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PHD THESIS:

Essays on Globalization and Conflict

–The Impact of Income and Environmental Shocks in Africa–

A Thesis submitted by Beatriz Manotas Hidalgo for the degree of Doctor of Philosophy at the Public University of Navarra

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To my family

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Summary

This thesis considers the importance of spatial patterns and the use of geo-localized data in panel and repeated cross-section data econometrics by addressing causality issues to obtain further insights into the causes and consequences of conflict in a globalized world. Chapter Two analyzes the link between globalization and the incidence of civil conflict in a panel dataset of 159 countries over the period 1972-2009. Distinctions are drawn between several dimensions of globalization identified in political economy literature, i.e. economic, social, and political globalization. I address the potential endogeneity of the globalization variables by introducing country-fixed effects into the analysis. I also use a novel spatial instrumental variable based on the degree of integration of neighboring countries. Chapter Three uses geo-localized information to study the ethnic drivers of food-related income shocks and their effects on conflict in Africa to explain underlying conflict processes. Thus, I propose the use of a panel database of a full grid of African countries divided into sub-national units of 0.5 per 0.5 degrees of latitude and longitude (10,638 cells) that covers the period 1998-2013. The study contributes to the relevant literature by analyzing several competing theories on the effects of income shocks on conflict, using geo-localized data which considers the interaction between those income shocks and ethnic diversity. Finally, Chapter Four examines the environmental damage that conflict may cause, such as oil spills in Nigeria and their impact on agricultural production. Thus, I use a consumer-producer household framework to explain how oil-spill pollution might result in changes in the optimal behavior of households. I estimate an agricultural production function using repeated cross-sections of micro-data geo-referenced for farming households and four waves of data from 2009 to 2018 taken from the Nigeria General Household Survey (GHS-Panel). To calculate a proxy for oil spill pollution, I create a function that uses geospatial data with information on around 12,000 oil spills from the Nigerian Oil Spill Monitor.

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Chapter 1

Introduction

According to The World Bank (2018), "Fragility, conflict, and violence (FCV) is a critical development challenge that threatens efforts to end extreme poverty, affecting both low- and middle-income countries. By 2030, up to 2/3 of the world's extreme poor could live in FCV settings. Conflicts also drive 80% of all humanitarian needs"[1]. Looking at the scale of this challenge, it is easy to understand why the study of the causes and consequences of conflicts has been an influential subject for scholars for decades. Blattman and Miguel (2010) summarize the relevant literature up to the first decade of the 21st century, emphasizing both limitations and areas of future research. Among other issues, they highlight the importance of different definitions of conflicts, the collection of new data, the role of political divisions, the proper identification of models in empirical analysis, the importance of geographic patterns, the role of institutions, and the legacies of conflict. The fact that income has a role as a determinant of conflict is one of the most robust conclusions (Collier and Hoeffler, 1998; Fearon and Laitin, 2003), but conflict has also been found to hurt development (Abadie and Gardeazabal, 2003). For these reasons, most conflict is expected to be prone to concentrate in low-to-middle income countries. However, the direction of causality between different mechanisms and conflict remains an open question among academics. The evidence as to direction is inconclusive in some cases, despite the fact that new data analysis and new methods

[1]Source: `http://www.worldbank.org/en/topic/fragilityconflictviolence/overview` , accessed Oct 01, 2020

have been proposed to clarify the effect (Berman and Couttenier, 2015; Berman et al. 2017).

This thesis brings together three research topics that span the fields of political economy, development, and environmental economics. Bearing in mind the gap in the literature mentioned above, I consider the importance of spatial patterns and the use of geo-located data in my research by addressing causality issues to obtain further insights into both the causes and the consequences of conflict in a globalized world. There is currently a wide consensus that globalization wears down the significance of national borders, leading to complex relations between multiple actors on a multicontinental scale (Norris, 2000). The complexity of these relations has numerous consequences in many major areas ranging from the highly positive (economic growth) to the highly negative (conflict and poverty). Understanding the interactions between the actors in the globalization framework is thus essential to determine who wins and who loses both within countries and across countries. I consider these aspects in all the chapters of this thesis, looking at different actors, perspectives, and approaches.

In particular, Chapter 2 takes a macro-level perspective in studying the role of globalization in conflict. In this chapter, entitled, *"Is there a link between globalization and civil conflict?"*[2] my co-adviser Roberto Ezcurra and I address the question of how globalization affects the incidence of civil conflict in a panel dataset of 159 countries over the period 1972-2009. We distinguish several dimensions of globalization identified in the political economy literature, such as economic, social, and political integration. This perspective enables us to derive a broader picture than most earlier studies, given that the various dimensions of globalization do not necessarily affect conflict in the same way. To that end, we use the KOF Globalization Index as a measure of globalization. [3] As a baseline measure of conflict incidence, we use the variable PRIO25,[4] developed by the UCDP/PRIO Armed Conflict Dataset.[5] The KOF Globalization Index is based

[2]This chapter has been published in The World Economy (2017), vol. 40(12), pp. 2592-2610. `https://doi.org/10.1111/twec.12514`

[3]The KOF Globalization Index was constructed by Dreher (2006) and updated by Dreher et al. (2008).

[4]PRIO 25 reports all internal conflicts with 25 or more battle-related deaths in a year.

[5]Uppsala Conflict Data Program (UCDP) at the department of Peace and Conflict Research, Uppsala

on a set of 23 variables that connect different aspects of globalization. In particular, it distinguishes the social and political dimensions of integration from an economic perspective. By contrast with previous literature, which has also considered the three dimensions of globalization mentioned above, we also address the potential endogeneity of the globalization variables. This is particularly important for establishing a causal link between the effect of integration and conflict. To that end, we use two strategies: The first is to introduce country fixed effects into the analysis, which leads to control of those time-invariant aspects that affect both globalization and conflict. In fact, the introduction of country fixed effects is useful for determining the impact on long-run determinants of both globalization and conflict. The second strategy is to use an instrumental variable approach to estimate the causal effect of the degree of integration on conflict. Thus, for each globalization index used in the study, we construct a novel spatial instrumental variable based on the degree of integration of neighboring countries. The results show that the introduction of country fixed effects eliminates the statistical relationship between the degree of integration of the world and the conflict incidence. Moreover, the use of instrumental variables shows no causal effect between globalization and civil war. These results are independent of both the dimension of globalization considered here and the definition of civil conflict.

The conclusions of the chapter cast doubts on whether there is a direct link between globalization and civil conflict. Nevertheless, the presence of factors (such as ethnic heterogeneity, horizontal inequalities or natural resource abundance) that could potentially interact with globalization could better explain this relationship. Moreover, mechanisms that explain how globalization leads to conflicts are far from simple and could act in opposite directions.

Therefore, although a macro level analysis is interesting in helping to understand credible identification, it might not be sufficient to explain some underlying conflict processes . For example, as mentioned above, the impact of income on violence has been widely studied in the literature. A frequent practice has been to use commodity price

University and the Centre for the Study of Civil War at the Peace Research Institute Oslo (PRIO) have collaborated to produce a dataset of internal and external armed conflicts from 1946 to the present.

fluctuations to capture external income shocks to isolate the effect. However, previous literature shows mixed results at country level. For instance, Bazzi and Blattman (2014) conclude that a significant link between commodity price shocks and conflict incidence is only detected when specific samples, estimators or definitions of civil war are used. Berman et al. (2017) note that one of the reasons for these contradictory effects is that using country-year data as a unit of observation is just too aggregate. Many country conflicts are concentrated in specific regions (such as the Kurdish area in Turkey or the Niger Delta in Nigeria). By contrast, in analyzing the nexus between commodity prices or natural resources and conflict, the results at the micro-level point to a more robust causal relationship (for example, the use of disaggregated data for a single country, as in Dube and Vargas (2013) for Colombia, or in Aragon and Rud (2013) for Peru).

Recently, a new generation of researchers in the area of conflict has taken the cell-year level as a unit of observation. For instance, Fjelde (2015), Berman et al. (2015 and 2017), Montalvo and Reynal-Querol (2017), and McGuirk and Burke (2020), among others, use this unit of observation, which is based on detailed information on the date and location of conflict events. They work with full grids of African countries, divided into sub-national units of 0.5 per 0.5 degrees latitude and longitude, so the unit of observation is the cell-year. There are two specific reasons for using such a unit of observation. First, taking grid-cell level data instead of administrative boundaries is appropriate to ensure that the unit of observation is not endogenous to conflict events. Second, the possibility of analyzing disaggregated cells that relate main crops, natural resources, climate variables, etc. to information on conflicts over a whole continent (for example Africa) yields a big gain in terms of external validity.

For these reasons, I turn to the micro level analysis in the next two chapters of my thesis. Taking this approach, I seek to study underlying mechanisms and consequences of conflict. In particular, in Chapter 3 I focus on the whole of Africa, working with grid-cells. In Chapter 4, I concentrate specifically on Nigeria.

I have chosen Africa because it is a very vulnerable part of the world with a relatively low capacity for adaptation. It is the region most affected by conflicts since World War

II. According to Francisco Ferreira, the World Bank´s Chief Economist for the Africa Region,[6] "The shifts in the nature and geographical distribution of conflict across Africa make identifying both the causes of conflict and the ways to help countries avoid and end these conflicts, ever more challenging".

In Chapter 3 entitled, *"The role of ethnic characteristics in the effect of income shocks on African conflict"*[7] my coauthors Fidel Pérez-Sebastián and Miguel Angel Campo-Bescós and I use geo-localized information to study the ethnic drivers of the effect of food-related income shocks on African conflict. The role of ethnic cleavages in generating conflict has been studied in depth by both economists and political scientists, but there have been no previous studies at cell-year level focused on the role of ethnic status in the propagation of income shocks. This is a clear gap, given that both ethnic political marginalization and diversity could act as amplifiers of perceived economic cost and benefits. We suggest that a positive income shock might have different impacts that depend on the political status of ethnic groups and the degree of ethnic diversity of a cell. We contribute to the literature by analyzing several competing theories on the effects of income shocks (the opportunity cost, the state-is-a-prize, and the state capacity theories) on conflict, using geo-localized data which consider the interaction between these income shocks and ethnic diversity. Thus, we propose the use of a panel database of a full grid of African countries divided into sub-national units of 0.5 per 0.5 grades latitude and longitude (10,638 cells) that covers the period 1998-2013. The identification strategy is based on the use of income shocks that can be considered at exogenous at cell level. To that end, we combine sub-national, time-invariant maps of crop suitability and production capacity from the FAO's global agro-ecological zones (GAEZ) with information on movements in global commodity prices and four different variables of ethnicity (fractionalization, polarization, ethnic groups excluded from central power, and monopoly ethnic groups). We also move the topic onwards by introducing the spatial

[6]Keynote address for the second edition of the Annual Bank Conference on Africa (ABCA), 2015. Source: `https://www.worldbank.org/en/news/feature/2015/07/05/confronting-conflict-and-fragility-in-africa`

[7]This chapter was published in World Development,137 (2021)105153 `https://doi.org/10.1016/j.worlddev.2020.105153`

ethnic fractionalization index developed at cell level by Montalvo and Reynal-Querol (2017) and by adapting the spatial ethnic polarization index at cell level.[8]No previous studies have introduced ethnic political inequality in conjunction with ethnic diversity in a grid-panel data context.[9]

Following McGuirk and Burke (2020), we also differentiate between factor and output conflict, and between producing cells and consumer cells. Large-scale conflict, such as battles for control of territory and means of production, are classed as factor conflict. Smaller-scale conflicts aimed at appropriating surpluses are classed as output conflict. Food prices in food-producing cells are captured through a producer price index, and in food-consuming cells through a consumer price index. We also consider droughts as another proxy for income shocks and estimate their effect jointly with food prices. This is because we expect the SPEI drought index to capture variations in the quantity of local crop production much more closely than international prices. Finally, we also take a step further and distinguish between output conflict comprising violence against civilians (which also requires organized armed force) and comprising riots (which is by definition non-organized conflict). We use different measures and datasets of conflict events (such as the ACLED and UCDP-GED datasets),[10] to test the theories behind the models and the robustness of our results.

The results show that distinguishing between organized armed force (battles and violence against civilians) and non-organized conflict (riots) can be more informative than between factor and output conflict. In line with the competing theories, we show evidence that conflict is driven by the opportunity cost and state capacity mechanisms. Furthermore, ethnic cleavages have a larger role in the transmission process of income shocks in organized armed-force conflict than in non-organized violence. The sensitivity

[8]The spatial ethnolinguistic fractionalization and polarization indexes are computed with the Geo-referencing Ethnic Power Relation (GeoEPR) 2014 database. In turn, excluded groups are based on the number provided by the PRIO-GRID 2.0 dataset, while the monopoly groups dummy variable is built up by matching the settlement areas from Ethnic Power Relations (EPR) Dataset Core 2014 with the grid structure provided in PRIO-GRID v.2.0.

[9]To the best of my knowledge, there are no studies at country level.

[10]The Armed Conflict Location and Event Dataset or ACLED (Raleigh Dowd, 2015); and the Uppsala Conflict Data Program Georeferenced Event dataset or UCDP-GED, version 5.0 (Sundberg Melander, 2013; Croicu Sundberg, 2016).

to ethnic heterogeneity is much greater for producer-price and droughts shocks than for consumer-price changes.

Finally, in Chapter 4, entitle *"Addressing oil spillages and agricultural productivity. Evidence of pollution in Nigeria"*, I examine the environmental damage that might be caused as a consequence of particular types of violence, such as oil spills in Nigeria and their impact on agricultural production. There is a large body of literature that argues that natural resources might be more of a curse than a blessing for economic and political development in weakly institutionalized countries. Nigeria, which is the largest oil producer in Africa, is a case in point of a territory cursed by natural resources (Bruederle and Hodler, 2019; Sala-i-Martin and Subramanian, 2013). Crude oil accounts for more than 90 per cent of the revenues generated by the government. Nevertheless, the gains from oil exports have created a highly enriched small minority, while most of the population has become increasingly impoverished (Nriagu, 2019). Frequent oil spillages in pipeline networks also represent major ecological disasters which have exacerbated economic, environmental, and social problems. According to Madu et al. (2018), "[..] about 70 per cent of the oil spillages events in the Niger Delta area can be attributed to vandalism or theft of oil from the pipelines of major oil companies like Exxon, Chevron, and Shell, among others. The success or failure of the implementation of any sustainability-related initiatives still dominates major debates in the public arena. There is significant policy resistance in the area culminating in the formation of the militant groups that have adopted the strategy of blowing up the oil pipelines". Therefore, several socio-political factors are associated with pipeline vandalism. Issues related to resource control and the revenue allocation formula used by the government in the distribution of oil revenues to the states are often cited as particular causes of such sabotage. The call for the right of self-determination in the Niger Delta area is another determining factor in the increase in violence targeting oil pipelines.

Communities near pipelines bear the brunt of the oil spill pollution derived from this vandalism. The same polluting effects are also generated due to operational spills (such as corrosion, engineering equipment failures, and human errors). However, the proportion of oil spills caused by sabotage in Nigeria, in the context of vandalism associated with conflict, gives me the chance to study this issue in Chapter 4 of my dissertation and link it as one consequence of conflict. In particular, farmers are included in the analysis of how pollution from oil spillages affects agricultural production of nearby farmers by reducing the agricultural total factor productivity.

To that end, in my identification strategy I follow the methodology proposed by Aragón and Rud (2016), who study the effect of air pollution on agricultural production given the expansion of mining activities in Ghana. Thus, I use a consumer-producer household framework, where households are both consumers and producers of agricultural goods in the context of incomplete input markers, to understand how oil spill pollution might generate adjustments in the optimal behavior of households. Then I approximate an agricultural production function using a repeated cross-sections model of micro-data geo-referenced for farming households, taken from the Nigeria General Household Survey (GHS-Panel). I use four waves of data: 2010-2011, 2012-2013, 2015-2016, and 2018-2019. To calculate a proxy for oil spill pollution, I create a function that uses geospatial data with information on around 12,000 oil spills from The Nigerian Oil Spill Monitor. [11] In order to estimate the model, I apply a difference-in-difference strategy with continuous treatment, in which the treated group comprises locations within 10 kilometers of oil spill events and the control group is made up of the rest of the places from my dataset.

I find that farmers located less than 10 kilometers from oil spills experience a relative reduction in total factor productivity of around 2.73%. I also examine alternative mechanisms and find that oil spill pollution may explain my results. I also detect less owner-occupied land and a drop in labor income in urban areas close to oil spills that could also be explained by a decrease in the labor productivity component. This study highlights an externality through which the oil industry affects the living conditions of rural areas and the importance of clean-up aspects in areas close to oil spillages.

[11] The Nigerian Oil Spill Monitor provides the data collected by the National Oil Spill Detection and Response Agency (NOSDRA).

In short, the subsequent chapters of this dissertation analyze some causes and one of the consequences of conflict linked to globalization , using various methodologies related to spatial patterns and geo-localized data.

Chapter 2

Is there a link between globalization and civil conflict?

[Authors: Roberto Ezcurra and Beatriz Manotas. This chapter has been published in The World Economy (2017).[1]]

2.1 Introduction

The consequences of globalization are nowadays the subject of an active public debate in different forums (Rodrik, 2012; Milanovic, 2016). The interest surrounding this issue is clearly related to the increasing relevance of the process of globalization currently underway. This does not imply that globalization is a new phenomenon, as its origins go back to at least the 19th century (Findlay and O'Rourke, 2007). Nevertheless, during the last few decades the world has experienced unprecedented levels of integration, surpassing the peak reached before the First World War. This process is characterized by the opening of national borders to a variety of flows, including people, goods and services, capital, information and ideas (Clark, 2000). Although it is difficult to agree on a precise definition, there is wide consensus that globalization tends to erode the relevance of national borders, generating complex relations among different actors at multi-continental distance (Norris, 2000). These increasing mutual interactions have

[1]The World Economy (2017), vol. 40(12), pp. 2592-2610.
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important consequences on many relevant facets of contemporary societies, including economic, social, cultural and political aspects. Accordingly, understanding the effects of globalization is essential to address the numerous challenges posed by this process, and be able to identify who wins and who loses, not only within each country but also across countries.

