by grid and year using in (Armand et al. (2020)), $Temp_{kt}$ which corresponds to the standardized temperature deviations by grid and year also used in (Armand et al. (2020)). The variable $EL()(j)_k$ measure the ethnolinguistic diversity. This variable can be $ELF(j)_k$, referring to the ethno-linguistic fractionalization at aggregation level j, or $ELP(j)_k$, the ethno-linguistic polarization at aggregation level j. The levels of aggregation used in this work are: 1, 5, 10 and 15. Level 1 is the most aggregated one and level 15 the most disaggregated.

The coefficient of interest, α_3, is the coefficient of the interaction term between the double-standardized rainfall deviations and variable $EL()(j)_k$. This coefficient captures the possible variation on rainfall shock depending of the linguistic diversity of cell k. In all estimations, $\mathbf{FE}_k$ are cell fixed effects and $\mathbf{FE}_{it}$ are year-country fixed effects. They control for time-invariant characteristics of cells and time-varying national trends that may be related to both, the number of armed groups and the interaction term between the rainfall shock and the ethnic diversity.

Due to the inclusion of fixed effects, my identification strategy depends on the exogeneity of the interaction term $Prep_{kt} \times EL()(j)_k$. Hence, we rely on the exogeneity between the rainfall shock and conflict, given that the level of precipitation is randomly produced, and the high persistence of $EL()(j)_k$ over time, which is determined before my dependent variable is reported (Desmet et al. (2012))

In all the estimations, the standard errors are estimates with a spatial HAC correction allowing for both cross-sectional spatial correlation and location-specific serial correlation, applying (Conley (1999); Hsiang, Burke, and Miguel (2013)) and using the code of (Fetzer (2014)). The spatial correction is allowed within a 500 km radius and for infinite serial correlation, the same specification than (Berman et al. (2017)).

4.2 Methodological Issues: price-main shock

To measure whether there is a heterogeneity effect of a mineral shock on the number of armed groups depending on the ethno-linguistic diversity I take advantage of the specification of (Berman et al. (2017)). I estimate the following equation:

$$\text{Log(Nactors)}_{kt} = \alpha_1 M_{kt} + \alpha_2 lnp^W_{kt} + \alpha_3 \left(M_{kt} \times lnp^W_{kt}\right) + \alpha_4 \left(M_{kt} \times lnp^W_{kt} \times EL()_k\right) + \mathbf{FE}_k + \mathbf{FE}_{it} + \varepsilon_{kt} \quad (4)$$

where (k,t,i) denote respective cell, time (year) and country. The explanatory variable M_{kt} is a binary variable which takes value 1 if at least there is one active mine at the cell-year level. The variable p^W_{kt} corresponds to the world price of the main mineral generated by the mines existing in cell k and in year t. The coefficient α_3 is the coefficient of interest in (Berman et al. (2017)), the interaction between the mining activity variable and the price. The middle interactions between lnp^W_{kt}, M_{kt} and $EL()_k$ are skipped to facilitate the interpretation of the coefficients. However, for the sake of completeness and robustness, Tables (20) and (21) in Appendix B show the results including all the middle interactions.

In this part, I focus primarily on the estimation of α_4, the coefficient of the interaction term between the shock on minerals and variable $EL()(j)_k$. It captures a possible heterogeneous effect of the mines shocks on the number of armed groups depending on the ethno-linguistic diversity of the grid-cell. In this case, cell fixed effects are included with the goal of attenuating a possible systematic difference in terms of collect violent events because some regions can have better medias coverages than others with the consequence of makes the results bias. Moreover, it allows to control for time-invariant characteristics affecting both my interest interaction term and the number of armed groups. Country-year fixed effect control for country time-varying characteristics affecting the quantity of armed groups and mines.

Like equation (3), I am estimating a reduced form, focusing on the net effect of an income shock on the number of violent actors. Hence, with the inclusion of fixed effects, my identification strategy rely on the exogeneity of the terms making up the interaction $M_{kt} \times lnp_{kt}^{W} \times EL()_k$. Berman et al. (2017) justify the exogeneity of $M_{kt} \times lnp_{kt}^{W}$ with two checks. First, they eliminate from the sample the countries with power to influence the world price of the mineral market, to check for the exogeneity of prices. Second, they restrict the sample to cells in which there are an active mine, in order to avoid reverse causation from conflict to mines. Their results are robust to both of them. To this, I add the high persistence of $EL()_k$ overtime to justify the exogeneity of $M_{kt} \times lnp_{kt}^{W} \times EL()_k$.

As in Section 4.1, in all the estimations the standard errors are estimate with a spatial HAC correction, applying Conley (1999).

5 Results

I now show the baseline results of this work as well as some robustness check of my results. Section 5.1 presents the results of the rainfall shock, equation (3); and 5.2 displays the results with the price-mine shock, equation (4). Section 5.3 presents the robustness checks.

5.1 Rainfall Shock

In this subsection, I present the baseline estimation of equation (3). Table (1) displays the results of equation (3) with the interaction between the rainfall shock and the ethno-linguistic fractionalization at different levels of aggregation. In the left part, the dependent variable is the logarithm of the number of actors by grid and year; in the right part, the results are presented without the log-transformation [2].

The coefficient of the rainfall shock is positive and significant in all columns. A Rainfall deviation increases the number of armed actors in cells where the shock is produced. This result is consistent with the opportunity cost channel (Dube and Vargas (2013); Miguel et al. (2004); Hidalgo et al. (2010)). Rainfall is a negative shock that decreases the agricultural income, lowering the return. Since the agricultural sector is labour intensive and the opportunity cost of fighting is lower, more people are willing to form an armed group.

[2] In these specifications I do not control for rainfall shock and standard temperature deviation. To see the results, see Tables (14) and (15) in Appendix

I see that in all columns, the interaction term between ELF and the rainfall shock is negative and significant for more disaggregated levels of ethno-linguistic fractionalization. ´This suggests that the effect of a rainfall shock on the number of actors is heterogenous by the ethno-linguistic diversity of the cell. In cells with high fractionalization, it is more difficult to form an armed group based on ethnicity because the cost of organization is greater. Since the rainfall shock induces conflict lowering the opportunity cost of the fight, in high fractionalized cells the number of armed groups decreases when a rainfall shock occurs. In sum, the results reveal that it is more difficult to form an armed group based on ethnicity when a rainfall shock occurs.

To compute the magnitudes of the coefficients it has to take into account that the dependent variable is in logarithm. For example, focusing on column 4, when I interact the rainfall shock with the measure of linguistic diversity at aggregation level 15, the coefficients suggest that one standard deviation change in rainfall shock increases the number of violent actors in 2.15%. However, when the cells are high fractionalized, one standard deviation change in the rainfall shock reduce the number of violent actors by 2.39%.

The fact that linguistic diversity is significant in finer classifications of linguistic cleavages suggests that measures of fractionalization based on more disaggregated levels of aggregation tend to matter more than more aggregated ones. Finer linguistic classifications are associated to be more important to explain economic outcomes related with a lack of coordination Desmet et al. (2012). Hence, it seems reasonable to suggest that at the time of formed an armed group, when the collective action problems can arise, more disaggregated levels of ethno-linguistic diversity matter more. When I do not take the log-transformation of the dependent variable, the sign of the interaction remains the same, with higher coefficients but a bit less significant.

Table (2) replicates the results with the ethno-linguistic polarization in the interaction term instead of the ethno-linguistic fractionalization. The coefficient of the interaction term remains with negative sign in all columns and the coefficients are higher than in Table (1). Hence, the effect of the rainfall shock on the number of armed actors is more heterogeneous by ethno-linguistic polarization than by ethno-linguistic fractionalization. Taking into account that ethno-linguistic polarization and ethno-linguistic fractionalization can be a proxy of ethnic fractionalization and ethnic polarization respectively, these results can be in the line of (Esteban and Ray (1994); Montalvo and Reynal-Querol (2005)), in which the polarization may be more relevant to explain civil conflict than fractionalization. Nevertheless, as it has been shown in Section (3.5), the correlation between ELF and ELP is high and hence these results has to be considered with precaution.

It is relevant to say that usually in the literature it has not been found heterogeneity by ethnic fractionalization when the relationship between conflict and income has been studied (Miguel et al. (2004); Hegre and Sambanis (2006); Laitin et al. (2007)). This is a surprising result due to the strong negative association between economic outcomes and social divisions (Alesina and Ferrara (2005); Easterly and Levine (1997)). Hence, at the best of my knowledge, this is the first work in which it is proved that ethnic diversity matter to explain the relationship between income and conflict. The explanation can be that the proxy used to measure ethnic diversity is theoretically appropriated.

Table 4

Number of actors and interaction between rainfall shock and ELF

Estimator	OLS							
Dependet Variable	Log (Number of actors) by grid and year				Number of actors by grid and year			
	ELF1	ELF5	ELF10	ELF15	ELF1	ELF5	ELF10	ELF15
Rain	0.0215*	0.0266**	0.0354**	0.0364**	0.0785*	0.0851*	0.113**	0.109**
	(0.0502)	(0.0119)	(0.0132)	(0.0143)	(0.0403)	(0.0469)	(0.0530)	(0.0143)
Temp	0.00396	0.00423	0.00396	0.00393	-0.0111	-0.00948	-0.0103	-0.0102
	(0.0396)	(0.0396)	(0.0396)	(0.0396)	(0.0145)	(0.0145)	(0.0145)	(0.0145)
ELF*Rain	-0.0544	-0.0499	-0.0624**	-0.0603**	-0.230	-0.146	-0.189*	-0.162*
	(0.0512)	(0.0353)	(0.0293)	(0.0280)	(0.166)	(0.116)	(0.100)	(0.0903)
Year-Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cell Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	14235	14235	14235	14235	14235	14235	14235	14235

Standard errors in parentheses

* p <0.1, ** p <0.05, *** p <0.01

Table 5

Number of actors and interaction between rainfall shock and ELP

Estimator	OLS							
Dependet Variable	Number of actors by grid and year				Log (Number of actors) by grid and year			
	ELP1	ELP5	ELP10	ELP15	ELP1	ELP5	ELP10	ELP15
Rain	0.0215*	0.0255*	0.0401***	0.0405***	0.0765*	0.0780	0.123**	0.115**
	(0.0119)	(0.0136)	(0.0147)	(0.0146)	(0.0405)	(0.0484)	(0.0538)	(0.0486)
Temp	0.00405	0.00413	0.00441	0.00432	-0.0105	-0.00959	-0.00894	-0.00911
	(0.0145)	(0.0145)	(0.0145)	(0.0145)	(0.0396)	(0.0396)	(0.0395)	(0.0396)
ELP*Rain	-0.118	-0.123	-0.255**	-0.252**	-0.463	-0.311	-0.729**	-0.630**
	(0.113)	(0.102)	(0.104)	(0.105)	(0.369)	(0.338)	(0.338)	(0.317)
Year-Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cell Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	14235	14235	14235	14235	14235	14235	14235	14235

Standard errors in parentheses

* p <0.1, ** p <0.05, *** p <0.01

5.2 Mine Shock

I now present the results of the estimation of equation (4). Table (3) displays the results of equation (4) with the interaction between the shock on minerals and the ethno-linguistic fractionalization at different levels of aggregation. In the left part, the dependent variable is the logarithm of the number of actors by grid and year; in the right part, the results are presented without the log-transformation. In this section, I do not control for rainfall deviation either standard temperature deviation, to check the results with that controls, see Tables (14) and (15) in Appendix B.