Against this background, numerous studies have been published in recent years on the impact of globalization on economic development and growth (Frankel and Romer, 1999; Dreher, 2006), income inequality and poverty (Dollar and Kraay, 2004; Milanovic, 2005), labour markets (Dreher and Gaston, 2007; Tomohara and Takii, 2011), environmental quality (Antweiler et al., 2001; Frankel and Rose, 2005), or democracy and human rights (Rudra, 2005; Dreher et al., 2012). Likewise, there are various contributions that examine the potential link between globalization and civil conflict using different indicators of trade openness and foreign direct investment to measure the relevance of globalization (e.g. Bussmann and Schneider, 2007; Martin et al., 2008; Sorens and Ruger, 2014). From a policy perspective, the relationship between these variables and civil conflict is clearly important, as it provides information on the role that economic integration plays in this context. Nevertheless, the degree of trade openness and foreign direct investment are not useful to capture the incidence of other dimensions of globalization identified in the political economy literature, such as social integration and political integration (Prakash and Hart, 1999; Keohane and Nye, 2000). This is potentially important, given that it is not evident that the various dimensions of globalization affect internal conflict in the same way. Bearing this in mind, and in a quest for empirically well-founded stylized facts, this paper aims to provide a comprehensive analysis of the relationship between globalization and the incidence of civil conflict. We adopt a broader perspective than that found in most of the existing studies on this topic and investigate in a systematic way the consequences that the economic, social and political dimensions of globalization have on civil conflict.

To the best of our knowledge, only Nieman (2011), Olzak (2011), and Flaten and de Soysa (2012) have thus far considered the multidimensional nature of the process of globalization in this context. Nieman (2011) finds that changes in the degree of integration imply greater risk of internal conflict. The results of Olzak (2011) show that economic and cultural globalization is positively associated with the intensity of ethnic conflicts, while sociotechnical aspects of integration increase fatalities from ethnic conflicts but decrease deaths from non-ethnic conflicts. Finally, the empirical evidence provided by Flaten and de Soysa (2012) suggests that globalization, particularly economic and social globalization, leads to lower risk of civil war.

These results are potentially important. Nevertheless, previous studies do not adequately address the potential endogeneity of the globalization variables, which is particularly important to establish a causal link between the degree of integration with the rest of the world and civil conflict. In this paper we use two strategies to tackle this issue. Our first strategy is to include in the analysis country fixed effects in order to control for those time-invariant factors affecting both conflict and globalization, such as geographical and historical features. This is a first important difference between our paper and Nieman (2011), Olzak (2011), and Flaten and de Soysa (2012). While the fixed effects estimation is useful in removing the influence of long-run determinants of both conflict and globalization, it does not necessarily estimate the causal effect of the degree of integration with the rest of the world on civil conflict. For this reason, unlike existing studies, our second strategy is to use an instrumental variables approach in this context. To that end, we construct an instrument for globalization based on the degree of integration of neighbouring countries.

The paper also differs from Nieman, (2011), Olzak (2011), and Flaten and de Soysa (2012) in the definition of conflict used in the analysis. Nieman (2011) and Flaten and de Soysa (2012) examine the impact of globalization on the onset of civil war and respect for human rights, whereas the dependent variable used by Olzak (2011) is the number of fatalities from conflict, which is a measure of the intensity of conflict. In contrast, we are interested in the effect of integration on the *incidence* of civil conflict. This allows us to relate our paper to the abundant literature on the determinants of the incidence of intrastate conflicts (e.g. Miguel et al. 2004; Montalvo and Reynal-Querol, 2005; Esteban et al., 2012a,b). Nevertheless, we also explore the robustness of our results with respect to conflict onset.

Unlike existing studies, we find no evidence of a significant impact of globalization on civil conflict. The results of the paper show that the inclusion of country fixed effects removes the statistical association between the degree of integration with the rest of the world and the incidence of internal conflict. Our instrumental variables estimates also show no causal effect of globalization on civil conflict. These findings do not depend either on the specific dimension of globalization considered or the measure of conflict used in the analysis.

The remainder of the paper is organized as follows. After this introduction, section 2 reviews several of the theoretical arguments proposed in the literature to justify the possible connection between globalization and internal conflict. Section 3 describes the measures used in our study to quantify the relevance of globalization and internal conflict in the various countries. Section 4 presents the empirical analysis undertaken to investigate the link between globalization and civil conflict. The robustness of our findings is examined in section 5. The main conclusions of our work are discussed in the final section.

2.2 The relationship between globalization and civil conflict

From a theoretical perspective, there are several arguments to believe that globalization and civil conflict may be related. Nevertheless, this is a complex relationship, as attempting to explain how globalization affects conflict implies taking into consideration multiple factors and mechanisms that often work in opposite directions. Specifically, it is important to note that economic, social and political integration can have different effects on conflict (Nieman, 2011; Olzak, 2011; Flaten and de Soysa, 2012).

Most of the existing literature has focussed exclusively on the link between international trade and civil conflict. According to Martin et al. (2008), there are two mechanisms relating trade and the opportunity cost of internal conflict, which work in opposite directions. The first of these mechanisms is the deterrence effect. This effect is based on the idea that the opportunity cost of conflict is positively associated with the degree of trade openness of the country in question, as the economic benefits generated by international trade can be threatened by the existence of intrastate violence. According to this effect, trade openness reduces the potential risk of civil conflict. However, Martin et al. (2008) also recall that international trade can be a substitute for internal trade during civil conflict episodes, thus acting as an insurance and reducing the opportunity cost of conflict. This insurance mechanism also implies the weakening of the degree of economic interdependence of the various regions and ethnic groups within a country, which in turn increases the feasibility of conflict (Martin et al., 2008). The final impact of international trade on the incidence of civil conflict depends ultimately on the magnitude of both effects, which may be related to the degree of intensity of conflict. The deterrence effect should be more relevant in high intensity conflicts, whereas the insurance effect should be less important in this type of conflicts (Martin et al., 2008).

The opening of national economies to world markets has led to greater inequality in numerous countries (Milanovic, 2016). According to the traditional view, economic inequality is perceived as a major driver of social conflict. As pointed out by Sen (1973, p. 1), "the relationship between inequality and rebellion is indeed a close one". Yet, intuitive and natural as it might seem, the link between income inequality and conflict has not yet received conclusive and definitive empirical support (Esteban et al., 2012 a,b). However, other dimensions of inequality are also potentially important in this context. For example, economic globalization contributes to increasing spatial inequality (i.e. inequality across the various regions of a country) (Ezcurra and Rodríguez-Pose, 2014). This is particularly relevant in this context, since a high level of spatial inequality may lead to internal conflicts about the territorial distribution of resources (Østby et al., 2009; Deiwiks et al., 2012). Furthermore, the impact of economic globalization is often unevenly distributed across the members of different ethnic groups, favouring some groups over others and affecting ethnic inequality (i.e. inequality across ethnic groups) (Olzak, 2011). The implications of economic globalization on ethnic inequality are especially important in lower income countries, where the benefits from the process of integration tend to improve the relative situation of ethnic groups that hold a political dominant situation (Chua, 2003). In order to keep their privileged situation and limit the degree of mobilization of disadvantaged groups, the dominant ethnic group usually adopts practices including the deterioration of civil and political rights of minority groups. This setting leads to an intensification of social unrest based on ethnic cleavages (Wimmer et al., 2009), which is consistent with the increasing relevance of violent ethnic conflicts in the last decades (Chua, 2003).

The social dimension of globalization can also affect conflict. The flows of information and ideas that characterize social integration boost internal movements based on claims for self-determination and expanded minority rights (Olzak, 2011; Flaten and de Soysa, 2012). Social globalization contributes to reducing the cultural distance between countries, thus providing an ideological platform and an international audience predisposed to support these claims (Olzak, 2011). In this setting, minority groups have a greater capacity to mobilize against repressive regimes that deny them their rights, which in turn raises the risk of armed conflict. Moreover, the advances in this dimension of globalization give rise to an increase in migratory flows across national borders (Goldberg and Pavcnik, 2007). These migratory flows often lead to a negative reaction of native citizens and the aggravation of existing ethnic tensions.

Social globalization also exerts greater international pressure on repressive regimes as a result of the increasing information available nowadays via the Internet and other global communication media (Dreher et al., 2012). In this context, the existence of a violent conflict within a country negatively affects the likelihood of receiving foreign investment and international aid. Indeed, this effect is particularly important in countries highly dependent on tourism, as the economic gains generated by tourism are put at risk due to the negative publicity of internal violence. This argument seems to suggest that this aspect of social globalization increases the opportunity cost of civil conflict. However, at the same time, the advance of the new information technologies also enhances the mobilization capacity of insurgents.

Finally, political globalization may also be connected with the incidence of intrastate conflict through different mechanisms. An important aspect of this dimension of globalization has to do with the increasing relevance of supranational organizations such as the WTO, the IMF, or regional trade unions. The decisions adopted by these organizations tend to be based on asymmetric trade and financial relations, which can affect the internal situation and the economic performance of low- and middle-income countries (Stiglitz, 2002). This may have implications on the level of dispersion of the income distribution, the degree of ethnic inequality or the magnitude of spatial disparities within these countries. As outlined above, all these factors are important in explaining the potential for social unrest and civil conflict.

Empirical research is key to illustrating the potential link between globalization and conflict. In recent years, several studies have investigated this relationship empirically, paying particular attention to the impact of international trade and financial liberalization on civil conflict (e.g. Bussmann and Schneider, 2007; Martin et al., 2008; Sorens and Ruger, 2014). These analyses are doubtless useful to examine the effect of economic globalization on internal conflict, but they do not provide any information on the role played by social and political globalization in this context. Although the different aspects of globalization are often positively correlated, this omission is potentially important, as the various arguments discussed above show that social and political globalization may have a direct effect on the incidence of conflict. Accordingly, the impact of economic integration on conflict observed in the literature may be affected by the omission of social and political globalization from the analysis. Bearing this in mind, in this paper we follow the strategy adopted by Nieman (2011), Olzak (2011), and Flaten and de Soysa (2012) and use an extensive concept of globalization, which allows us to comprehensively examine the overall effect of economic, social, and political integration on civil conflict. Nevertheless, our research does not aim to propose a new theory or to test empirically the relevance of a specific channel linking globalization and internal violence. As pointed out in the introduction, our main contribution to the literature has to do with the strategies adopted to investigate the causal link between the degree of integration with the rest of the world and civil conflict.

2.3 Measuring globalization and civil conflict

Our empirical analysis requires comparable and reliable information on the incidence of globalization in the various countries. Nevertheless, this is not an easy task because, as discussed above, globalization is a multidimensional process and cannot be captured by a single variable (Clark, 2000; Keohane and Nye, 2000). The measure of globalization that we use is the KOF index of globalization constructed by Dreher (2006) and updated by Dreher et al. (2008). This is a composite index widely employed in the recent literature to examine different aspects of the consequences of globalization.[2]

The KOF index is based on a set of 23 variables associated with different dimensions of globalization. These variables are used to obtain three indices on the incidence of economic, social and political integration by means of principal component analysis (for further details see Dreher et al. (2008)). The information provided by these three indices is employed to calculate an overall index of globalization. The index of economic integration is a weighted average of two subindices that respectively measure actual economic flows and existing restrictions on trade and capital. The index of social integration is a weighted average of three subindices that respectively capture the importance of personal contacts, information flows and cultural proximity. The degree of political integration is proxied by the number of embassies in a country, membership in international organizations, participation in UN peacekeeping missions, and the ratification of international treaties. Finally, the overall index of globalization is obtained as a weighted average of the three indices of economic, social and political integration.[3] Table A.2 in the Appendix A displays the correlation coefficients between

[2] A comprehensive list of papers based on the KOF index of globalization can be found at http://globalization.kof.ethz.ch/.

[3] Table A.1 in the Appendix A includes further details on the different components of the KOF index, as well as the weights attached to each individual variable to derive the various indices.

the overall measure of globalization and the three indices of economic, social and political integration. As expected, all the correlation coefficients are positive and statistically significant at the 1% level. Their magnitude, however, reveals the existence of discrepancies between the various dimensions of globalization identified by the KOF index. This shows that the distinction between economic, social and political globalization is empirically relevant and is not only a conceptual issue.

In order to conduct the analysis, we also need to quantify the incidence of civil conflicts in the various countries. This information is drawn from the UCDP/PRIO Armed Conflict Dataset. We follow the common practice in the literature and take as our baseline PRIO25, which reports all internal conflicts with 25 or more battle-related deaths in a year (e.g. Miguel et al., 2004; Esteban et al., 2012a,b; Nunn and Qian, 2014). According to this criterion, 92 countries experienced at least one episode of civil conflict between 1972 and 2009, which shows that intrastate violence is not concentrated in a small number of countries.

2.4 Is there an empirical link between globalization and civil conflict?

2.4.1 The model

In this section we investigate the relationship between globalization and civil conflict in 159 countries over the period 1972-2009. To that end, we estimate different versions of the following model:

$$C_{it} = \alpha + \beta C_{it-1} + \gamma G_{it-1} + \delta' X_{it-1} + \eta_i + \lambda_t + \varepsilon_{it} \qquad (2.1)$$

where C is a binary variable that takes a value of one if a civil conflict occurred in country i during year t, zero otherwise. The lagged value of this variable is included on the right-hand side to capture the inherent persistence in conflicts. G is the KOF index of globalization described above, and X denotes a set of variables that control for additional factors that are assumed to have an influence on civil conflict. In turn, η stands for country-specific effects, while λ are year dummies common to all countries. Finally, ε is the corresponding disturbance term. The coefficient of interest throughout the paper is γ, which measures the effect of globalization on the incidence of civil conflict.

The control variables included in vector X have been selected on the basis of existing studies on the explanatory factors of civil conflict.[4] Thus, there is an increasing body of research that shows the association between economic conditions and internal violence. The level of GDP per capita can be interpreted as a proxy for "a state's overall financial, administrative, police and military capabilities" (Fearon and Laitin, 2003, p. 80), which suggests that rebels can expect a greater probability of success in low-income countries. Furthermore, episodes of conflict tend to be preceded by negative income shocks (Miguel et al., 2004). In fact, the lower the growth rate, the lower the opportunity cost of enlisting as a rebel and engaging in a civil conflict (Collier and Hoeffler, 2004). Taking these arguments into account, we control for the level of GDP per capita and the growth rate of this variable, using data taken from the Penn-World Table (Heston et al., 2011).[5]

Democratic and autocratic states tend to have few civil conflicts, while intermediate regimes are the most conflict-prone (Hegre et al., 2001; Fearon and Laitin, 2003). In view of this, we use a democracy index drawn from the Polity IV Project to construct two dummy variables in order to identify anocratic and democratic regimes (autocratic states are the omitted category).[6] Natural resource abundance may also be related to civil conflict (e.g. Ross, 2006; Brunnschweiler and Bulte, 2009). An unfair distribution of gains from natural resources could lead to social unrest and violence. Moreover, natural resources may provide an important source of funding for rebel forces, making conflict more feasible (Collier et al., 2009). Bearing this in mind, we include in our

[4] See Hegre and Sambanis (2006) and Blattman and Miguel (2010) for surveys of this literature.

[5] Note that the inclusion of the level of GDP per capita and its growth rate in model (2.1) is debatable, as these variable may be considered as proximate outcomes of globalization (Frankel and Romer, 1999; Dreher, 2006). Nevertheless, the results of the paper are unaffected if we remove the level of GDP per capita and its growth rate from model (2.1).

[6] Although there are arguments suggesting that globalization may also affect democracy, the available empirical evidence is far from being conclusive (Rudra, 2005; Doces and Magee, 2015). In any case, we checked that our main findings still hold if we remove these dummies from the list of controls.

model the data on total natural resources rents (as a percentage of GDP) provided by the World Development Indicators.[7]

When considering the specification of model (2.1), it is important to note that the inclusion of country fixed effects allows us to control for those time-invariant elements relevant in this context, such as geographical and historical factors. As pointed out by Sunde and Cervellati (2014), country fixed effects should also account for all potential determinants of civil violence in which most of the variation throughout the study period is across countries rather than over time. This is the case, for example, of the degree of ethnic diversity, population size, or regional disparities. Many of these factors are also likely to be correlated with globalization, which implies that removing the country fixed effects from model (2.1) may lead to biased and inconsistent estimates.

2.4.2 Results

Table 2.1 presents the results obtained when various versions of model (2.1) are estimated with the KOF index as our measure of globalization. Taking into account the approach adopted by Nieman (2011), Olzak (2011), and Flaten and de Soysa (2012), we begin by estimating the model without fixed effects, using a probit model and a linear probability model. As can be observed in columns 1 and 2, in both cases the coefficient of the globalization index is negative and statistically significant, which seems to suggest that a higher level of integration with the rest of the world is associated with a lower incidence of civil conflict. This result would be consistent with those arguments defending that the advances of globalization can help to promote stability and peace, and reduce the risks of internal conflicts (Bhagwati, 2004; Barbieri and Reuveny, 2005). Nevertheless, although statistically significant, the effect of globalization is quantitatively small. For example, the estimates in column 2 indicate that, conditional on the remaining covariates, a one standard deviation increase in the globalization index is associated with a reduction of around 2% in the probability of conflict.[8] However, if this pooled OLS regression

[7] Table A.3 in the Appendix A shows some descriptive statistics for the different variables used in the analysis.

[8] The impact derived from the probit model in column 1 is very similar.

identified the causal effect of globalization on the incidence of civil conflict, then the long-run effect would be larger than this, because of the inclusion of the lagged dependent variable on the right-hand side. The implied cumulative effect of a one standard deviation increase in the globalization index would reduce the probability of conflict by around 10%. These findings should be treated with caution, as column 3 shows that the coefficient of the globalization index is no longer statistically significant once country fixed effects are included in model (2.1). This suggests that the association between globalization and civil conflict observed in columns 1 and 2 is driven by time-invariant omitted variables, such as historical and geographical factors.

Table 2.1: Globalization and conflict incidence: Main results.

	Pooled Probit (1)	Pooled OLS (2)	FE-OLS (3)	FE-2SLS (4)
Lagged conflict	2.805***	0.796***	0.599***	0.599***
	(0.126)	(0.025)	(0.038)	(0.037)
Overall index of globalization	-0.014***	-0.001**	-0.001	-0.002
	(0.005)	(0.000)	(0.001)	(0.003)
GDP per capita (log)	0.019	0.004	0.017	0.021
	(0.060)	(0.006)	(0.016)	(0.020)
Economic growth	0.434	0.051	0.022	0.022
	(0.495)	(0.076)	(0.076)	(0.074)
Democracy	0.160	0.015	0.004	0.005
	(0.113)	(0.011)	(0.019)	(0.019)
Anocracy	0.285***	0.029**	0.044**	0.043**
	(0.087)	(0.011)	(0.019)	(0.019)
Natural resources	0.000	-0.000	-0.000	-0.000
	(0.002)	(0.000)	(0.001)	(0.001)
Country fixed effects	No	No	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes
R-squared	0.588[a]	0.654	0.694	0.693
Root mean square error	–	0.221	0.212	0.207
Countries	159	159	159	159
Observations	4,864	4,864	4,864	4,864

Notes: The dependent variable is a binary variable that takes a value of one for conflicts with 25 or more battle-related deaths in a year, zero otherwise (Prio25). Robust standard errors clustered at the country level in parentheses. [a] Pseudo R-squared. * Significant at 10% level, ** significant at 5% level, *** significant at 1% level.

As mentioned in the introduction, fixed effects regressions do not necessarily identify the causal effect of globalization on civil conflict. In fact, it is possible that

$Cov(G_{it-1}, \varepsilon_{it}) \neq 0$ because of the potential reverse impact of conflict on the spread of globalization. The empirical evidence provided by Martin et al. (2008) shows that the destruction of trade due to civil conflicts can be quantitatively very important and persistent over time. In particular, in the case of civil wars with reported casualties over 50,000 deaths, these authors observe a fall in trade around 25% from its natural level in the first year of the war. The destruction of trade increases with time and it is still present at around 40% 25 years after the conflict's onset. The effect is lower in magnitude but still present and persistent in the case of less-intensity conflicts (Martin et al., 2008). In addition to this reverse causality problem, there may be time-varying omitted determinants of conflict correlated with the degree of integration. Finally, the values of the globalization index may be affected by measurement errors. All of these problems could be solved if we had a suitable instrument for globalization. Such an instrument must not be correlated with the disturbance term in model (2.1), but account for the cross-country variation in the incidence of globalization.

As pointed by Flaten and de Soysa (2012), finding an instrument that fulfils these two conditions is not an easy task in our context given the nature of the KOF index. While we do not have an ideal source of exogenous variation, we consider that the (weighted) average of the incidence of globalization in neighbouring countries can be a plausible instrument. To calculate this average the values of the globalization index are weighted by a spatial weights matrix, W, which describes the spatial interdependences among the sample countries. In particular, W is defined as follows:

$$W = \begin{cases} w_{ij} = 0 \quad \text{if} \quad \mathrm{i} = \mathrm{j} \\ w_{ij} = \frac{1/d_{ij}^2}{\sum\limits_j 1/d_{ij}^2} \quad \text{if} \quad \mathrm{i} \neq \mathrm{j} \end{cases} \tag{2.2}$$

where d_{ij} is the geographic distance between countries i and j, which in itself is strictly exogenous. As can be observed, W is row standardized, so that it is relative and not absolute distance which matters. Analogously, one can calculate the (weighted) average of the degree of economic, social and political globalization in neighbouring countries. The rationale for using this instrument has to do with the notion that geography and spatial interdependence are important factors for the spread of globalization, which is consistent, for example, with numerous theoretical models developed in the so-called "New Economic Geography" (e.g. Krugman, 1998; Fujita and Thisse, 2002). There is abundant evidence showing that trade flows are more likely between neighbouring countries, as transport costs increase with geographic distance (e.g. Anderson and Van Wincoop, 2004; Disdier and Head, 2008). Similarly, the cultural distance between two countries depends directly on the geographic distance between them (Disdier et al., 2010). These arguments suggest that a country's level of globalization tends to be higher, the higher the degree of integration of its neighbouring countries with the rest of the world.

The first stage regressions in Table 2.2 confirm the relevance of the instrument in explaining the cross-country variation in the incidence of globalization. The coefficient of the instrument is in all cases positive and statistically significant at the 1% level, regardless of the specific dimension of globalization considered. The partial regression plots displayed in Figure A1 in the Appendix A indicate that the association between the instrument and the degree of globalization is not driven by potential outliers. Furthermore, the values of the F-statistic for the excluded instrument shown in Table 2.2 suggest that there is no reason to believe that our estimates are biased by a weak instrument.

To be a valid instrument, however, the degree of globalization in neighbouring countries should not affect the incidence of conflict in any given country beyond its impact on the level of globalization of that country. This condition cannot be tested formally in the absence of other instruments, but we consider that it is a plausible assumption. Nevertheless, one may argue that the degree of integration of neighbouring countries may influence the dependent variable in model (2.1) through cross-border conflict spillovers. However, as can be seen in section 5, our main results still hold when we control for the incidence of conflict in neighbouring countries.

Table 2.2: First stage regressions.

	(1)	(2)	(3)	(4)
Dependent variable	Overall globalization	Economic globalization	Social globalization	Political globalization
Overall globalization in neighbouring countries	0.346***			
	(0.053)			
Economic globalization in neighbouring countries		0.348***		
		(0.070)		
Social globalization in neighbouring countries			0.433***	
			(0.069)	
Political globalization in neighbouring countries				0.395***
				(0.109)
Lagged conflict	-0.266	-0.126	-0.448	-0.482
	(0.367)	(0.740)	(0.431)	(-0.837)
GDP per capita (log)	2.731***	1.425	4.037***	2.400
	(0.995)	(1.403)	(1.063)	(1.516)
Economic growth	0.491	5.211**	-2.718**	1.476
	(1.082)	(2.035)	(1.176)	(1.971)
Democracy	1.189*	1.812	-0.154	3.003**
	(0.616)	(1.040)	(0.821)	(1.333)
Anocracy	-0.677	-0.678	-2.300***	2.054*
	(0.479)	(0.745)	(0.548)	(1.052)
Natural resources	-0.030	0.079**	-0.068**	-0.042
	(0.024)	(0.033)	(0.027)	(0.033)
Country fixed effects	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes
R-squared	0.970	0.939	0.965	0.907
Root mean square error	3.232	4.910	4.126	6.900
F-test excluded instrument	43.17***	24.38***	38.88***	13.25***
Partial R-squared	0.110	0.070	0.155	0.040
Countries	159	139	159	160
Observations	4,864	4,431	4,864	4,884
Second stage results	Table 1, col. 4	Table 3, col. 3	Table 3, col. 6	Table 3, col. 9

Notes: Robust standard errors clustered at the country level in parentheses. * Significant at 10% level, ** significant at 5% level, *** significant at 1% level.

Column 4 of Table 2.1 reports the 2SLS estimates of model (2.1).[9] The results reveal the absence of a significant relationship between globalization and civil conflict, thus confirming the information provided by the OLS estimates with fixed effects in column 3 of Table 2.1. Therefore, our analysis shows no evidence on the existence of causal effect of the degree of integration with the rest of the world on intrastate conflict, which should be taken into account by policy makers and international organizations when considering the consequences associated with the process of globalization currently underway.

With respect to the control variables included in model (2.1), Table 2.1 reveals that conflict incidence is deeply affected by the existence of previous episodes of violence.[10] In turn, civil conflict is more likely in anocratic regimes, which is consistent with the empirical evidence provided by Hegre et al. (2001) and Fearon and Laitin (2003), among others. The remaining covariates are not significantly related to conflict incidence in our regressions.

So far we have investigated the overall impact of globalization on the incidence of civil conflicts. In order to complement our results, in Table 2.3 we use the information provided by the KOF index to examine the role played in this setting by economic, social and political integration. This is particularly interesting, given that it is not clear a priori that these three dimensions of globalization affect civil conflict in the same way. We begin the analysis by discussing the OLS estimates of model (2.1) without country fixed effects. This specification shows that the measures of economic and social globalization seem to be negatively and significantly associated with conflict incidence. The existence of a negative relationship between economic globalization and intrastate conflict is in line with the findings reported by Barbieri and Reuveny (2005), Bussmann and Schneider (2007) or Flaten and de Soysa (2012), but it contrasts with the results in

[9]As pointed out by Miguel et al. (2004), 2SLS is typically preferred even in cases in which the dependent variable is dichotomous (Angrist and Kreuger, 2001), as strong specification assumptions are required to justify the use of alternative methods, such as those proposed by Rivers and Vuong (1988).

[10]Note that including the lagged of the dependent variable on the right-hand side is unlikely to result in the Nickell (1981) bias, as the time dimension of our panel is relatively large ($T = 38$). Using Monte Carlo simulations, Judson and Owen (1999) and Beck and Katz (2004) show the limited influence of the lagged dependent variable on other covariates when the time dimension is moderately large.

Martin et al. (2008) and Olzak (2011). The empirical evidence provided by Olzak (2011) indicates that cultural and sociotechnical aspects of integration increase the number of fatalities in ethnic conflicts. However, in the case of non-ethnic conflicts, she finds that sociotechnical aspects of globalization are negatively correlated with casualties. In turn, the results reported by Flaten and de Soysa (2012) suggest that social globalization reduces the risk of conflict onset. Table 2.3 also shows that the measure of political globalization is positively and significantly related to the dependent variable. Nevertheless, the employment of alternative estimation strategies sheds considerable doubt on these findings. In fact, the estimates in Table 2.3 reveal that, once country fixed effects are introduced in the model and 2SLS regressions are used, the relationship between the various measures of globalization and civil conflict disappears, which is consistent with our previous findings.

Table 2.3: The various dimensions of globalization and conflict incidence.

	Pooled OLS (1)	FE-OLS (2)	FE-2SLS (3)	Pooled OLS (4)	FE-OLS (5)	FE-2SLS (6)	Pooled OLS (7)	FE-OLS (8)	FE-2SLS (9)	Pooled OLS (10)	FE-OLS (11)	FE-2SLS (12)
Lagged conflict	0.805***	0.618***	0.618***	0.791***	0.599***	0.599***	0.796***	0.601***	0.602***	0.801***	0.617***	0.618***
	(0.026)	(0.039)	(0.038)	(0.025)	(0.038)	(0.037)	(0.025)	(0.037)	(0.036)	(0.025)	(0.039)	(0.040)
Economic globalization	-0.001***	-0.001	-0.001							-0.001*	-0.00	0.002
	(0.000)	(0.001)	(0.002)							(0.000)	(0.001)	(0.014)
Social globalization				-0.002***	-0.001	-0.002				-0.001**	-0.001	-0.003
				(0.000)	(0.001)	(0.002)				(0.000)	(0.001)	(0.012)
Political globalization							0.001**	-0.000	0.002	0.001*	-0.000	0.002
							(0.000)	(0.001)	(0.002)	(0.000)	(0.001)	(0.002)
GDP per capita (log)	0.003	0.004	0.004	0.013**	0.019	0.023	-0.013***	0.010	0.004	0.010	0.012	0.006
	(0.005)	(0.020)	(0.021)	(0.007)	(0.017)	(0.020)	(0.005)	(0.016)	(0.018)	(0.008)	(0.020)	(0.046)
Economic growth	0.108	0.043	0.046	0.044	0.017	0.014	0.065	0.029	0.026	0.099	0.038	0.016
	(0.081)	(0.084)	(0.084)	(0.075)	(0.075)	(0.074)	(0.076)	(0.075)	(0.075)	(0.082)	(0.084)	(0.141)
Democracy	0.016	0.004	0.004	0.013	0.002	0.001	0.002	0.002	-0.004	0.011	0.002	-0.011
	(0.011)	(0.019)	(0.019)	(0.011)	(0.019)	(0.019)	(0.011)	(0.019)	(0.020)	(0.011)	(0.019)	(0.029)
Anocracy	0.031***	0.044**	0.043**	0.027**	0.042**	0.040**	0.020*	0.045**	0.041**	0.027**	0.041**	0.036
	(0.011)	(0.019)	(0.019)	(0.011)	(0.019)	(0.020)	(0.011)	(0.019)	(0.019)	(0.011)	(0.019)	(0.024)
Natural resources	0.000	0.001	0.001	-0.000	-0.000	-0.000	0.000	-0.000	-0.000	0.000	0.001	0.001
	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)	(0.002)
Country fixed effects	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.679	0.713	0.713	0.655	0.694	0.694	0.653	0.693	0.692	0.680	0.713	0.711
Root mean square error	0.216	0.208	0.203	0.221	0.212	0.207	0.222	0.213	0.209	0.216	0.208	0.204
Countries	139	139	139	159	159	159	160	160	160	139	139	139
Observations	4,431	4,431	4,431	4,864	4,864	4,864	4,884	4,884	4,884	4,431	4,431	4,431

Notes: The dependent variable is a binary variable that takes a value of one for conflicts with 25 or more battle-related deaths in a year, zero otherwise (PRIO25). Robust standard errors clustered at the country level in parentheses. * Significant at 10% level, ** significant at 5% level, *** significant at 1% level.

2.5 Robustness checks

The analysis carried out so far suggests that the degree of integration with the rest of the world does not exert a significant effect on conflict incidence, regardless of the specific dimension of globalization considered. In this section we investigate the robustness of this result.

Influential countries

We begin by examining whether our findings are robust to the elimination of regions that can be considered especially conflictive. As is known, civil conflicts have been particularly persistent during the last decades in Sub-Saharan Africa, Asia and Latin America. We carry out different estimations of model (2.1) in which we exclude the countries in these regions in turn. Table A.4 in the Appendix A shows that our findings are not driven by countries located in the most conflictive regions in the world. Table A.4 also reveals that the results still hold when we remove from the sample the high-income countries according to the World Bank classification.

Cross-border conflict spillovers and the exclusion restriction

The exclusion restriction implied by our 2SLS regressions is that, conditional on the set of controls included in the baseline specification of model (2.1), the instrument has no effect on the incidence of civil conflict, other than their impact through globalization. As mentioned above, the validity of this assumption may be problematic in the case of the globalization of neighbouring countries, as one may argue that this variable could be correlated with the level of violence registered by neighbouring countries within their borders, which could in turn affect the risk of civil conflict in a particular country. In this line, the international relations literature has highlighted that conflict in one nation can cause violence in neighbouring countries in many different ways (Brown, 1996; Lake and Rothchild, 1998). As an example, we might mention the existence of refugee flows or armed rebel groups seeking protection or wreaking havoc on neighbouring states to internationalize the conflict, alliances between transnational ethnic groups, or territorial demands involving two different nations. In fact, the empirical relevance of these cross-border conflict spillovers has been confirmed by several studies (e.g. Hegre and Sambanis, 2006; Buhaug and Gleditsch, 2008; Bosker and de Ree, 2014).

In view of this, we now control for the incidence of conflict in neighbouring countries in the previous year.[11] Table 4 presents the results obtained when this additional covariate is included in our baseline specification. As can be seen, the presence of a civil conflict in neighbouring countries seems to have a positive and statistically significant effect on conflict incidence, which is consistent with the existence of cross-border conflict spillovers. Nevertheless, Table 1.4 shows that the inclusion of this additional control in model (2.1) does not affect the previous results on the impact of globalization on civil conflict, thus confirming the robustness of our findings.[12]

[11] This variable has been constructed following the same method described in section 4.2 to calculate the degree of globalization in neighbouring countries.

[12] As shown in Table A.5 in the Appendix A, the main results of the paper remain unaffected if we consider alternatively the average incidence of conflict in neighbouring countries over the last five years.

Table 2.4: Robustness analysis: The impact of cross-border conflict spillovers.