Surprisingly, the coefficients of the Mine*Price are negative, meaning that a spike in mineral prices reduces the number of armed groups. Although the coefficients are not significant, this could go in the opposite direction to the result in (Berman et al. (2017)), where an increase in the mineral prices raises the conflict in cells where the mineral is produced. Another option could be that the determinants of conflict are different from the determinants of the number of armed groups. I let this result for future research.

The coefficient of the triple interaction is significant at 5% and 10% levels in most of the columns. The effect of a mineral shock on the number of armed actors is heterogeneous by the ethno-linguistic diversity of the cell. In cells with high fractionalization, there is a higher number of groups when there is a shock on mineral prices. The reason is that although in high fractionalization places the cost of form an armed group is higher, when a shock increases the resources to fight, more groups are formed because they want to appropriate the new rents. There are no remarkable differences in the levels of aggregation of linguistic diversity. I do not observe differences when I remove the logarithm transformation of the dependent variable.

Hence, linguistic diversity has a different relationship with the two channels: the rapacity channel and the opportunity cost channel. When an income shock lowers the opportunity cost to fight, more fractionalized places see a reduced number of armed groups. However, when the income shock increases the resources to extract, more fractionalized places see an increment in the number of armed groups due to the prize of winning is greater.

Table (2) replicates the results with the ethno-linguistic polarization in the interaction term instead of the ethno-linguistic fractionalization. The coefficient of the interaction of interest remains positive, which suggests that the effect of the mineral shock is also heterogeneous by the ethno-linguistic polarization of the cell. In the same line as when the rain shock is produced, the coefficients are greater than in the interaction with ELF although less significant. Due to the high correlation between ELP and ELF, differences between them have to be considered with precaution.

Table 6

Number of actors and interaction between mining activity, prices and ELF

Estimator	OLS							
Dependet Variable	Log (Number of actors) by grid and year				Number of actors by grid and year			
	ELF1	ELF5	ELF10	ELF15	ELF1	ELF5	ELF10	ELF15
Mine	-0.274	-0.197	-0.303	-0.287	-0.653	-0.512	-0.713	-0.684
	(0.189)	(0.192)	(0.197)	(0.197)	(0.434)	(0.426)	(0.463)	(0.462)
Price	0.021	-0.021	-0.036	-0.040	0.181	0.104	0.079	0.072
	(0.149)	(0.139)	(0.134)	(0.132)	(0.311)	(0.297)	(0.286)	(0.284)
Mine*Price	-0.084	-0.071	-0.057	-0.057	-0.397	-0.374	-0.349	-0.349
	(0.145)	(0.138)	(0.130)	(0.129)	(0.356)	(0.347)	(0.332)	(0.330)
ELF*Prices*Mines	0.061*	0.078**	0.069**	0.070**	0.129**	0.148**	0.130**	0.130**
	(0.036)	(0.035)	(0.031)	(0.033)	(0.065)	(0.061)	(0.054)	(0.057)
Year-Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cell Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Temp and Rain controls	No	No	No	No	No	No	No	No
N	6676	6676	6676	6676	6676	6676	6676	6676

Standard errors in parentheses

* p <0.1, ** p <0.05, *** p <0.01

Table 7

Number of actors and interaction between mining activity, prices and ELP

Estimator	OLS							
Dependet Variable	Log (Number of actors) by grid and year				Number of actors by grid and year			
	ELP1	ELP5	ELP10	ELP15	ELP1	ELP5	ELP10	ELP15
Mine	-0.274	-0.192	-0.331*	-0.331*	-0.653	-0.508	-0.764	-0.763
	(0.189)	(0.194)	(0.199)	(0.201)	(0.434)	(0.429)	(0.472)	(0.475)
Price	0.022	-0.025	-0.023	-0.031	0.181	0.100	0.108	0.095
	(0.149)	(0.137)	(0.134)	(0.132)	(0.311)	(0.294)	(0.285)	(0.282)
Mine*Price	-0.084	-0.071	-0.066	-0.067	-0.397	-0.376	-0.368	-0.370
	(0.145)	(0.136)	(0.132)	(0.130)	(0.356)	(0.344)	(0.335)	(0.332)
ELP*Price*Mine	0.121*	0.269**	0.209*	0.232*	0.258**	0.501**	0.381*	0.417*
	(0.073)	(0.113)	(0.112)	(0.123)	(0.131)	(0.197)	(0.198)	(0.221)
Year-Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cell Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Temp and Rain controls	No	No	No	No	No	No	No	No
N	6676	6676	6676	6676	6676	6676	6676	6676

Standard errors in parentheses

* p <0.1, ** p <0.05, *** p <0.01

5.3 Robustness

Removing Unidentified Groups.

In ACLED database when an armed group is not identified due to a lack of information, it is considered as Unidentified Armed Group (Country)', where the country reflects the territory in which the group perpetrates the violence. In the baseline results, I have included the unidentified groups as another armed group. It could be the case that with this method I count two times the same group: one time with the original name of the group and another time with the "Unidentified Armed Group (Country)" if the original group perpetuates a violent act in the cell but with anonymity. Hence, I have removed from the baseline results all the unidentified groups. The results are presented in Tables (8) and (9). My results are consistent with this sensibility test. Both, the sign and the significance of the coefficients remain similar. The interaction with ELP is shown in Tables (16) and (17) in Appendix B.