	FE-OLS (1)	FE-2SLS (2)	FE-OLS (3)	FE-2SLS (4)	FE-OLS (5)	FE-2SLS (6)	FE-OLS (7)	FE-2SLS (8)	FE-OLS (9)	FE-2SLS (10))
Lagged conflict	0.598***	0.597***	0.616***	0.616***	0.597***	0.597***	0.599***	0.600***	0.615***	0.614***
	(0.037)	(0.037)	(0.039)	(0.039)	(0.037)	(0.037)	(0.036)	(0.036)	(0.039)	(0.041)
Overall globalization	-0.001	-0.002								
	(0.001)	(0.003)								
Economic globalization			-0.001	-0.001					-0.000	0.004
			(0.001)	(0.002)					(0.001)	(0.015)
Social globalization					-0.001	-0.002			-0.001	-0.004
					(0.001)	(0.002)			(0.001)	(0.012)
Political globalization							-0.000	0.001	-0.000	0.002
							(0.001)	(0.002)	(0.001)	(0.002)
GDP per capita (log)	0.021	0.025	0.008	0.008	0.023	0.028	0.015	0.010	0.016	0.019
	(0.016)	(0.020)	(0.019)	(0.021)	(0.017)	(0.020)	(0.016)	(0.019)	(0.020)	(0.054)
Economic growth	0.018	0.018	0.043	0.043	0.014	0.011	0.026	0.023	0.037	0.001
	(0.072)	(0.072)	(0.081)	(0.082)	(0.072)	(0.072)	(0.072)	(0.073)	(0.080)	(0.141)
Democracy	0.004	0.005	0.004	0.004	0.003	0.002	0.003	-0.002	0.003	-0.013
	(0.019)	(0.019)	(0.019)	(0.018)	(0.019)	(0.019)	(0.018)	(0.021)	(0.018)	(0.029)
Anocracy	0.039**	0.038**	0.039**	0.039**	0.037**	0.034*	0.040**	0.037*	0.036*	0.029
	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.020)	(0.019)	(0.019)	(0.019)	(0.026)
Natural resources	-0.001	-0.001	0.001	0.001	-0.001	-0.001	-0.000	-0.000	0.001	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Conflict in neighbouring countries	0.123**	0.122**	0.129**	0.129**	0.124**	0.123**	0.126**	0.121*	0.130**	0.146
	(0.061)	(0.060)	(0.062)	(0.060)	(0.061)	(0.061)	(0.060)	(0.064)	(0.062)	(0.091)
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.694	0.694	0.714	0.714	0.694	0.694	0.694	0.693	0.714	0.709
Root mean square error	0.207	0.207	0.203	0.203	0.207	0.207	0.208	0.208	0.203	0.205
Countries	159	159	139	139	159	159	160	160	139	139
Observations	4,864	4,864	4,431	4,431	4,864	4,864	4,884	4,884	4,431	4,431

Notes: The dependent variable is a binary variable that takes a value of one for conflicts with 25 or more battle-related deaths in a year, zero otherwise (Prio25). Robust standard errors clustered at the country level in parentheses. * Significant at 10% level, ** significant at 5% level, *** significant at 1% level.

Alternative measures of conflict

As mentioned above, the dependent variable in model (2.1) is Prio25, a binary variable that reports conflicts with 25 or more battle-related deaths in a given year. Our findings, however, may be affected by the choice of this specific threshold of deaths. For this reason, as an additional robustness check, we now examine to what extent the previous results depend on the definition of civil conflict used to construct the dependent variable in model (2.1). To that end, we now use two alternative indicators based on the UCDP/PRIO data. The first one is Prio25 augmented by the requirement that the conflict must yield at least 1,000 deaths over its course (Priocw). The second one considers exclusively conflicts with 1,000 or more deaths per year (Prio1000), which allows us to focus on high-intensity conflicts. Table A.6 in the Appendix A presents the results obtained when Priocw and Prio1000 are used as dependent variables. As can be seen, the estimates continue to show no significant relationship between globalization and conflict incidence.

The analysis performed so far examines the effect of the degree of integration with the rest of the world on conflict incidence. However, globalization may also affect the outbreak of conflicts (Nieman, 2011; Flaten and de Soysa, 2012). In order to explore this issue, we use an alternative dependent variable which is coded one for the first year of a conflict episode (Prio25 definition) that follows at least two years of peace, zero otherwise. The onset regressions are displayed in Table A.7 in the Appendix A. The results are very similar to those described above for conflict incidence. Our estimates reveal that there is no evidence for a significant effect of globalization on conflict outbreak. The only exception is the measure of social globalization, whose coefficient is negative and statistically significant at the 10% level in column 3 of Table A.7. This suggests that this aspect of globalization may contribute to reducing the risk of conflict onset, although its effect is not statistically significant in the specification including all dimensions of globalization jointly (column 5 of Table A.7).

2.6 Conclusions

Civil conflicts account for an enormous share of deaths and hardship in the world today. In addition to the direct impact on battle-related deaths, intrastate conflicts give rise to an important number of indirect deaths due to disease and malnutrition, as well as the forced displacement of refugees. It is estimated that civil wars have caused three times as many deaths as wars between states since the end of the Second World War (Fearon and Laitin, 2003). Intrastate conflicts also have a negative impact on political stability and economic development. Therefore, the analysis of the explanatory factors of internal conflicts is particularly relevant. In view of this, in this paper we have investigated the link between globalization and civil conflict using data on 159 countries over the period 1972-2009. Unlike most of the existing studies on this issue, this paper employs an extensive notion of globalization including its three main dimensions: economic, social and political integration.

The results show that the inclusion of country fixed effects removes the statistical association between the degree of integration with the rest of the world and the incidence of internal conflict. We present instrumental variables estimates that also show no causal effect of globalization on civil conflict. These findings do not depend either on the specific dimension of globalization considered or the measure of conflict used in the analysis. Likewise, the absence of a relationship between globalization and civil conflict is not driven by countries located in the most conflictive regions in the world.

The conclusions of the paper shed considerable doubt on those arguments that claim the existence of a direct link between globalization and conflict. Nevertheless, some caution is necessary in interpreting our results. First, it is important to note that our findings do not allow us to dismiss the possibility that the impact of globalization on conflict might be conditional on factors such as ethnic heterogeneity, horizontal inequalities, or natural resource abundance. Further research is required to explore the relevance of these potential interaction effects. Second, the various arguments laid down in section 2 show that the relationship between globalization and civil conflict is far from simple and involves multiple factors and mechanisms that often work in opposite directions. Additional analyses are required to isolate and quantify the relevance of the different transmission channels which may link the degree of integration with conflict. Only by pursuing these strands will we be able to attain a more complete understanding of the relationship between globalization and civil conflict.

Chapter 3

The Role of Ethnic Characteristics in the Effect of Income Shocks on African Conflict

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3.1 Introduction

Conflict is among the most robust determinants of low economic growth and high mortality (see, e.g., Collier and Hoefler, 2004, and Hegre and Sambanis, 2006). It causes unemployment, human capital loses, reductions in income and displacements of the population, and is a leading cause of hunger and general food insecurity in several parts of the world. Therefore, understanding the determinants of conflict is an important objective that investigators have integrated into their research agendas.

Among those determinants, the impact of income on conflict has been widely studied in the literature.[2] Economists and political scientists have also emphasized the role of

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[2]A common approach has been to employ external shocks captured by fluctuations in commodity prices in order to isolate the effect. At the country level, as Berman and Couttenier (2015) argue, results have been mixed. At the micro-level, on the other hand, the analysis points out a more robust

ethnic cleavages on the generation of violence.[3] However, much less attention has been devoted to the study of the role of ethnic status in the propagation of income shocks. This is an important gap, because ethnic marginalization and diversity may work as amplifiers of the perceived economic costs and benefits—through for example a sense of grievance—and also as means of filtering areas where governments might be stronger.

We fill this gap focusing on Africa, a very vulnerable part of the world with a relatively low capacity of adaptation. In fact, Africa is the region most affected by conflicts after the Second World War. In early January of 2016, twenty-eight countries and 201 militias-guerrillas were involved in conflicts. More specifically, we answer the following question. How do the diversity and political status of ethnic groups affect the impact of income shocks on conflict? We focus on shocks coming from agriculture, because of its importance in food security, and because the agricultural sector still employs more than 50% of the total labor force in Sub-Saharan Africa according to ILO (2019). Unlike previous literature, we work with a full grid of African countries divided into sub-national units of 0.5 x 0.5 degrees latitude and longitude, and consider different measures of ethnic status, namely, spatial polarization and fragmentation, and monopoly and excluded political power. Our approach exploits the arguably exogenous nature at the cell level of variations in income shocks related to international commodity prices and climate conditions.[4] To further preserve exogeneity, international prices are weighted at the cell level using information about crop suitability from the FAO's global agroecological zones (GAEZ) as in Berman and Couttenier (2015), and ethnic variables are measured before the start of the sample period.

Nevertheless, even though the effect of this interaction on conflict is still far from

causal relationship. For instance, Dube and Vargas (2013), Fjelde (2015), and Berman et al. (2017) find that agricultural price shocks are negatively correlated with conflict, whereas mineral and oil prices are positively correlated.

[3]In particular, the role of ethnic fractionalization and ethnic polarization in civil wars have been studied, among others, by Montalvo and Reynal-Querol (2005), Esteban and Ray (2008 and 2011) and Esteban et al. (2012); and the importance of the presence of ethnic groups excluded from political power and ethnic groups that enjoy monopoly over the state have been analyzed, for example, by Cederman et al. (2009) and as Cederman et al. (2011).

[4]Bazzi and Blattman (2014) argue that several African nations produce a large volume of commodity output, leading to a potential endogeneity problem related to prices. For example, from the supply side, a conflict could lead to reduced production, and hence, increase commodity prices. Even though this can be important at the country level, it is much less so at the cell level.

being well understood, it has already received some interest. Janus and Riera-Crichton (2015) analyze it, but at the country level, focusing on the onset of conflict instead of its incidence, employing fully aggregated price shocks, and considering only ethnic polarization and fragmentation.[5] We change the level of observation and consider additional variables. More specifically, our analysis concentrates on a grid-country cell level, combining sub-national, time-invariant maps of crop suitability with information on the movement of global commodity prices, climate conditions, and the four different ethnic-status variables mentioned previously (fragmentation, polarization, excluded groups and monopoly groups). We also make a step forward by introducing the spatial ethnic fractionalization index developed at the cell level by Montalvo and Reynal-Querol (2017) and by adapting the spatial ethnic polarization index to the cell level.

Following the work of McGuirk and Burke (2020) (MB from now on), which also employs geocoded data, we differentiate between two sources of violence—factor conflict and output conflict—and between two types of locations—food-producing cells and food-consuming cells. Factor conflict is related to large-scale conflict such as battles over the control of territory and production means. Output conflict, in turn, is associated to smaller-scale conflict over the appropriation of surplus. Food prices in food-producing areas are captured through a producer price index, and in food-consuming cells through a consumer price index.

MB estimate a negative impact of food prices on factor conflict in food-producing cells but a positive one in food-consuming cells. As argued by MB, this opposing-effects result is difficult to reconcile with theories that emphasize a one-direction impact such as the state capacity mechanism or the rapacity effect, and provides evidence that the opportunity-costs channel, whose direction can vary depending on whether agents are producers or consumers, is a main source of conflict. They also find that food prices have a positive impact on output conflict in both food-producing and food-consuming areas, which gives also support to the opportunity cost mechanism.[6]

[5] Albeit not focusing directly on violence, Brückner and Gradstein, (2015) find that, across countries, the marginal effect of oil price changes on political risk increases with ethnic polarization.

[6] See Section 2.5.5 for a more detailed discussion.

Our findings reinforce the ones obtained by MB but add new aspects and point out an important role of state-capacity (as in Bazzi and Blattman, 2014) and ethnic grievance as determinants of conflict. More specifically, results reproduce the ones obtained by MB for factor and output conflict even when ethnic heterogeneity is considered in the regression. Support for the state capacity channel, on the other hand, comes from the interactions of the agricultural-commodity income shocks with the ethnic diversity variables. The sign of the estimates is always positive across price indices and conflict definitions. That is, the effect of food-price shocks tends to be less negative (or more positive) in more ethnically fractionalized and polarized areas. The lack of opposing effects in food-producing and food-consuming areas on factor conflict makes the result inconsistent with the opportunity cost mechanism. Moreover, the necessary dominance of opportunity costs over the rapacity effect to get the MB results leads us to interpret this finding as pointing to an important role of state capacity, given that more fractionalized or polarized societies signal weaker states suffering more from social tensions (Esteban and Ray, 1999).

Additionally, our estimates imply that the effect of the interaction between food prices and political ethnic cleavages depends on the type of cell and conflict. In food-producing areas, the impact is negative with battles and with output conflict. In food-consuming areas is, on the other hand, positive with both types of violence as well. These results provide evidence and add a location dimension that supports the argument put forward by Roessler (2011) that excluded ethnic groups can have different effects depending on the type of conflict. He sustains that the gain in government's power (or state capacity) from the exclusion of certain groups may come at the cost of displacing the conflict from politics to society, due to the feeling of grievance induced on the excluded population. It could be argued that this trade-off shows in our estimates: in food-consumption cells, the grievance mechanism dominates, possibly exacerbating the perceived opportunity cost, and due to a larger capacity of excluded-group members to get organized in urban areas. In food-producing cells, on the contrary, the state capacity effect dominates at least in the output conflict regression; otherwise, the sign would have to be positive.

We also disaggregate the measure of output conflict, which is the one considered by MB, in its two components: riots and violence against civilians. Both measures are taken from the Armed Conflict Location and Event Data Project (ACLED). Riots represent violent events where rioters engage in disruptive acts. Violence against civilians, in turn, refers to an organized armed-group inducing violence upon unarmed civilians. Hence, violence against civilians is an intermediate type of conflict that lies between organized armed-group battles—which in the main analysis is taken from the Uppsala Conflict Data Program (UCDP) to proxy factor conflict—and riots. This distinction shows up clearly in our estimations. In particular, the response of violence against civilians to the income shocks shares with factor conflict more than twice the number of coefficient signs and significance than with riots. They share, for example, with one exception, all signs of the coefficients related to both producer and consumer prices, possibly signaling that in both cases conflict is exerted by organized armed groups. However, like riots and unlike factor conflict, violence against civilians responds positively to consumer prices in urban areas; thus, implying that this type of output conflict has an important urban component. It is also interesting that, unlike violence against civilians, riots respond much less to political ethnic heterogeneity.

Another interesting result from the disaggregation is that the estimated direct effect of food-prices on riots is negative; and although the coefficient is not significant in the main analysis, it becomes significant in some of the robustness tests, and the rest of robustness exercises retain the sign. This negative direct impact of food prices in food-consuming cells suggests an increase in state capacity to control insurgence, because the other two theories (i.e., opportunity cost and surplus predation) are not consistent with the estimated sign, and because the employed consumer price is a country-wide index that should reflect, at least in part, the capacity of local and central governments to raise revenues.

We consider droughts as another proxy for income shocks and estimate its effect jointly with food prices. The reason is that we expect that droughts capture variations in the quantity of local crop production much more closely than international prices. Following Harari and La Ferrara (2018) (HF from now on), we employ the SPEI Global Drought Monitor database that provides estimates of the potential evapotranspiration (PET). Without ethnic variables, the regression gives a positive impact of droughts on conflict. However, this direct effect tends to disappear once the political ethnic variables are included. In general, the qualitative results are the same than for producer prices, although as expected, with the opposite sign—notice that higher food prices and levels of droughts represent positive and negative income shocks, respectively. Our results are consistent with von Uexkull et al. (2016) who find, using georeferenced data, that droughts help sustain civil conflict battles, especially for agriculturally-dependent politically-excluded groups. We confirm their factor-conflict findings with our sample and methodology. In addition, when we look at the determinants of output conflict, the existence of excluded groups turns out insignificant for riots, whereas excluded and monopoly groups raise the marginal effect of droughts on violence against civilians.

The rest of the paper is organized as follows. Section 2 reviews the mechanisms proposed in the literature to justify a possible connection of income shocks and ethnicity with conflict. The data and the econometric methodology are presented in sections 3 and 4, respectively. Section 5 shows our main results. Several robustness checks of the results are conducted in section 6. Section 7 concludes.

3.2 Theories of Conflict

There exist several competing theories of the effect of income shocks on conflict. All of them are based on the economic insight that rational individuals weight the relative returns, costs, and risk for choosing between to produce or predate (Becker, 1968). One of them is the opportunity cost theory. Models of rebellion suggest that civilian's incentives to rebel rises as economic opportunities and household's real income decline (Grossman, 1991). As MB show, the effect can be positive or negative depending on the type of shock and conflict definition. If labor productivity (e.g., due to proper weather) or producer prices increase, real wages will go up and individuals will have less incentives to join armed groups. This predicted strong inverse relationship between commodity prices and conflict have been used in several papers such as Dal Bò and Dal Bò (2011). However, as MB argue, if consumer prices go up, the real wage of workers will go down, and individuals will have more incentives to fight.

A second theory, based on the state-is-a-prize mechanism suggests that rising prices should increase the risk of insurrection as a mechanism to capture rents or the surplus. This channel is also known as predatory behavior or the rapacity effect. It is especially relevant in the case of mineral and oil and gas that are many times controlled by the state. Nevertheless, as MB show, even though surplus predation can be also present in the case of agricultural income shocks in food-producing areas, its effect is dominated by the opportunity costs mechanism.

A third channel, the state capacity theory (see, e.g., Ross, 2012), states that rising rents provide the state with a stronger capacity to buy off the opposition, counter insurgents and strengthen control, and therefore, help prevent conflict. In addition, we argue that the state capacity effect does not need to show up only at the country level. All different layers of government—central, regional and municipal—have, many times, transferred revenue-collection and expenditure discretionary powers. Therefore, the capacity to buy off opponents and control rebellion and violence can vary between different cells that experience different shocks. Notice that predictions based on the state capacity mechanism are the opposite to the ones from the state-is-a-prize theory.

Moving now to the impact of ethnic diversity, papers such as Blattman and Miguel (2010) have emphasized ethnic nationalism as a preeminent source of group cohesion. Conflict can be rooted in intense emotional reactions based on deep biological, cultural or psychological nature of ethnic cleavages (Alesina et al., 1999; Alesina and La Ferrara, 2000). Consequently, indexes of fractionalization and polarization as measures of diversity have been used in several empirical studies with the idea that ethnically diverse societies have a higher probability of ethnic conflicts (Collier and Hoeffler, 2004; Fearon and Laitin, 2003; Miguel et al, 2004). Whereas ethnic fractionalization measures the probability that two randomly selected individuals from a given location do not belong to the same ethnic group, the polarization index assesses how far the distribution of the ethnic groups is from a bipolar distribution. Results using fractionalization indexes are surprisingly murky. However, papers like Montalvo and Reynal-Querol (2005) have found polarization as significant to explain the incidence of civil war.

Finally, political sciences have emphasized the potential importance of ethnic political diversity and political marginalization of ethnic groups in the incidence of conflict (Gurr, 1970; Horowitz, 1985; Baseadu and Pierskalla, 2014; Cederman et al., 2009, 2010, 2011; Wimmer et al. 2009). For example, Cederman et al. (2011) find the political inequality affects positively civil wars through grievance-based mechanisms.[7] Other authors argue that the effect may depend on the type of conflict and political inequality. Roessler (2011) argues that the exclusion of certain ethnic groups from politics increases the government's power, reducing the risk of a coup, but raises the threat of suffering a future ethnoregional rebellion. Baseadu and Pierskalla (2014), focusing on the interaction with the oil and gas endowment, hypothesize that ethnic exclusion should amplify the risk of conflict, while monopoly power of ethnic groups should cause the opposite effect through an state-capacity channel; they find evidence of the latter effect but not of the former.

In this paper, we consider both excluded groups from the central power and monopoly groups. Excluded groups are defined as relevant ethnic communities that are excluded from government relevant processes, whereas monopoly groups mean that elite members hold monopoly power in the executive that leads to the exclusion of members of other ethnic groups. Both excluded and monopoly ethnic groups can or cannot be at the same cell at a given point in time.[8] Few papers (e.g., Baseadu and Pierskalla, 2014; and von Uexkull et al., 2016) have used these variables in a grid-panel data context and never in conjunction with other measures of ethnic diversity.

Our key contribution is analyzing whether a plausible effect of ethnicity on conflict

[7]von Uexkull et al. (2016) point out that politically excluded groups are more likely to be barred from government-sponsored compensation programs or even aid in the case of negative income shocks such as floods and severe droughts.

[8]As we can see in Figure B.3 in the Appendix B, most African countries have excluded ethnic groups, whereas only Angola, Mali, Rwanda, Libya, and Egypt have settled monopolist ethnic ones.

can be indirect. That is, we hypothesize that a positive income shock might have a different impact depending on the degree of ethnic diversity and the political status of ethnic groups. For example, a positive agricultural shock can decrease the probability of incidence of battles because of the opportunity cost mechanism. However, if trade among different ethnic groups involves monitoring costs because of the lack of trust between them, this opportunity cost effect will be weaker in cells with a higher degree of ethnic fragmentation. Another example, social tension that leads to weaker governments in more ethnically fractionalized or polarized societies can also cause a lower state capacity to benefit from positive income shocks. A third one, the presence of monopoly groups might exacerbate income inequality within the cell, thus reducing the opportunity cost of poor individuals, or alternatively allow the dominant tribe to more tightly control natural-resource rents that can provide the means to repress military threats or buy peace. Therefore, the type and degree of ethnic heterogeneity can affect the impact of income shocks on the probability of conflict, but the sign and magnitude of this effect is uncertain; it will depend on how ethnic characteristics alter the state capacity, state-as-a-prize and opportunity costs channels. We want to provide empirical evidence that help advance in this direction.

In sum, the main hypotheses that we want to test are the following. (i) If the opportunity cost channel dominates, positive income shocks reduce armed conflict in food-producing cells, but increase it in food-consuming areas. (ii) If the state-capacity mechanism dominates, positive income shocks decrease conflict in both food-producing and food-consuming locations. (iii) If the rapacity effect predominates, positive income shocks rise conflict in both locations. (iv) Ethnic fractionalization and polarization signal weaker states with less capacity to deliver the possible conflict-reducing effects of positive income shocks. (v) The existence of ethnic groups with monopoly political power signals stronger governments that enjoy stronger state capacity to get advantage of positive income shocks and reduce conflict. (vi) Political marginalization of ethnic groups (either monopoly or excluded) may increase the sense of grievance, thus raising the opportunity costs perceived.

3.3 Data

Our baseline unit of analysis is a full grid of Africa divided into sub-national units of 0.5 x 0.5 grades latitude and longitude (which corresponds to a cell of roughly 55 km x 55 km at the equator).[9] This is the result of intersecting a grid of 10,638 cells provided by PRIO-GRID (http://www.prio.no/Data/PRIO-GRID/) with a map of the entire Africa and their national political borders provided by the Global Administrative Unit Layers, 2010 release, a project from the United Nations Food and Agricultural Organization (FAO). From the PRIO-GRID database, we download most of our non-conflict variables. The level of aggregation is the cell-year rather than ethnicity or administrative boundaries, in order to ensure that our unit of observation is not endogenous to conflict events. The sample coverage of the conflict data goes from 1998 to 2013 across forty-nine African countries. In the rest of this section, definitions and sources for the main variables employed in our regressions are given.[10]

3.3.1 Conflict data

We use two different datasets containing the geo-location of conflict events in Africa: the Armed Conflict Location and Event Dataset or ACLED (Raleigh and Dowd, 2015); and the Uppsala Conflict Data Program Georeferenced Event dataset or UCDP-GED, version 5.0 (Sundberg and Melander, 2013; Croicu and Sundberg, 2016). As will become evident, the use of different datasets allows us to test different competitive theories and the robustness of our results. UCDP defines a conflict event as an incident 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.[11] However, UCDP records events related to battles in consecutive years between an organized

[9]See Figure B..1 in the Appendix B.

[10]The Appendix B provides this information in more detail, including several descriptive statistics tables (Tables A1 to A9) organized by variable, country, crop and natural resource, and maps (Figures B.2 to B6) that illustrate the different independent variables considered. The explanations for the socioeconomic variables employed in the regressions mainly as controls (i.e., the commodity price indices for oils and gas and mines, and urban area) are also relegated to the Appendix B.

[11]According to UCDP-GED, two-side armed force battles are classified as state-based conflict or non-state conflict, and armed-force violence against civilians as one-sided violence.

armed-group dyad only when they have caused at least 25 fatalities in at least one of those consecutive years. In this case, events are included for the entire period, that is, both for the years when such conflict crossed the 25 battle-related deaths threshold and for the years when it did not.

The ACLED dataset, in turn, has a broader perspective and records violent activity both within and outside the context of a civil war, and does not require any battle-related deaths threshold. We will use as dependent variable three different ACLED aggregates: political violence in the form of (i) battles and (ii) violence against civilians; and protest events in the form of (iii) riots.

Given that factor conflict represents large-scale violence related with the permanent control of territory, MB argue that the appropriate measure is the UCDP-GED one, because it captures organized armed-force conflict. We later in the paper, for robustness, employ also ACLED battles as an alternative proxy. Output conflict, on the other side, captures conflict generated for the transitory appropriation of surplus. We are then targeting events that are less organized than large-scale battles. Therefore, and again following MB, output conflict will be measured using the ACLED categories riots and violence against civilians.

To create the measure of conflict incidence, we follow Berman et al. (2017) and MB and aggregate to the cell-year, coding with a value of 1 if cell c experienced a conflict during the year, and zero otherwise. In the robustness section, we also employ information on conflict intensity from the same sources.

3.3.2 Food-price indices

Our identification strategy is based on the use of income shocks related to agricultural commodities that can be considered exogenous at the cell level. We employ three proxies: an agricultural producer price (APP) index, a consumer price (CP) index, and a measure a droughts. The construction of the first two follow MB and employ international prices, and the construction of the third one follows HF and uses weather variables. Droughts are introduced in the regressions jointly with prices, because local climate conditions are more closely related to the quantity of production. Next we explain how we construct them.

To construct the agricultural-production price shocks, we combine time-series data on international commodity prices from the International Monetary Fund (IMF), the International Finance Statistics and the World Bank Global Economic Monitor with cell-specific time-invariant data of crops suitability and potential production from the FAO's Global Agro-Ecological Zones (GAEZ) dataset.[12] GAEZ provides crop potential production data constructed using location characteristics such as soil properties and climate conditions (temperature and rainfall), considering the average climate during the baseline period 1961-1990. This information is combined with crops growing requirements to generate a global GIS raster on the potential suitability of a cell for each crop potential production. A cell is considered suitable for crop production if it could achieve at least 40% of its maximum capacity. For each cell, these data can be used to have exogenous weights for agricultural-commodity prices, because the weights are not based on actual levels of production and consumption. In addition, we take the potential capacity in years before the starting date of our database sample. GAEZ produces spatial detail at the 0.0833 decimal degree, which we aggregate to our 0.5 degree cell level.[13]

We cover the following crops: banana, barley, cocoa, coffee, coconut oil, groundnuts, maize, oranges, oil palm, olive oil, rice, soybeans, sugar cane, sunflower, tea, tobacco and wheat. The next step is aggregating the monthly international commodity prices to an annual price series for each commodity, normalized to 1 in year 1990 (Fjelde, 2015; and Bruner and Ciccone, 2010). At each date t, the APP index in cell i at time t (APP_{it}) is the average across the $j = 1, .., n$ agricultural commodities of the international crop prices (P^A_{jt}) weighted by the time-invariant potential production shares (w_{ij}) of suitable

[12] `http://www.imf.org/external/np/res/commod/index.aspx`, `https://datacatalog.worldbank.org/dataset/global-economic-monitor,and"http://gaez.fao.org/Main.html#`.

[13] In the robustness section, we also try alternative data on crop production from the M3-Crops dataset (Monfreda et al., 2008).

crops; that is,

$$APP_{it} = \sum_{j=1}^{n} w_{ij} P^{A}_{jt}. \tag{3.1}$$

Our consumer price index is built using country-level data on food consumption patterns from the FAO Balance Sheets following the methodology in MB. The measure of food consumption is the calories per person-day available for human consumption from each primary commodity. Data on food supply are calculated combining statistics of production, imports and stock changes, corrected to eliminate the fed to livestock, the use of seeds, and losses during storage and transportation.[14] The resulting time-invariant consumption shares represent averages over the period 1990-2013. The reason for taking average shares is minimizing data issues based on gaps in the quality of the consumption series across countries and time.[15]

From the consumption side, the aggregation of prices is performed in a similar way as for the APP Index, although using the same time-invariant crop shares for all the cells that belong to the same country. The time variability of our index is given by the vector of commodity prices P^{A}_{jt}. In particular, the CP index in year t and a cell i that belongs to country c is given by:

$$CP_{ct} = \sum_{j=1}^{n} \kappa_{jc} P^{A}_{jt}; \tag{3.2}$$

where κ_{jc} represents the crop share of calories per day and person in country c; and crops $j = 1, ...n$ are contained in the set of primary commodities consumed for which international prices exist. Most of the important staple food, like maize, sorghum and wheat, are included in the index, along with more processed commodities such as sugar cane, oil olive and palm oil. All together, these products represent a big proportion of the calorie intake consumed by people in Africa.

[14] http://www.fao.org/faostat/en/data/FBSH.

[15] Notice as well that, in the case of the consumption shares, endogeneity issues should be much less important due to the relative stability of consumer tastes and the possibility of importing products.

3.3.3 Climate variables

We complete agricultural income shocks considering a measure of droughts, given the dependence of agriculture on weather conditions. Following von Uexkull et al. (2016) and HF, we focus on a crop-specific climate shock, the drought SPEI Growing Season, which captures low SPEI episodes occurring during the growing season of the main crop in a given cell.[16] Higher values of this variable means low levels of SPEI in the growing season in consecutive months, that is, a higher incidence of drought. We look at the impact of climatology during the crop growing season because is then when crops are more sensitive to adverse climate conditions, and hence, affect more intensively farms' future agricultural income and food availability. Robustness checks are conducted also for the climate variable adding the annual average SPEI.

3.3.4 Spatial ethnic diversity and political status

Our next task is describing the construction of the four different ethnic diversity measures: ethnolinguistic fractionalization, polarization, monopoly groups, and excluded groups. Their values in the regressions are maintained constant at their 1997 level, that is, one year before the starting point of the conflict data to mitigate possible endogeneity issues. We follow Montalvo and Reynal-Querol (2017) to compute the spatial ethnolinguistic fractionalization index (EF). Firstly, we use Vogt et al. (2015) that codes the settlement patterns of politically relevant ethnic groups in independent states based on the group list in the Geo-referencing Ethnic Power Relation (GeoEPR) 2014 database. Matching our grid structure and the regional and statewide ethnic groups patterns for the year 1997, we estimate the share of the territory settled by a specific

[16] SPEI stands for Standardized Precipitation-Evapotranspiration Index. These data are provided by the PRIO-GRID project from the Global Precipitation Climatology Center. The SPEI Global Drought Monitor is based on the Thortnthwaite equation for estimating potential evapotranspiration (PET). According to HF, PET depends on several factors, including most notably temperature but also rainfall, sunshine exposure, latitude and wind speed. Variable definition from PRIO-GRID codebook: https://grid.prio.org//codebook.

ethnic group. In particular, the index in cell i takes the form:

EF$_i$= 1-$\sum_{j=1}^{N} \pi_j^2 = \sum_{j=1}^{N} \pi_j(1-\pi_j)$; (3.3)

where π is the proportion of area that belongs to ethnic group j (for $j = 1, ..., N$).[17]

The calculation of the spatial ethnolinguistic polarization index (EP), on the other side, follows Montalvo and Reynal-Querol (2005). In particular,

EP$_i$= $4\sum_{j=1}^{N} \pi_j^2(1-\pi_j)$.(3.4)

These two ethnic diversity measures are bounded below by zero and above by one, but differ in a key aspect: while fractionalization increases monotonically if existing ethnic groups are divided into smaller groups, polarization is maximized when there are precisely just two, equally large groups.

Moving now to the spatial political ethnic diversity proxies, we control for both excluded and monopoly groups reflecting these political statuses. Excluded groups is based on the numbers directly supply by PRIO-GRID 2.0. Specifically, the excluded-group variable counts the number of excluded groups (discriminated or powerless) in a particular cell. The monopoly group proxy feeds from the Ethnic Power Relations (EPR) Dataset Core 2014. It is a dummy variable coded as 1 if there is at least a monopoly group in cell i, and as 0 otherwise. To create this variable, we use the groups identifiers provided by Cederman et al. (2011) and match our grid structure with the information on the political status of monopoly ethnic groups from the EPR 2014 data.[18]

[17]Because the sum of the shares of the territory that are occupied by each ethnic group can sum to more than one, they are re-scaled so that the sum equals one.

[18]These databases also provide information about ethnic groups that are part of power-sharing arrangements and groups that are politically dominant. We have chosen the two extremes, like Basedau and Pierskalla (2014) for example, because they seem more appropriate to capture the impact of grievance and government power.

3.4 Empirical Methodology

As we mentioned previously, the aim of the paper is to study the sensitivity of the effect of agricultural-commodity income shocks on the likelihood of conflict to ethnic diversity and political status. In order to achieve this goal, we build on MB and propose a fixed-effect framework that takes the form:

$$Conflict_{ict} = D_i + T_{ct} + \sum_{k=0}^{2} ACIP_{ict-k}\beta_{t-k} + \sum_{j\in J}\sum_{k=0}^{2}(EC_{ic}^{j} * ACIP_{ict-k})\gamma_{t-k}^{j} + \sum_{k=0}^{2} Z_{ict-k}\delta_{t-k} + \varepsilon_{ict}.$$

This general estimation equation for conflict serves to explain all the different versions employed in our regression. In the main estimations, $Conflict_{ict}$ is a binary variable that takes on one if there have been conflict incidents in cell i, at country c and time period t and zero otherwise.[19] When the outcome variable wants to capture factor conflict, it will represent armed-force incidence from the UCDP-GED dataset in the benchmark estimation, and later for robustness we will use battles from ACLED and conflict intensity from UCDP-GED.[20] If, on the other hand, the dependent variable proxies output conflict, it will consist of the category social unrest from ACLED or its components riots and violence against civilians.

The variable D_i is a cell fixed-effect dummy. The term T_{ct} controls for time effects and can take two different formats. When the country-wide CP index is not included in the regression, $T_{c,t}$ corresponds to a set of country-year fixed effect dummies. However, when the three income-shock proxies are present, the country-year dummies would subsume the effect of the CP index, and consequently, to avoid this problem, T_{ct} is formed

[19] According to Beck and Katz (2011), estimated coefficients can be biased when using incidence if lags of the dependent variable are not included as additional aggressors due the persistence of conflict. This problem is particularly important at the country level. Which has led some papers to explore the robustness of their results to using conflict onset and conflict offset as dependent variables, because they do not suffer from this potential problem. At a cell level, however, conflicts are less persistent. As Berman and Couttenier (2015) for example argue, using cell-level observations, about 75% of conflict events do not last more than 2 years. We therefore decide not to use onset and ending as dependent variables.

[20] Conflict intensity is not a binary variable. It gives the number of events in a given year and cell.

by two components—an year fixed effect dummy and a country-specific time trend. Because shock variables could be correlated with other cell-specific characteristics such as economic activity, our benchmark specification incorporates the matrix Z_{ict}, a set of control variables that include the oil-and-gas price index and the mineral-commodity price index described in the previous subsection. Later, this control matrix is expanded to consider the fraction of urban area and its interaction with the CP index.[21]

The variable ε_{ict} is the disturbance term. Because the shocks and the conflict measures can be clustered in time and space, we allow for serial and spacial correlation applying the method developed by Conley (1999) and Hsiang et al. (2011).[22] More specifically, the coefficients' standard errors are estimated employing a spatial heteroskedasticity and autocorrelation consistent (HAC) covariance matrix that allows for both location-specific 5-year-lag serial correlation and cross-sectional spatial correlation in a radius of 110 km. Following Berman et al. (2017), later we test the robustness of our results to spatial kernels from 55 to 1000 km, and serial correlations from 2 lags to assuming a temporal decay for the Newey-West/Bartlett kernel so slow that makes the serial correlation vanish in an infinite amount of (i.e. 100,000) years.