Table 8

Number of actors and interaction between mining activity, prices and ELF (removing unidentified groups)

Estimator	OLS							
Dependet Variable	Number of actors by grid and year				Log (Number of actors) by grid and year			
	ELF1	ELF5	ELF10	ELF15	ELF1	ELF5	ELF10	ELF15
Rain	0.0937**	0.0817*	0.121**	0.118**	0.0339***	0.0300**	0.0445a	0.0460***
	(0.0392)	(0.0459)	(0.0517)	(0.0499)	(0.0128)	(0.0145)	(0.0158)	(0.0158)
Temp	-0.00771	-0.00578	-0.00702	-0.00708	0.00340	0.00396	0.00352	0.00341
	(0.0411)	(0.0410)	(0.0411)	(0.0411)	(0.0151)	(0.0151)	(0.0151)	(0.0151)
ELF*Rain	-0.255	-0.0759	-0.177*	-0.153*	-0.0721	-0.0189	-0.0587*	-0.0585*
	(0.166)	(0.116)	(0.101)	(0.0923)	(0.0555)	(0.0380)	(0.0325)	(0.0307)
Year-Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cell Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	12247	12247	12247	12247	12247	12247	12247	12247
adj. R^2	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001

Standard errors in parentheses

* p <0.1, ** p <0.05, *** p <0.01

Table 9

Number of actors and interaction between mining activity, prices and ELF (removing unidentified actors)

Estimator	OLS							
Dependet Variable	Number of actors by grid and year				Log (Number of actors) by grid and year			
	ELF1	ELF5	ELF10	ELF15	ELF1	ELF5	ELF10	ELF15
Mine	-0.772**	-0.600**	-0.788**	-0.768**	-0.353***	-0.269**	-0.372***	-0.361**
	(0.325)	(0.306)	(0.360)	(0.362)	(0.122)	(0.134)	(0.143)	(0.146)
Price	0.122	0.114	0.082	0.065	0.005	-0.005	-0.023	-0.033
	(0.275)	(0.271)	(0.260)	(0.258)	(0.140)	(0.135)	(0.130)	(0.128)
Price*Mines	-0.392	-0.409	-0.379	-0.374	-0.088	-0.094	-0.077	-0.074
	(0.356)	(0.353)	(0.341)	(0.337)	(0.150)	(0.143)	(0.137)	(0.134)
ELF*Prices*Mines	0.781	0.155**	0.125**	0.135**	0.355	0.083**	0.069**	0.075**
	(0.617)	(0.069)	(0.057)	(0.061)	(0.335)	(0.042)	(0.034)	(0.036)
Year-Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cell Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Temp and Rain controls	No	No	No	No	No	No	No	No
N	5737	5737	5737	5737	5737	5737	5737	5737
adj. R^2	0.000	0.001	0.000	0.001	0.000	0.001	0.001	0.001

Standard errors in parentheses

* p <0.1, ** p <0.05, *** p <0.01

Alternative definition of violence.

To check if the income shock has a heterogeneous effect by linguistic diversity on the level of conflict, I test for an alternative measure of violence. I consider the total number of fatalities in ACLED database, adding up by grid cell and year. The dependent variable now is the log-transformation of the number of fatalities. Tables (10) and (11) shows the results of equation (3) and (4) with the new dependent variable, respectively. In the left part, the interaction is with ELF and in the right part, the interaction is with the ELP. In Table (19) in the appendix I estimate equation (4), adding the rainfall shock and temperature as controls.

The coefficients maintain the same sign. However, the significance is greater for all levels of aggregation and both, ELF and ELP. These outcomes give consistency to my result: the effect of an income shock on the level of conflict is heterogeneous by the linguistic diversity of the cell. It is remarkable that the coefficient of Mines*Prices in Table (11) is positive, meaning that a shock in the price of minerals increases the number of fatalities (level of conflict). This result goes in the same direction as Berman et al. (2017) and it is contrary to the one I found in Table (6). As I said in Section 5.2, I let this result to future research.

Table 10

Fatalities and interaction between rain with ELF and ELP

Estimator	OLS							
Dependet Variable	Log(Number of Fatalities) by grid and year				Log(Number of Fatalities) by grid and year			
	ELF1	ELF5	ELF10	ELF15	ELP1	ELP5	ELP10	ELP15
Rain	0.0233	0.0422	0.0593	0.0550	0.0245	0.0461	0.0584	0.0481
	(0.0326)	(0.0361)	(0.0381)	(0.0379)	(0.0327)	(0.0372)	(0.0395)	(0.0384)
Temp	-0.00493	-0.00364	-0.00416	-0.00403	-0.00461	-0.00439	-0.00264	-0.00276
	(0.0437)	(0.0436)	(0.0437)	(0.0437)	(0.0437)	(0.0436)	(0.0437)	(0.0437)
ELF*Rain	-0.235*	-0.202**	-0.196**	-0.168**	-	-	-	-
	(0.140)	(0.0989)	(0.0784)	(0.0732)	-	-	-	-
ELP*Rain	-	-	-	-	-0.533*	-0.594**	-0.640**	-0.517**
	-	-	-	-	(0.304)	(0.274)	(0.275)	(0.261)
Year-Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cell Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	14235	14235	14235	14235	14235	14235	14235	14235

Standard errors in parentheses

* p <0.1, ** p <0.05, *** p <0.01

Table 11

Fatalities and interaction between mines, prices and with ELF and ELP

Estimator	OLS							
Dependet Variable	Log(Number of Fatalities) by grid and year				Log(Number of Fatalities) by grid and year			
	ELF1	ELF5	ELF10	ELF15	ELP1	ELP5	ELP10	ELP15
Mine	-0.367	-0.231	-0.524	-0.487	-0.368	-0.312	-0.577	-0.560
	(0.375)	(0.374)	(0.386)	(0.383)	(0.375)	(0.363)	(0.401)	(0.398)
Price	-0.174	-0.222	-0.251	-0.233	-0.173	-0.171	-0.171	-0.147
	(0.173)	(0.160)	(0.158)	(0.162)	(0.173)	(0.176)	(0.180)	(0.188)
Price*Mines	0.314	0.317	0.349	0.337	0.314	0.294	0.306	0.289
	(0.225)	(0.214)	(0.212)	(0.214)	(0.226)	(0.216)	(0.219)	(0.223)
ELF*Prices*Mines	0.356***	0.217***	0.183***	0.160**	-	-	-	-
	(0.055)	(0.052)	(0.061)	(0.068)	-	-	-	-
ELP*Prices*Mines	-	-	-	-	0.711***	0.510**	0.413*	0.334
	-	-	-	-	(0.111)	(0.236)	(0.234)	(0.229)
Year-Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cell Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Temp and Rain controls	No	No	No	No	No	No	No	No
N	6676	6676	6676	6676	6676	6676	6676	6676

Standard errors in parentheses

* p <0.1, ** p <0.05, *** p <0.01

Removing State and External Forces.