Moving now to our main variables of interest. The agricultural-commodity income proxy matrix $ACIP_{ict}$ can include, depending on the version, the APP index, the SPEI index for droughts, and the CP index. Because local weather events in producer countries could generate a correlation between international prices and the error term if those events are linked to global weather patterns such as the El Niño-Southern Oscillation (see, e.g., MB) the climate variable is always present in our regressions. These price and weather variables are incorporated over three consecutive years—the current period and two lags—to take into account possible effects of past shocks. We do the same for the control set Z_{ict}. Later in the paper we check results considering up to five lags. All

[21]Other standard controls employed by the literature include geographic characteristics, population size and satellite night lights (see, e.g., Alesina et al., 2016). We do not use them as regressors because the geographic characteristics are time invariant, and therefore, their effect is subsumed in the cell dummy, and population and night lights suffer from strong endogeneity concerns with conflict and the latter can also possibly generate a post-treatment bias.

[22]We use the STATA routine based on Hsiang et al. (2011) and its extension to multidimensional fixed effects by Fetzer (reg2hdfespatial.ado).

price indices are introduced in the regression taking logs as in Berman et al. (2017).

The set J provides indices for each of the four ethnic characteristics considered in the paper. In particular, the different ethnic variables EC_{ic}^{j} are the following: the excluded group, the monopoly group dummy, ethnolinguistic fractionalization, and ethnic polarization. Notice that in the regression the ethnic variables are time invariant—we assign pre-sample values of the ethnic characteristic to all periods in order to mitigate endogeneity concerns. Because of this, we exclusively focus on the interactions with the income shock variables, and do not include in the estimation model their independent effects, as they are captured by the cell fixed-effect dummies.

Finally, the vectors β_t, γ_t^j and δ_t are composed of the coefficients that we want to estimate. The βs capture the direct impact on conflict of the exogenous income shocks, and the γs provide the effect of their interactions with the ethnic variables. Equation (7) is estimated as a fixed effect linear probability model (LPM). We prefer this estimator to alternative frameworks for binary dependent variables such as the probit or the logit because it allows for a clear interpretation of the coefficients. The estimated coefficient measures the change in the probability of conflict incidence if, *ceteris paribus*, the explanatory variable of interest increases in one unit. Nevertheless, in the robustness section, we also perform estimation employing a conditional fixed-effect logit.

3.5 Results

In all cases, the conflict variable is a binary measure of incidence. The tables (all of them located in the Appendix B) report, for each independent variable, the sum of the contemporaneous and lagged effects and the corresponding Conley (1999) standard error.[23] First, we describe the findings when the dependent variable is factor conflict. Second, we search for the determinants of output conflict measured as a compound of

[23]Reporting the sum is desirable at least for two reasons. To start with, the sum gives a more direct idea of the total effect of the shock. In addition, if the regressor is highly correlated over time or space, the sum is estimated with much more precision (see, e.g., MB). In the Appendix B, Figures B.7 to B.12 present the results for the different lags of interaction variables that are significant in the full regressions—columns (10) and (12).

riots and violence against civilians. Third, we analyze the determinants of each of the two components of output conflict separately. Fourth, we test for the role of urban area on the effect of consumer prices. Finally, we interpret the results in light of the existing theories.

The structure of Tables B.10 to B.13 is the same. Column (1) provides results when only the APP and the drought indices are considered as variables of interest. Column (2) shows the results when the CP index is added to the other two agricultural-commodity income-shock indices. Columns (3) to (12) search for the sensitivity of the income-shock effects to ethnic heterogeneity. Ethnolinguistic fractionalization and ethnic polarization are never jointly considered in the regressions because of the severe multicollinearity problem that this brings—the correlation between the two variables in our sample is 0.98. The most important columns are the last four, which consider how estimated coefficients and consistent standard errors in columns (1) and (2) change when the political and diversity ethnic measures are included together.

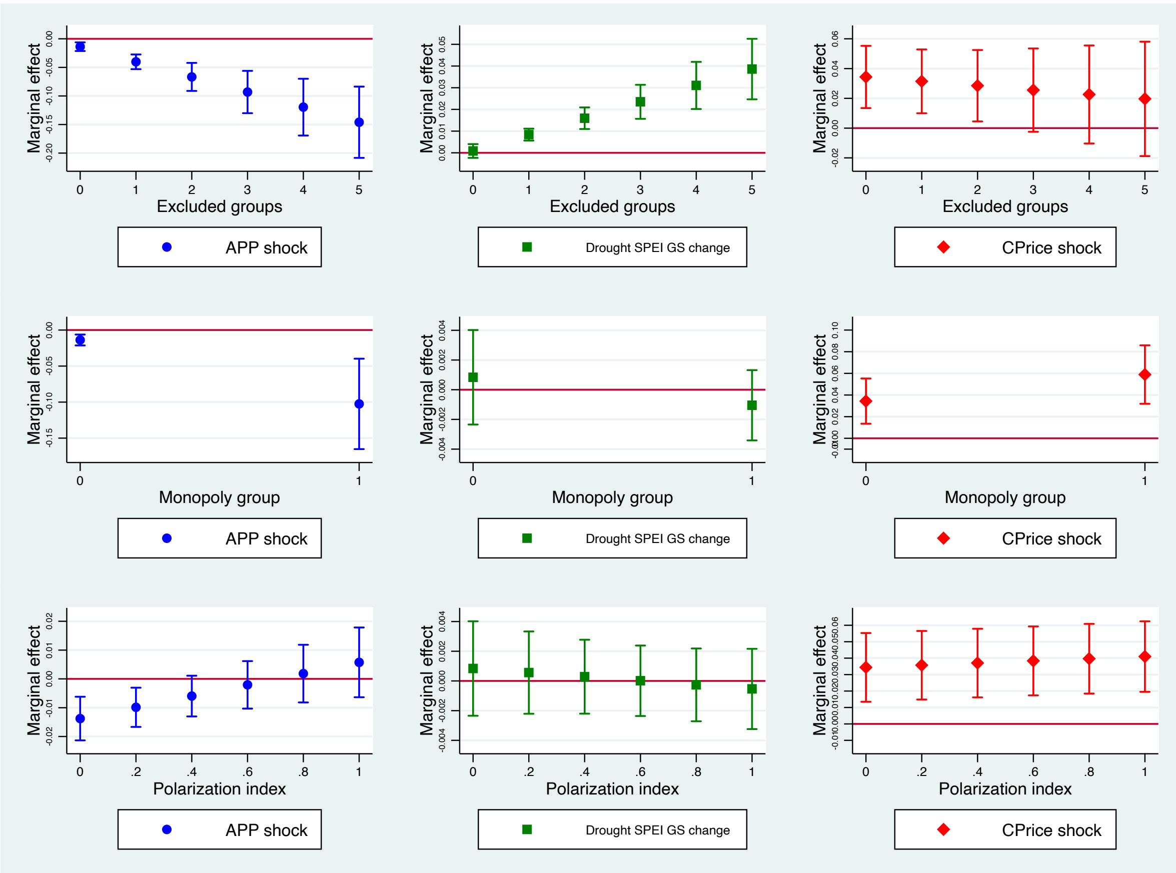
Looking at the tables, it is immediate that results with fractionalization are almost identical to the ones with polarization and quantitatively very similar.[24] This high similarity occurs in all regressions estimated in this paper, due to the high correlation between the two ethnic diversity variables in our sample. The main difference between including one ethnic diversity variable or the other is just the precision of the estimated coefficients. In general, the coefficients of variables that contain polarization show significantly narrower confident intervals that the corresponding ones that include fractionalization. Given this, we will comment exclusively on the results obtained with polarization.

Moving now to the figures, Figures 2.1 to 2.4 share the same structure as well. Each figure consists of nine charts split in three columns of three charts. They are constructed employing the estimated coefficients and standard errors provided by our

[24]Previous literature, however, has found different results. For example, at the country level, Janus and Riera-Crichton (2015) and Gimenez-Gomez and Zergawu (2018) find that adverse changes in prices increase the probability of political instability in countries with higher level of ethnic polarization, whereas ethnic fractionalization has a mixed impact. In contrast, we find that both variables have a well-defined effect for all definitions of violence.

preferred regression, column (12) in the tables, which represents the most complete model with polarization.[25] The goal is to show the sensitivity of the income-shock effects to the different ethnic measures separately. The first column of charts provides the estimated marginal effect on conflict and its 90% confidence interval of a one unit increase in the log of the APP index, as a function of the number of excluded groups (first row), whether there is or not a monopoly group (second row) and the degree of polarization (third row), assuming that the other ethnic characteristics take on zero. The second and third columns of charts give the same information but focusing on the drought index and the log of the CP index, respectively.

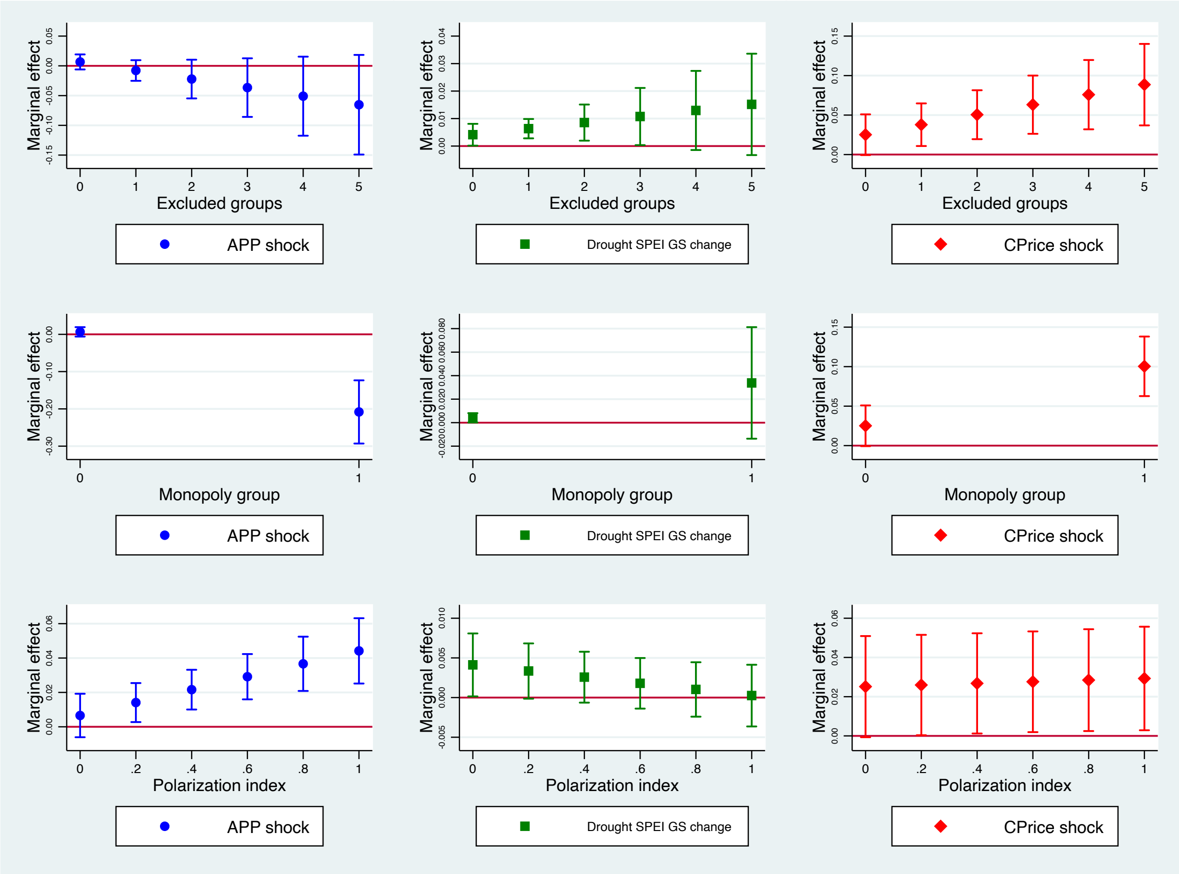
Figure 3.1: Factor conflict - UCDP incidence.



Note: The charts give the estimated marginal effect of each income shock and their 90% confidence intervals for each value of the corresponding ethnic variable.

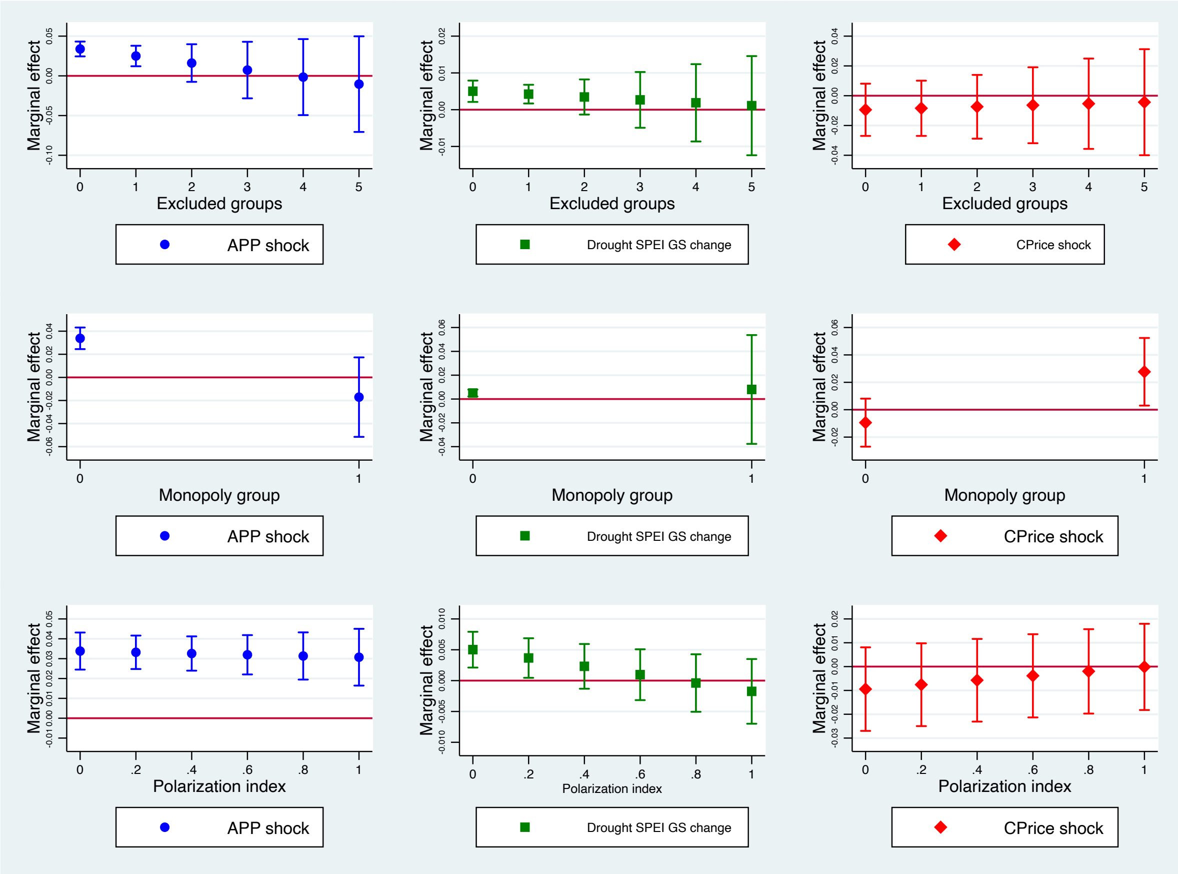
[25]The model associated to column (11) gives very similar results.

Figure 3.2: Output conflict - ACLED riots and violence.



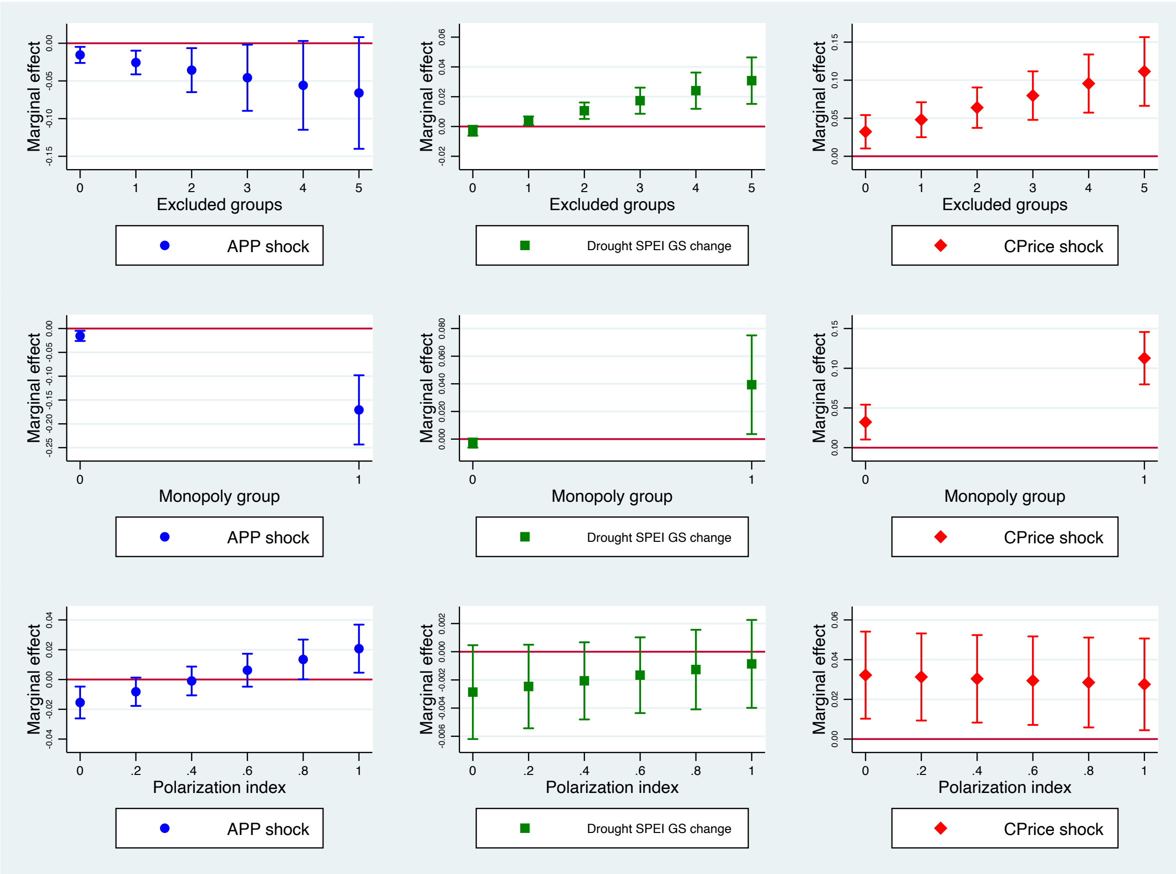
Note: The charts give the estimated marginal effect of each income shock and their 90% confidence intervals for each value of the corresponding ethnic variable.