I am interested in explaining the number of violent actors around the African continent. With this goal, I have included the State and External Forces to obtain a general picture of the total number of violent actors who can act in a given territory, without considering any distinction. However, since can be seen in Appendix A, State forces can include military or police forces. On the other hand, external forces can contain actors from European countries or the private security of a company. See Appendix A for more details. Thus, the inclusion of these types of actors can bias the results due to the high possible number of Government actions. In Tables (12) and (13), I estimate equations (3) and (4) respectively, removing all the state and external forces from the sample. Both estimations remain with the same sign and significance as the baseline results.

Table 12

Number of actors and interaction between rain and ELF (removing State and External Forces)

Estimator	OLS							
Dependet Variable	Number of actors by grid and year				Log (Number of actors) by grid and year			
	ELF1	ELF5	ELF10	ELF15	ELF1	ELF5	ELF10	ELF15
Rain	0.0479	0.0665*	0.0841**	0.0814*	0.0174	0.0284**	0.0333**	0.0325**
	(0.0338)	(0.0380)	(0.0424)	(0.0418)	(0.0119)	(0.0131)	(0.0141)	(0.0140)
Temp	-0.0107	-0.0102	-0.0106	-0.0106	0.00595	0.00582	0.00576	0.00574
	(0.0396)	(0.0393)	(0.0393)	(0.0393)	(0.0155)	(0.0155)	(0.0155)	(0.0155)
ELF*Rain	-0.117	-0.143	-0.157*	-0.137*	-0.0323	-0.0651*	-0.0616**	-0.0545*
	(0.138)	(0.0949)	(0.0821)	(0.0769)	(0.0550)	(0.0369)	(0.0304)	(0.0290)
Year-Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cell Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	10727	10727	10727	10727	10727	10727	10727	10727

Standard errors in parentheses

* p <0.1, ** p <0.05, *** p <0.01

Table 13

Number of actors and interaction between mining activity, prices and ELF (removing State and External Forces)

Estimator	OLS							
Dependet Variable	Number of actors by grid and year				Log (Number of actors) by grid and year			
	ELF1	ELF5	ELF10	ELF15	ELF1	ELF5	ELF10	ELF15
Mines	-0.302	-0.250	-0.400	-0.387	-0.117	-0.084	-0.168	-0.160
	(0.404)	(0.401)	(0.432)	(0.430)	(0.243)	(0.243)	(0.255)	(0.253)
Price	0.148	0.087	0.097	0.092	0.036	-0.002	0.001	-0.001
	(0.141)	(0.143)	(0.145)	(0.147)	(0.080)	(0.077)	(0.080)	(0.080)
Price*Mine	-0.310	-0.307	-0.293	-0.293	-0.089	-0.086	-0.077	-0.078
	(0.265)	(0.261)	(0.259)	(0.258)	(0.135)	(0.132)	(0.131)	(0.130)
ELF*Prices*Mines	0.139**	0.128***	0.091**	0.091*	0.066**	0.071**	0.052*	0.052*
	(0.054)	(0.045)	(0.046)	(0.049)	(0.033)	(0.028)	(0.027)	(0.029)
Year-Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cell Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	4915	4915	4915	4915	4915	4915	4915	4915

Standard errors in parentheses

* p <0.1, ** p <0.05, *** p <0.01

6 Conclusion

This work provides an analysis about whether the effect of two-income shocks on the number of violent actors varies across different levels of linguistic diversity, using a panel data of 0.5 x 0.5 degree and covering the period 1997-2017. I have considered all violent actors registered in ACLED. When the shock considered is a rainfall shock, I find that in more fractionalized cells, there is a lower number of groups when an irregular level of precipitation happens. However, when the shock is on the price of the minerals, I find that in more fractionalized cells there is a higher number of groups when the price of minerals raises. According to the literature, both shocks affect conflict in a different way to conflict: through an opportunity cost and through a rapacity channel.

I show that linguistic diversity has a different relationship depending on the shock considered. When the shock is about capturing resources, higher linguistic diversity implies a higher number of violent actors. Nevertheless, when the shock affects the opportunity cost of fight, higher linguistic diversity implies a lower number of violent actors. A possible collective action problem can explain that results. Moreover, another important conclusion is that linguistic diversity matters to explain the relationship between income and conflict, a new result in the literature which opening the door to more future research.

My findings corroborate previous results about the importance of income shocks on conflicts. Furthermore, it also contains policy implications. Insurance programs or more protection in extracting zones can have an effect on the number of violent groups, paying attention to the linguistic diversity of each zone. However, more research is need about the precise mechanism in which ethnic divisions affect the number of violent actors and different relevant outcomes, considering good proxies to measure ethnic diversity as the one used in this work. Moreover, another important discussion for future research is if the determinants of conflicts are the same as the determinants of the number of violent actors.

7 Appendix

7.1 Appendix A

In this part of the Appendix I define all the ACLED actors, according to the goal and information of each group used in this work. I take this information from the Final Codebook of ACLED for the year 2019. The last codebook available at the moment to do this work.

- State Forces: actors who perform government actions, including military and police, over the territory of the country.
- Rebel groups: violent actors whose objective is to opposite to the national government by violent acts. They want to replace the national power or support some kind of separatism.
- Political Militias: violent actors who are created with a specific goal and for a concrete time period to obtain a political purpose by violence.
- Identity Militias: violent actors coordinate around a common characteristics such as religion or ethnic. They act on behalf of an identity.
- Rioters: it collects the existence of violence during demonstrations or in other type of acts.
- Protesters: unarmed demonstrators.
- External/Other forces: actors such as international organizations, private companies or state forces who acts outside of their home country.

7.2 Appendix B

Table 14

Number of actors and interaction between mining activity, prices and ELF (controlling for rain and temperature)

Estimator	OLS							
Dependet Variable	Log (Number of actors) by grid and year				Number of actors by grid and year			
	ELF1	ELF5	ELF10	ELF15	ELF1	ELF5	ELF10	ELF15
Mine	-0.273	-0.198	-0.302	-0.286	-0.650	-0.511	-0.711	-0.682
	(0.185)	(0.189)	(0.193)	(0.193)	(0.428)	(0.420)	(0.457)	(0.456)
Price	0.013	-0.029	-0.043	-0.047	0.168	0.093	0.068	0.060
	(0.152)	(0.142)	(0.137)	(0.136)	(0.316)	(0.301)	(0.291)	(0.288)
Price*Mine	-0.077	-0.064	-0.051	-0.051	-0.386	-0.364	-0.339	-0.339
	(0.148)	(0.142)	(0.134)	(0.133)	(0.361)	(0.352)	(0.336)	(0.334)
ELF*Price*Mine	0.061*	0.077**	0.068**	0.069**	0.130**	0.147**	0.129**	0.129**
	(0.036)	(0.035)	(0.031)	(0.033)	(0.065)	(0.060)	(0.054)	(0.057)
Year-Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cell Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Temp and Rain controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	6676	6676	6676	6676	6676	6676	6676	6676

Standard errors in parentheses

* p <0.1, ** p <0.05, *** p <0.01

Table 15

Number of actors and interaction between mining activity, prices and ELP (controlling for rain and temperature)

Estimator	OLS							
Dependet Variable	Log(Number of actors) by grid and year				Number of actors by grid and year			
	ELP1	ELP5	ELP10	ELP15	ELP1	ELP5	ELP10	ELP15
Mine	-0.274	-0.193	-0.330	-0.329	-0.651	-0.508	-0.762	-0.760
	(0.185)	(0.191)	(0.195)	(0.197)	(0.428)	(0.423)	(0.465)	(0.469)
Price	0.0134	-0.0325	-0.0295	-0.0379	0.168	0.0890	0.0969	0.0837
	(0.152)	(0.140)	(0.137)	(0.135)	(0.316)	(0.298)	(0.290)	(0.287)
Mine*Price	-0.0773	-0.0649	-0.0600	-0.0609	-0.386	-0.366	-0.358	-0.361
	(0.148)	(0.140)	(0.136)	(0.134)	(0.361)	(0.349)	(0.339)	(0.336)
ELP*Price*Mine	0.120	0.265*	0.205	0.228	0.260*	0.495*	0.376	0.412
	(0.0727)	(0.113)	(0.111)	(0.123)	(0.132)	(0.197)	(0.198)	(0.221)
Year-Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cell Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Temp and Rain controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	6676	6676	6676	6676	6676	6676	6676	6676

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 16

Number of actors and interaction between mining activity, prices and ELP (removing unidentified actors)

Estimator	OLS							
Dependet Variable	Number of actors by grid and year				Log (Number of actors) by grid and year			
	ELP1	ELP5	ELP10	ELP15	ELP1	ELP5	ELP10	ELP15
Rain	0.0912**	0.0721	0.126**	0.123**	0.0333***	0.0272*	0.0472***	0.0509***
	(0.0396)	(0.0477)	(0.0525)	(0.0484)	(0.0129)	(0.0150)	(0.0163)	(0.0162)
Temp	-0.00708	-0.00563	-0.00578	-0.00619	0.00357	0.00401	0.00392	0.00370
	(0.0410)	(0.0411)	(0.0410)	(0.0410)	(0.0151)	(0.0151)	(0.0151)	(0.0151)
ELP*Rain	-0.507	-0.0900	-0.638*	-0.585*	-0.146	-0.0179	-0.225**	-0.253**
	(0.372)	(0.342)	(0.337)	(0.318)	(0.124)	(0.110)	(0.114)	(0.113)
N	12247	12247	12247	12247	12247	12247	12247	12247
adj. R^2	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001

Standard errors in parentheses

* p <0.1, ** p <0.05, *** p <0.01

Table 17

Number of actors and interaction between mining activity, prices and ELP (removing unidentified actors)

Estimator	OLS							
Dependet Variable	Number of actors by grid and year				Log (Number of actors) by grid and year			
	ELP1	ELP5	ELP10	ELP15	ELP1	ELP5	ELP10	ELP15
Mine	-0.775**	-0.593**	-0.758**	-0.776**	-0.355***	-0.265**	-0.356**	-0.367**
	(0.326)	(0.302)	(0.355)	(0.368)	(0.122)	(0.131)	(0.142)	(0.148)
Price	0.120	0.117	0.111	0.083	0.004	-0.003	-0.008	-0.025
	(0.275)	(0.270)	(0.262)	(0.258)	(0.140)	(0.134)	(0.131)	(0.129)
Price*Mine	-0.389	-0.407	-0.398	-0.393	-0.087	-0.093	-0.087	-0.084
	(0.357)	(0.353)	(0.345)	(0.339)	(0.150)	(0.143)	(0.139)	(0.136)
ELP*Price*Mine	1.624	0.341**	0.268*	0.349**	0.742	0.184*	0.150	0.200*
	(1.268)	(0.158)	(0.157)	(0.175)	(0.688)	(0.096)	(0.093)	(0.104)
Year-Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cell Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Temp and Rain controls	No	No	No	No	No	No	No	No
N	5737	5737	5737	5737	5737	5737	5737	5737
adj. R^2	0.000	0.000	0.000	0.000	0.000	0.001	0.000	0.001