Figure 3.3: Output conflict - ACLED riots.



Note: The charts give the estimated marginal effect of each income shock and their 90% confidence intervals for each value of the corresponding ethnic variable.

Figure 3.4: Output conflict - ACLED violence against civilians.



Note: The charts give the estimated marginal effect of each income shock and their 90% confidence intervals for each value of the corresponding ethnic variable

3.5.1 Factor conflict

We start by presenting in Table B.10 and Figure 2.1 results when in regression (7) the dependent variable signals whether there have been large-scale organized-armed-group conflict events according to UCDP-GED. We can see that without ethnic variables columns (1) and (2) in Table B.10 reproduce the qualitative findings obtained by MB and HF. As in MB, the coefficient for the APP index is negative and significant with both time-effect formats, and the CP index is positive and significant. Additionally, as in HF, the coefficient for droughts is positive and significant in both columns.[26]

[26]In HF, the estimated coefficient is negative because they use a reversed scale. That is, in our regressions, SPEI growing season is introduced such that higher values of the variable imply a higher incidence of droughts; whereas in their work, they imply lower drought incidence.

Feeding on the results in column (12) of Table B.10, Figure 2.1 displays the sensitivity of the income-shock effects to ethnic cleavages. Notice that the estimated values and confidence intervals when the ethnic variables take on zero give the direct impact of the income shocks and its significance. We can see that the APP and CP indices show significant direct effects, the former with a negative value and the latter with a positive coefficient, as in MB. The largest amplification effects are associated to the presence of excluded groups, and its interaction is significant with APP and with droughts (see Table B.10).[27] For example, compared to cells without them, locations with two (five) excluded groups multiply the negative effect of APP shocks on the risk of factor conflict by 4.8 (10.6) times. This number for drought shocks is 20.0 (48.5) times.

The second row of charts imply that the presence of monopoly groups is important for the transmission of a producer price shock. In particular, its negative impact is 7.4 times larger when these groups exist. The existence of monopoly groups also multiply the positive effect of the CP shocks by 1.7 times. This difference in the case of consumer prices and droughts is not significant.

The role of polarization (third row) is the weakest. In Figure 2.1, differences across ethic diversity levels in the marginal impact of the shocks are only significant in the case of APP. In particular, a sufficiently large degree of ethnic polarization makes the estimated effect of changes in producer prices become positive. Looking now at Table B.10, it is interesting to notice as well that the interaction between consumer prices and polarization is positive and close to showing significance; later when we introduce urban area, it will do so.

To further quantify the results, we again concentrate on column (12) of Table B.10 and measure, following a standard procedure in the literature, what we call from now on the "implied total impact". More specifically, we look at the effect, in percentage points, of a one standard deviation change in an income proxy on the probability of conflict when

[27] A sufficient condition for the significance of the difference between the marginal effect when the ethnic variable takes on zero and when it takes on positive values is that the corresponding confidence intervals do not overlap over the range shown in the vertical axis. However, this is not a necessary condition, because the two marginal effects are perfectly positively correlated.

all the ethnic variables take on their average value.[28] The impact measure, therefore, tells us the estimated change in the probability of conflict incidence in the average cell.

The implied total impact of the APP index equals -5.33. That is, a one standard deviation decrease in the log of the APP index raises the probability of armed conflict in the average cell by 5.33 percentage points; with the direct effect and the interaction with excluded groups contributing each of them about half of the impact. The interaction of producer prices with monopoly groups also decreases the probability of conflict by 1.06 percentage points, but this effect is almost exactly offset by ethnic diversity. The implied total impact of droughts is 0.23, due almost fully to the significant increase in the risk of conflict caused in cells with excluded groups. Finally, the implied total impact of consumer prices is 1.36. Hence, the strongest estimated effect is the one of producer prices and the smallest the one of droughts.

3.5.2 Output conflict

Next, we look at the determinants of output conflict, measured as events where riots and violence against civilians occur. Table B.11 and Figure 2.2 present our findings with the ACLED incidence as the dependent variable. In columns (1) and (2) of Table B.11, all the estimated coefficients are positive and, with the exception of the CP index, strongly statistically significant. These results are consistent with MB and HF.[29]

Figure 2.2 tells us that, compared to the regressions without ethnic variables, the direct effects maintain the signs, but only the drought index remains significant. It also conveys the message that, for output conflict, the existence of monopoly ethnic groups is the most important amplifier. Monopoly groups change the sign of the effect of an APP shock to negative and increase its impact by 32.0 times in absolute value. They

[28]The impact is computed as a marginal effect as follows. For a single independent variable, it is given by its standard deviation times the estimated coefficient multiplied by 100. For interaction terms X*Y, where X is the variable of interest, the marginal effect follows the same procedure described previously but multiplying also by the variable Y's mean. Finally, the implied total impact is the sum of the marginal effects across all the terms that contain the variable of interest.

[29]MB does not find significant the CP index, neither in the factor conflict regression, nor in the output conflict specification when year fixed effects are included, which in our case are always controlled for. They argue that consumer prices vary more over time than across space, and therefore, the inclusion of year fixed effects absorb a big part of the impact.

also multiply the effect of consumer prices by 4.0. The difference in the case of droughts is not significant.

Excluded groups are, in turn, only significant for changes in consumer prices (see Table B.11). The estimated marginal effect of the CP index experiences a 2-fold (3.5-fold) increase when the number of excluded groups goes up from zero to two (five). Finally, the sensitivity to polarization is only significant for the effect of producer prices. A fully polarized society experiences a positive effect of producer prices on output conflict that is 6.8 times larger than a society with zero polarization.

Quantitatively, employing the estimates in column (12) of Table B.11, the implied total impact of a one-standard-deviation increase in the APP index is -0.41 percentage points, much lower than in the case of factor conflict. The implied total impact of droughts equals 0.33 percentage points. Lastly, the total impact of the CP index on output conflict is 1.38.

Our estimates imply as well that the importance of ethnic cleavages in the risk of conflict depends on the type of shock and conflict definition. If we look at the sum of the absolute values of the different components of the implied total impact, the APP-index direct effect amounts to 36.34% of the total for factor conflict and 17.30% in the output conflict case. These figures for droughts are 16.45% and 50.56%, and for the CP index, 94.52% and 67.70%. Hence, looking at the sensitivity to ethnic heterogeneity, it is much higher for producer prices and droughts than consumer prices, and droughts provides the largest one in factor conflict, whereas producer prices gives the biggest in output conflict.

3.5.3 Riots versus violence against civilians

We now disaggregate output conflict in its two components. This is important because the ACLED category "violence against civilians" could be considered an intermediate case of violence. Unlike the one-sided violence recorded in UCDP, ACLED considers all events, independently of the number of casualties; and then, it can be considered a small-scale conflict measure. However, as the one-sided violence recorded in UCDP, ACLED violence against civilians represents violence carried out by organized armed groups. As will become evident in a moment, both subcategories respond differently to income shocks and ethnic characteristics. The results with riots are closer to the original MB's output conflict findings, whereas the determinants of violence against civilians are closer to the ones of factor conflict.

Tables B.12 and B.13 and Figures 2.3 and 2.4 present the estimation results based on this disaggregation. Looking at the findings for riots in Figure 2.3 and Table B.12, the direct effects of the APP index and droughts are positive and significant. Conversely, the one of the CP index is not. The effect of excluded groups is statistically non-important; whereas the one of monopoly groups matters for the impact of APP and CP shocks, although not for droughts. In particular, monopoly groups flip the sign of the effect of changes in both price indices. In turn, the significant interactions of polarization with droughts and the CP index tend to offset their direct effects.

Column (12) of Table B.12 implies a total impact of a one-standard-deviation rise in the APP index on the likelihood of riots of +5.11 percentage points; this is a consequence of its direct effect (6.86 percentage points) and the interaction with monopoly (-0.61). In turn, the implied total impact of droughts is 0.15 percentage points, and only its direct contribution and the one of its interaction with polarization are significant and equal to 0.28 and -0.12, respectively. Finally, the total impact of the CP index is -0.30 percentage points; as a consequence mainly of its direct effect, partially offset by the incidence of the ethnic variables. The largest impact is then again the one of producer prices.

In Figure 2.4 and Table B.13, we can see that, unlike in the case of riots, the direct effect of producer prices on violence against civilians is negative, the one of consumer prices is positive, and the one of droughts is insignificant. Also unlike in the case of riots, excluded groups play an important role as transmission channel for droughts and CP shocks. For example, the presence of two (five) excluded groups multiplies the effect of the droughts and CP indices on violence by -3.6 and 2.0 (-10.6 and 3.5), respectively.

Monopoly groups also play a larger role, and become important for the three types of income shocks. When monopoly ethnic groups are present, the effects of APP, droughts and CP on violence against civilians are 11.1, -13.6 and 3.5 times larger, respectively. Contrary to the case of riots, ethnic polarization in the case of violence only matters for APP shocks, making their effect go from negative to positive if ethnic diversity is sufficiently large.

In terms of the implied total impact, column (12) of Table B.13 delivers that the one of the APP index represents a decrease in the risk of violence of 3.12 percentage points: its direct effect contributes -2.87; and there are opposite indirect effects of politically-marginalized groups and ethnically diverse societies. The implied total impact of droughts and its components are the smallest among the three types of shocks and are always less than or equal to 0.20 percentage points. The total impact of a one-standard-deviation increase in consumer prices, in turn, equals 1.62 percentage points, with a direct effect of 1.20, and an amplifying effect of political ethnic variables of 0.47.

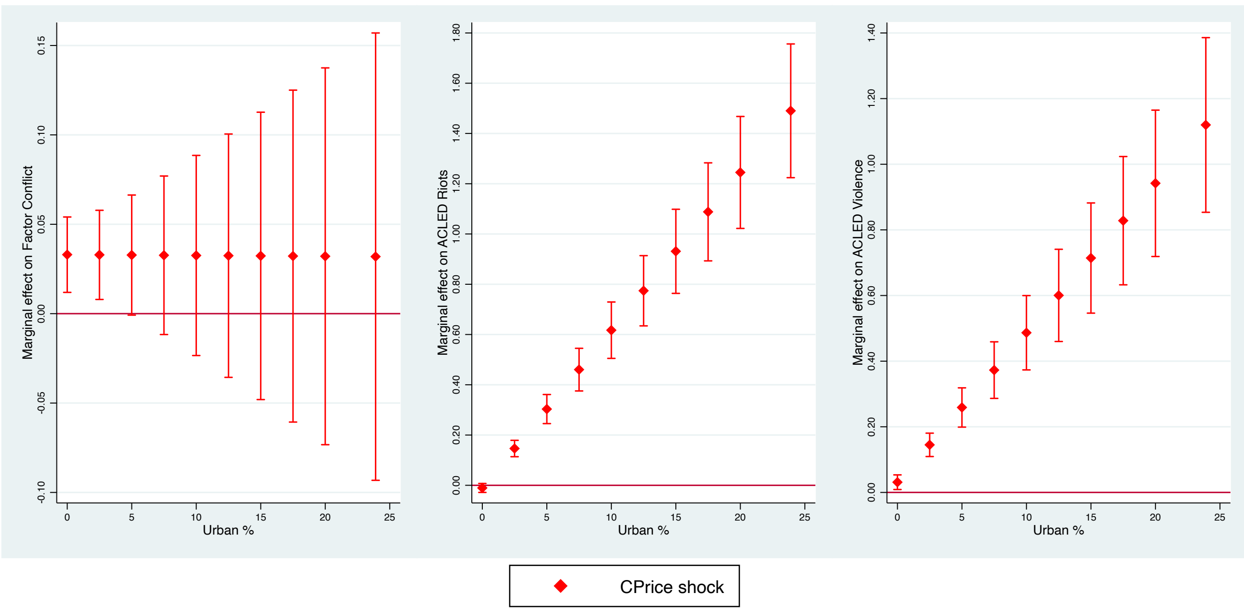
Comparing the importance of ethnic cleavages in riots and in violence against civilians, the direct effect in the case of riots represents 79.67%, 68.89% and 71.13% of the sum of all (direct and interaction) effects in absolute values for the APP index, droughts and the CP index, respectively. Thus meaning that ethnic differences are relatively less important. However, in the case of violence against civilians, the corresponding direct effects are 38.11%, 31.18% and 69.80% of the impact sum; that is, for producer-price and drought shocks, the sensitivity to ethnic cleavages is key. This, again, makes violence against civilians closer to factor conflict than to riots.

3.5.4 Consumer prices and urban area

We have not found MB's positive direct effect on riots of food-price increases in food-consuming cells. However, consumer prices for food should be relatively more important in urban areas, where the weight of the agricultural sector on total employment is significantly lower. Consequently, the last set of results that we present in this section correspond to the scenario in which the fraction of urban area and its interaction with the CP index are included in the estimation model.

Table B.14 and Figure 2.5 display the findings. Table B.14 has a different format than the previous ones. Columns (1) to (4), (5) to (8), and (9) to (12) give results when the dependent variable is UCDP conflicts, riots and violence against civilians, respectively. Figure 2.5, in turn, shows the marginal effect of the three shocks for different fractions of urban area in the cell. We deduce from the figure that the the sensitivity of the effect of CP shocks on riots (second chart) and violence against civilians (third chart) is positive and strongly significant, whereas the one of factor conflict (first chart) is insignificant. Thus confirming that, in urban areas, consumer prices do increase the probability of output conflict as predicted by the opportunity cost mechanism.[30] In addition, looking at Table B.14, the urban area fraction shows up as negative and significant for both output conflict variables.

Figure 3.5: Conflict - Consumer Price shock on urban %.



Note: The charts give the estimated marginal effect of consumer price shock on factor conflict (UCDP Incidence), and output conflict (ACLED Riots and Violence against civilians, respectively) and their 90% confidence intervals for each value of urban area (%).

[30]This is consistent with the work of Hendrix and Haggard (2015) for example.

Regarding the other regressors, most qualitative effects of the income shocks and the ethnic variables remain more or less unchanged for all outcome variables. The only remarkable changes are the following: in the factor conflict regression, the interaction of consumer prices and polarization becomes positive and significant; and in the case of riots, political ethnic variables lose power and only the interaction of the CP index with monopoly groups remains significant.

In terms of the magnitudes, the implied total impacts only experience a significant change in the case of both price indices for riots and the APP index for violence against civilians. Nevertheless, for the APP index in violence against civilians this sensitivity still explains 55% of the total.

3.5.5 Theories behind the results

Our results in the main analysis sections reinforce the economic mechanisms emphasized by MB, but at the same time, add new aspects and point out a greater role of grievance and state capacity as determinants of conflict. One difference is that we find that the ACLED category violence against civilians has more determinants in common with factor conflict than with riots. Therefore, differentiating between organized and non-organized conflict can be more informative than between factor and output conflict.

To start with, producer prices in our sample have a negative effect on conflict that involves any type of organized armed groups, namely, the UCDP evens and the ACLED violence against civilians. This is also found by MB but only with the UCDP data. Nonetheless, the interpretation suggested by MB is still valid. That is, the result suggests an important role of the opportunity cost of becoming a soldier: in food-producing areas, increases in food prices raise the real value of salaries and generate opportunity-cost incentives for workers not to join armies engaged in organized violence. We also find, as MB, a positive effect of consumer-price shocks on organized-group conflict (but not on riots). Therefore, the decrease in real wages caused by food-prices in food-consuming areas leads more workers to become organized fighters through an opportunity cost mechanism.

Droughts play a weaker role with all conflict definitions. We have defended that international prices and local climate conditions should proxy different aspects of agricultural income. Nevertheless, it cannot be fully discarded that prices at a certain extent capture the effect of droughts. Focusing on the direct effect, droughts during the growing season have a clear positive impact on riots. This effect has been already found by previous literature, like Almer et al. (2017). An opportunity costs mechanism is again more likely behind this result. As water, an important input of production, becomes scarcer, the productivity of land falls and the incentives to riot in favor of the appropriation of surplus increase.