Standard errors in parentheses

* p <0.1, ** p <0.05, *** p <0.01

Table 18

Fatalities and interaction between mines, prices and with ELF and ELP controlling by Temp and Rain

Estimator	OLS							
Dependet Variable	Log(Number of Fatalities) by grid and year				Log(Number of Fatalities) by grid and year			
	ELF1	ELF5	ELF10	ELF15	ELP1	ELP5	ELP10	ELP15
mines	-0.367	-0.231	-0.524	-0.487	-0.368	-0.312	-0.577	-0.560
	(0.375)	(0.374)	(0.386)	(0.383)	(0.375)	(0.363)	(0.401)	(0.398)
main_lprice	-0.174	-0.222	-0.251	-0.233	-0.173	-0.171	-0.171	-0.147
	(0.173)	(0.160)	(0.158)	(0.162)	(0.173)	(0.176)	(0.180)	(0.188)
main_lprice_mines	0.314	0.317	0.349	0.337	0.314	0.294	0.306	0.289
	(0.225)	(0.214)	(0.212)	(0.214)	(0.226)	(0.216)	(0.219)	(0.223)
ELF*Prices*Mines	0.356***	0.217***	0.183***	0.160**	-	-	-	-
	(0.055)	(0.052)	(0.061)	(0.068)	-	-	-	-
ELP*Prices*Mines	-	-	-	-	0.711***	0.510**	0.413*	0.334
	-	-	-	-	(0.111)	(0.236)	(0.234)	(0.229)
Year-Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cell Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Temp and Rain controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	6676	6676	6676	6676	6676	6676	6676	6676

Standard errors in parentheses
* p <0.1, ** p <0.05, *** p <0.01

Table 19

Fatalities and interaction between rain with ELF and ELP

Estimator	OLS							
Dependet Variable	Log(Number of Fatalities) by grid and year				Log(Number of Fatalities) by grid and year			
	ELF1	ELF5	ELF10	ELF15	ELP1	ELP5	ELP10	ELP15
mines	-0.367	-0.231	-0.524	-0.487	-0.368	-0.312	-0.577	-0.560
	(0.375)	(0.374)	(0.386)	(0.383)	(0.375)	(0.363)	(0.401)	(0.398)
main_lprice	-0.174	-0.222	-0.251	-0.233	-0.173	-0.171	-0.171	-0.147
	(0.173)	(0.160)	(0.158)	(0.162)	(0.173)	(0.176)	(0.180)	(0.188)
main_lprice_mines	0.314	0.317	0.349	0.337	0.314	0.294	0.306	0.289
	(0.225)	(0.214)	(0.212)	(0.214)	(0.226)	(0.216)	(0.219)	(0.223)
ELF*Prices*Mines	0.356***	0.217***	0.183***	0.160**				
	(0.055)	(0.052)	(0.061)	(0.068)				
ELP*Prices*Mines					0.711***	0.510**	0.413*	0.334
					(0.111)	(0.236)	(0.234)	(0.229)
N	6676	6676	6676	6676	6676	6676	6676	6676
adj. R^2	0.001	0.001	0.000	0.000	0.001	0.000	0.000	-0.000

Standard errors in parentheses
* p <0.1, ** p <0.05, *** p <0.01

Table 20

Number of actors and interaction between mining activity, prices and ELF (including all the interactions)

Estimator	OLS							
Dependet Variable	Number of actors by grid and year				Log(Number of actors) by grid and year			
	ELF1	ELF5	ELF10	ELF15	ELF1	ELF5	ELF10	ELF15
Mines	-0.760	-0.339	0.266	0.313	-0.329	-0.0692	0.157	0.180
	(0.467)	(0.480)	(0.592)	(0.601)	(0.208)	(0.206)	(0.287)	(0.294)
Prices	0.116	0.00696	0.0397	0.0212	-0.0129	-0.0563	-0.0531	-0.0629
	(0.335)	(0.357)	(0.364)	(0.365)	(0.166)	(0.171)	(0.180)	(0.180)
ELF*Mines	1.792	-4.980a	-4.179b	-4.205b	1.137	-3.117a	-1.957b	-1.969b
	(15.10)	(1.562)	(1.706)	(1.716)	(7.040)	(0.733)	(0.807)	(0.814)
ELF*Prices	2.709	1.311	0.520	0.523	1.309	0.559	0.227	0.232
	(1.779)	(1.057)	(0.588)	(0.583)	(0.861)	(0.505)	(0.277)	(0.273)
Prices*Mines	-0.521	-0.406	-0.519	-0.513	-0.140	-0.0901	-0.133	-0.131
	(0.359)	(0.370)	(0.353)	(0.354)	(0.151)	(0.155)	(0.149)	(0.150)
ELF*Prices*Mines	-0.120	0.400a	0.404a	0.408a	-0.0760	0.245a	0.198b	0.199b
	(0.948)	(0.107)	(0.149)	(0.152)	(0.438)	(0.0574)	(0.0787)	(0.0801)
Year-Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cell Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Temp and Rain controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	6676	6676	6676	6676	6676	6676	6676	6676

Standard errors in parentheses

* p <0.1, ** p <0.05, *** p <0.01

Table 21

Number of actors and interaction between mining activity, prices and ELP (including all the interactions)

Estimator	OLS							
Dependet Variable	Number of actors by grid and year				Log(Number of actors) by grid and year			
	ELF1	ELF5	ELF10	ELF15	ELF1	ELF5	ELF10	ELF15
mines	-0.764	-0.282	0.521	0.575	-0.330	-0.0367	0.254	0.284
	(0.468)	(0.487)	(0.635)	(0.647)	(0.208)	(0.210)	(0.310)	(0.320)
main_lprice	0.112	0.0610	0.116	0.109	-0.0138	-0.0298	-0.0141	-0.0188
	(0.336)	(0.349)	(0.362)	(0.359)	(0.166)	(0.168)	(0.179)	(0.176)
ELP*Mines	4.021	-12.63***	-13.53***	-14.02***	2.433	-8.143***	-6.138***	-6.415***
	(30.29)	(4.624)	(4.776)	(4.873)	(14.11)	(2.227)	(2.305)	(2.385)
ELP*Prices	5.767	1.537	0.378	0.200	2.732	0.555	0.0773	-0.00757
	(3.813)	(2.327)	(1.725)	(1.709)	(1.846)	(1.148)	(0.800)	(0.790)
main_lprice_mines	-0.524	-0.407	-0.480	-0.484	-0.140	-0.0930	-0.114	-0.116
	(0.358)	(0.363)	(0.366)	(0.363)	(0.151)	(0.153)	(0.155)	(0.154)
ELP*Prices*Mines	-0.279	1.231***	1.356***	1.450***	-0.166	0.753***	0.651***	0.704***
	(1.907)	(0.361)	(0.458)	(0.496)	(0.880)	(0.191)	(0.245)	(0.267)
Year-Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cell Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Temp and Rain controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	6676	6676	6676	6676	6676	6676	6676	6676

Standard errors in parentheses

* p <0.1, ** p <0.05, *** p <0.01

References

Alesina, A., Baqir, R., & Easterly, W. (1999). Public goods and ethnic divisions. *The Quarterly journal of economics*, *114*(4), 1243–1284.

Alesina, A., Devleeschauwer, A., Easterly, W., Kurlat, S., & Wacziarg, R. (2003). Fractionalization. *Journal of Economic growth*, *8*(2), 155–194.

Alesina, A., & Ferrara, E. L. (2005). Ethnic diversity and economic performance. *Journal of economic literature*, *43*(3), 762–800.

Armand, A., Atwell, P., & Gomes, J. F. (2020). The reach of radio: Ending civil conflict through rebel demobilization. *American economic review*, *110*(5), 1395–1429.

Berman, N., Couttenier, M., Rohner, D., & Thoenig, M. (2017). This mine is mine! how minerals fuel conflicts in africa. *American Economic Review*, *107*(6), 1564–1610.

Bohlken, A. T., & Sergenti, E. J. (2010). Economic growth and ethnic violence: An empirical investigation of hindu—muslim riots in india. *Journal of Peace research*, *47*(5), 589–600.

Brückner, M., & Ciccone, A. (2011). Rain and the democratic window of opportunity. *Econometrica*, *79*(3), 923–947.

Conley, T. G. (1999). Gmm estimation with cross sectional dependence. *Journal of econometrics*, *92*(1), 1–45.

Dal Bó, E., & Dal Bó, P. (2011). Workers, warriors, and criminals: social conflict in general equilibrium. *Journal of the European Economic Association*, *9*(4), 646–677.

Dell, M., Jones, B. F., & Olken, B. A. (2014). What do we learn from the weather? the new climate-economy literature. *Journal of Economic Literature*, *52*(3), 740–98.

Desmet, K., Ortuño-Ortín, I., & Wacziarg, R. (2012). The political economy of linguistic cleavages. *Journal of development Economics*, *97*(2), 322–338.

Dube, O., & Vargas, J. F. (2013). Commodity price shocks and civil conflict: Evidence from colombia. *The review of economic studies*, *80*(4), 1384–1421.

Easterly, W., & Levine, R. (1997). Africa's growth tragedy: policies and ethnic divisions. *The quarterly journal of economics*, *112*(4), 1203–1250.

Esteban, J.-M., & Ray, D. (1994). On the measurement of polarization. *Econometrica: Journal of the Econometric Society*, 819–851.

Fearon, J. D., & Laitin, D. D. (2003). Ethnicity, insurgency, and civil war. *American political science review*, *97*(1), 75–90.

Fetzer, T. (2014). Can workfare programs moderate violence? evidence from india.

Fjelde, H., & von Uexkull, N. (2012). Climate triggers: Rainfall anomalies, vulnerability and communal conflict in sub-saharan africa. *Political Geography*, *31*(7), 444–453.

Gomes, J. F. (2020). The health costs of ethnic distance: evidence from sub-saharan africa. *Journal of Economic Growth*, *25*, 195–226.

Hegre, H., & Sambanis, N. (2006). Sensitivity analysis of empirical results on civil war onset. *Journal of conflict resolution*, *50*(4), 508–535.

Hidalgo, F. D., Naidu, S., Nichter, S., & Richardson, N. (2010). Economic determinants of land invasions. *The Review of Economics and Statistics*, *92*(3), 505–523.

Hsiang, S. M., Burke, M., & Miguel, E. (2013). Quantifying the influence of climate on human conflict. *Science*, *341*(6151).

Hsiang, S. M., Meng, K. C., & Cane, M. A. (2011). Civil conflicts are associated with the global climate. *Nature*, *476*(7361), 438–441.

Laitin, D. D., Watkins IV, J. T., et al. (2007). *Nations, states, and violence*. Oxford University Press.

Maystadt, J.-F., Ecker, O., & Mabiso, A. (2013). *Extreme weather and civil war in somalia: Does drought fuel conflict through livestock price shocks?* Intl Food Policy Res Inst.

Michalopoulos, S., & Papaioannou, E. (2016). The long-run effects of the scramble for africa. *American Economic Review*, *106*(7), 1802–48.

Miguel, E., Satyanath, S., & Sergenti, E. (2004). Economic shocks and civil conflict: An instrumental variables approach. *Journal of political Economy*, *112*(4), 725–753.

Montalvo, J. G., & Reynal-Querol, M. (2005). Ethnic diversity and economic development. *Journal of Development economics*, *76*(2), 293–323.