The existence of politically excluded and monopoly groups reinforces also this channel for organized armed-group conflict and, unlike in Baseadu and Pierskalla (2014), amplify the risk of conflict in the same direction. More specifically, excluded and monopoly groups push the effect of an increase in the APP index or a decline in droughts towards a negative sign, and the one of a rise in consumer prices towards a positive sign. Given that increases in producer prices and less intense droughts can be seen both as positive income shocks that lead to higher real wages of farmers, the direction of their effect can be interpreted using the same theories. In particular, these results can be interpreted as an outcome of opportunity costs.[31] A lower degree of ethnic confrontation in government due to the exclusion or monopoly of certain groups can increase the sense of grievance, and therefore, the politically-harmed groups can become more sensitive to variations in the opportunity costs described in the previous paragraph that make food prices affect organized violence in opposite directions in food-producing and food-consuming areas. Notice that these opposing effects can be generated neither by the rapacity effect theory nor by the state capacity channel.

By the same token, the stronger positive response of organized armed-force conflict to both producer-price and consumer-price shocks that we find in more polarized societies when urban area is considered is not consistent with the opportunity cost effect. It cannot be either a consequence of a stronger predatory behavior in those areas, since

[31] The same effect is found by von Uexkull et al. (2016) for droughts in areas with excluded groups.

as MB argues the opportunity cost effect dominates rapacity in the response of factor conflict to producer-price shocks. Hence, this positive response of conflict must be a consequence of state capacity; that is, a larger degree of ethnic diversity signals weaker states suffering more from social tensions (Esteban and Ray, 1999) that are able to benefit less from the violence-reducing opportunities offered by positive income shocks.

The generation of riots is also affected by the opportunity cost and state capacity mechanisms but not in same way than factor conflict. The role of producer prices is now the opposite than in organized violence, it is positive. As MB shows, this can be caused by a combination of the opportunity-cost and predatory effects. To fully understand this, let us briefly explain how the MB theoretical model works. Output conflict arises if the individual reallocates effort from the production activity to the appropriation of surplus. Prices in their model can be associated to three types of goods: agricultural-commodities produced in the cell but exported to other cells; food-items produced and consumed within the same cell; and crops imported from other cells for consumption. The first two affect the producer-price index and the last two the consumer-price index. Consequently, when the cell's producer price goes up, this increase is larger than the rise in the cell's consumer price, because some commodities are imported. Therefore, the real (consumer-price-deflated) value of the cell's production rises if these food-items are exported, but the real wage falls if the produced food is for within-cell consumption. The former triggers a rapacity effect, whereas the latter describes an opportunity cost channel. Both of these effects make output conflict increase, that is, generate additional allocation of effort to steal goods.

Next, let us examine the impact of the CP index on riots. As discussed previously, the opportunity cost channel can explain its positive impact in urban areas and cells with monopoly groups, and the state capacity effect can be behind the estimated positive effect in more polarized areas.[32] We have also shown that, unlike in the case of organized

[32]There is, though, a possible alternative interpretation for the last result. The moderation of the state-capacity effect by polarization/fractionalization might be stronger in food-producing cells, and therefore, the positive sign in food-consuming areas can be still mainly capturing an opportunity cost mechanism. Notice that this alternative argument, although possible for the CP index, cannot be applied to food-producing cells, because there the negative sign is only compatible with the state-capacity channel.

armed-force conflict, political ethnic variables play a reduced role in the generation of riots. The lack of significance of political ethnic variables is especially evident when urban area is incorporated to the riots regression. Which suggests that the recruitment activity of organized violent groups is more successful if there is a sense of grievance in some ethnic groups, whereas this is much less important to become a temporary rioter.

Another interesting result is that the sign of the CP index is negative. Although the CP index coefficient is not always significant in the benchmark regressions, it shows again strong power and the same negative sign to explain riots in some of the robustness checks that we present next. This can be explained neither by the opportunity cost effect nor by surplus predation. Instead, it suggests an increase in state capacity to control insurgence.

3.6 Robustness Analysis

We perform nine different robustness checks of our main results, which are contained in the Appendix B. From them, we deduce that the findings obtained in Section 5 are generally robust. The main exceptions are when we use actual crop yields to construct the shares and when the size of our cells increases to 220 km x 220 km. However, these two scenarios are less suitable for our purposes than our main specifications (see explanations in the Appendix B). Overall, 72% of the estimated coefficients obtained with the full regressions in the robustness section agree with the main analysis in terms of either non-significance or sign and significance.

3.7 Conclusions

This paper has studied how agricultural-commodity shocks across ethnically-diverse cells affect several definitions of conflict outcomes. To that end, information on the location of conflict and social unrest for the entire African continent has been used, employing a fine-grained panel data for the period 1998-2013 with a spatial resolution of 0.5 x 0.5 degree latitude and longitude (equivalent to 55 km x 55 km at the equator). Our main contribution has been to disentangle whether ethnic political status and diversity serve as amplifying mechanisms of the effect of income shocks on conflict.

We have obtained multiple interesting results. First, violence against civilians clearly arises as an intermediate type of conflict that lies between battles and riots. Furthermore, we have shown that differentiating between organized armed-force conflict (battles and violence against civilians) and non-organized violence (riots) is more informative about the determinants of conflict than between large-scale factor conflict and low-scale output conflict (violence against civilians and riots). Nevertheless, differentiating the three categories seems to be preferable.

Second, our results emphasize an important role of opportunity costs in the decision of getting involved in any type of violence and that the existence of excluded and monopoly ethnic groups can amplify the perception of those costs. This shows up both in the negative impact on organized armed-force conflict of the opportunity cost channel in food-producing cells, and its positive impact on output conflict in food-consuming areas.

Third, we also show evidence of the importance of state capacity. This is suggested by our finding that more ethnically polarized or fractionalized societies tend to push the effect on conflict of an increase in the APP and CP indices or a decline in droughts towards a positive sign. The reason is that a larger degree of ethnic diversity signals weaker governments that are able to benefit less from the rebellion-repressing capability offered by positive income shocks. The state capacity channel seems to be stronger in the case of riots. In particular, besides its indirect effect through ethnic diversity, consumer food-prices in our sample also have a negative direct impact on riots, which is again only consistent with an important role of state capacity.

Fourth, the consumer-price impact and the category riots respond to a much lower extent to ethnic cleavages. In particular, the weight of ethnic variables in the total effect of the CP index is always below 32%. Whereas for the producer-price index and droughts, the average contribution of ethnic heterogeneity is 73%, 28% and 68% for battles, riots and violence against civilians, respectively. As a possible explanation of the low contribution of political ethnic variables in the generation of riots, we have suggested that a sense of grievance in some ethnic groups is much less important to become a temporary rioter than permanent soldiers.

From a policy side, the results could be interpreted as demanding an agricultural price-stabilization mechanism, because price fluctuations affect conflict. However, as we have also shown, whether this is the case and the right type of policy should depend on the nature of ethnic diversity and violence. This important issue clearly deserves further investigation. There are also several factors that can be behind the income-shock indirect-effect channeled through ethnic cleavages, and some of them have been pointed out in the text: trust, monitoring costs, labor market frictions, and quality of institutions. Incorporating these aspects into the analysis can represent as well a promising source of future research.

Chapter 4

Addressing Oil Spills and Agricultural Productivity. Evidence of Pollution in Nigeria

4.1 Introduction

Food insecurity[1] is driven by multiple factors. Understanding what they are and how they are related to one another is a challenge for scientists working in this field. Specifically, the main variables include conflicts, environmental degradation of livelihoods, climate change, and high volatility in commodity prices. Nigeria is Africa's most populous country and its largest oil producer. It is a particularly suitable example for studying the links between some of these variables and indicators. Nigeria is a country cursed by natural resources (Sala-i-Matin and Subramaian, 2013), which suffers from complex political issues including endemic corruption, inequality within and between ethnic groups, national disunity, oil disputes, environmental degradation, instability, and poverty. It also faces three sources of violence: Boko Haram insurgency, Middle-belt conflict, and the Niger Delta conflict.

Onshore oil operations are a key aspect related to environmental degradation. They

[1] "Food security exists when all people, at all times, have physical, social and economic access to sufficient, safe and nutritious food that meets their dietary needs and food preferences for an active and healthy life. Household food security is the application of this concept to the family level, with individuals within households as the focus of concern. Food insecurity exists when people do not have adequate physical, social or economic access to food as defined above." The State of Food Insecurity in the World, pg.4. FAO, 2010.

have damaged local soil and water resources, leading to problems in public health in nearby locations (Bruederle and Hodler, 2019). When focusing on the specific effects of oil spills in Nigeria it is useful to analyze negative externalities generated by extractive industries on places distant from the sources of production, e.g. pipeline networks, where traditional agricultural activities are the predominant source of subsistence. Oil spills are the biggest environmental disaster in Nigeria and have exacerbated environmental, social, and economic problems (Madu et al., 2018; Nwankwo, 2015).

The 2011 United Nations Environment Programme report on oil spills in Ogoniland,[2] a region which covers close to 1,000 square kilometers in Rivers State, southern Nigeria, is a turning point that further emphasizes the establishment of Corporate Social Responsibility (CRS) to clean up the area. However, host communities argue a lack of responsibility for environmental damage in the government of the federation and multinational oil corporations. The study also reports that oil spills could affect more territory than the areas estimated to be directly affected, through rivers and water bodies, and that effects are long-lasting. Thus, the damage to the environment could be greater than that directly calculated.

Keeping in mind the above conclusions, in this paper I attempt to assess an externality effect of onshore oil operations specifically related to pipelines on the agricultural sector. In particular, I study whether oil spillage shocks are associated with an economically significant reduction in agricultural total factor productivity, and hence, in agricultural production in nearby locations. The assumption is that the oil spills analyzed may not have affected farms directly, but that their could be affected indirectly by the filtration through the soil of nearby contaminated water and by air pollution from fires around the spills. I further hypothesize that the impact could be long-lasting. More specifically, I pose the following questions: Does the presence of

[2] "While oil exploration and production in the Niger Delta began in the late 1950s, operations were suspended in Ogoniland in the early 1990s due to disruptions from local public unrest. The oilfields and installations have since largely remained dormant. However, major oil pipelines still cross through Ogoniland, and oil spills continue to affect the region, due to such factors as a lack of maintenance and vandalism to oil infrastructure and facilities." United Nation Environmental Programme". `https://www.unenvironment.org/explore-topics/disasters-conflicts/where-we-work/nigeria/ogonilands-oil-history`

oil spills lead to a reduction in agricultural total factor productivity among farmers in nearby locations? Does the effect persist beyond the periods when oil spills happen?

Unlike previous literature that has studied the impact of oil spills on farming in Nigeria, I focus on all regions of the country, using geospatial data from oil spills, The Nigerian Oil Spill Monitor, which provides data collected by the National Oil Spill Detection and Response Agency (NOSDRA), and geo-referenced micro-data from farming households drawn from the Nigeria General Household Survey (GHS-Panel). The former gives information on the locations and dates of around 12,000 oil spills from January 2006 to December 2018. I have also calculated the geographical coordinates of oil spills not reported, dating from before 2013. The latter provides information on agricultural production and agricultural practices from around 1,425 farmers in four waves, covering the harvesting periods from 2010 to 2018. To the best of my knowledge, this is the first paper to use such data to assess the impact of oil spills on agricultural output through agricultural total factor productivity.[3]

In my identification strategy, I first observe the effect of oil-spill pollution on agricultural total factor productivity by estimating an agricultural production function. I use the analytical framework of consumer-producer household models with incomplete markets (Benjamin, 1992; Aragón and Rud, 2016). In these models, production and consumption decisions are not entirely separable, and household endowments could be used as inputs. The model helps to determine whether a variation a change in total factor productivity brings about a change in agricultural output, that is whether oil-spill pollution could affect the quality of essential inputs or whether the variation is the result of a change in input uses. Taking this approach that identifies how farmers act, I may be able to distinguish the channels through which pollution from oil spills affects agricultural output.

Second, I consider the empirical challenge posed by the fact that agricultural output could be regularly different in areas where oil spills happen. To overcome this issue, I

[3]This dataset has only been used before by Bruederle and Hodler (2019), who found clear evidence for harmful effects of nearby oil spills on surviving children.

also explore the methodology proposed by Fenske and Zurimendi (2017) and Aragón and Rud (2016), using a difference-in-difference approach. With this technique, I explore two sources of variation: A proxy of the quantity of pollution caused by spills that could also be persistent over time, and the distance of households from oil spills. This identification strategy means that in the absence of oil spills, any changes in agricultural output should be similar in both areas over time.[4]

As a proxy of accumulated oil spill pollutants, I create a function that covers all oil spill events per location in all the said periods. A key point in that function is that oil spills follow an exponential decay pattern on cultivable land. The same conclusion can be extended to labor productivity and crop yields. I also add further functions to check the robustness of my results.

I find evidence of a significant reduction in both total factor productivity and agricultural output attributed to oil spills. My estimations suggest that an increase of one standard deviation in my measurement of cumulative oil spill pollution is associated with a drop of around 8% in agricultural output in locations within 5 kilometers of oil spills. However, the data also suggests significant effects in areas 7.5 kilometers from oil spills. The results are similar if partial measurements such as crop yields are used. The findings are also robust to different model specifications, e.g. the inclusion of a definition of the proxy of oil-spill pollution based on different persistent effects, quantity of oil lost, additional agricultural practices, soil characteristics, climate variables, and heterogeneous location trends. The consumer-producer framework means that a reduction in agricultural output directly affects the consumption potential of households. Indeed, Oshienemen et al. (2018) report an increase in poverty as an indirect effect in villages near oil spills.

I also explore alternative channels that could explain my results. For instance, following Bruederle and Hodler (2019), I investigate whether the results only affect the Niger Delta area, where there are events associated with oil operation around the

[4]In particular, Bruederle and Hodler (2019) also used locations nearby oil spills as a part of their identification strategy.

extraction sites in these regions, or whether the findings are the consequence of violent attacks on oil infrastructures and other conflict incidents. I further focus on differences in the characteristics of agricultural workers and changes in property rights. Empirical evidence shows that households in locations near oil spills own less land. This result could reflect the risk of land expropriation by the state. For example, oil companies could require land close to pipelines to build access infrastructures. Thus, farmers could invest less in such land, thereby further decreasing agricultural factor productivity. Finally, I find a decline in labor incomes in urban areas close to oil spills, suggesting a drop in labor productivity as a plausible mechanism. These results could support the notion that a reduction in agricultural total factor productivity reflects the well documented cyclical penury and poverty among host communities (Nriagu, 2019; Madu et al., 2018).

To the best of my knowledge, Akpokodje and Salau (2015), Ojimba (2011), Ojimba(2012), and Inoni et al. (2005) also consider the economic effect of oil pollution[5] on crop production in the Niger Delta. Akpokodje and Salau (2015) assess the consequences of oil spills as a catalyst in accelerating deforestation and, hence, indirectly reducing agricultural output. Ojimba (2011) focuses on the economic effects of oil spills on crops, farms, and the size of farmland, while Ojimba (2012) examines the impact of crude oil and gas pollution on crop production. Finally, the empirical evidence provided by Inoni et al. (2005) focuses on the effect of oil spills on crop yield, land productivity, and farm income. All these authors find a negative impact of oil pollution in their main dependent variables. However, in Akpokodje and Salau (2015), the oil spillage variable is not significant, and it acts indirectly, leading to a loss of forest mass

The above results are potentially noteworthy. However, my work differs methodologically from their in several ways. Ojimba (2011) splits the dataset between oil-polluted and non-polluted farms, whereas Inoni et al. (2005) focus on the presence of oil spills with a dummy variable in the harvesting season. I consider that both the number and the persistence of oil spills need to be included to assess the effect of oil-spill

[5]5Oil and gas pollution could be driven by the pollution caused by all operations related to the extraction, production, and transport of oil and gas. Like Inoni et al. (2005), I only consider the effect of oil-spill pollution on agricultural output.

pollution on agricultural output. Moreover, all the papers mentioned above consider the impact of oil pollution only in particular regions of the Niger Delta,[6] while my research looks at the whole country, considering onshore oil spills far from oil-producing sites. Thus, I may find evidence that the consequences of oil spills in areas close to the oil transport network are at least as detrimental as in locations close to oil wells and gas flares themselves.

Akpokodje and Salau (2015) use country-level data in their analysis, while Ojimba (2011), Ojimba (2012), and Inoni et al. (2005) use data collected from interviews with almost 290 farmers in different locations from of the same regions. The methodology used in these last papers thus means that it is unlikely that their results could be extrapolated to other areas. Geo-referenced data also makes it possible to consider whether the consequences of oil spills can spread to nearby locations, which is a step forward towards assessing the environmental impact of oil spills.

Earlier studies do not adequately address the issue of potential endogeneity, which is particularly important in establishing a causal link between oil spills and agricultural output. In this paper, I use three strategies to tackle this issue. The first is to use district and time fixed effects to control for time-invariant factors affecting both agricultural output and oil spills, such as geographical and seasonal features. The earlier papers referenced do not use any fixed effects. I also use the above-mentioned difference-and-difference approach with the geo-referenced dataset of oil spills to create an oil-spill area around the pipelines and thus control for the issue of omitted variables. Finally, I use instrumental variables to control for the endogeneity of inputs in estimating agricultural production.

At a more general level, my paper contributes to the emerging body of literature at the intersection of environmental economics and development economics. This literature is filling an important gap given that most studies on the economic effects of pollution have hitherto been conducted in developed countries. For instance, the main focus has

[6]Ojimba focuses on Rivers State, while Inoni et al focus on Delta State. Both regions are considered part of the Niger Delta area, which is formed by nine regions, stretching over the Delta of the River Niger, the biggest river in West Africa.

been to assess the effect of pollution on labor productivity (Graff Zivin and Neidell, 2012), labor supply (Hanna and Oliva, 2011), and human capital accumulation (Currie et al., 2009). Like me, Bruederle and Hodler (2019), Aragón and Rud (2016) and Jayachandran (2009) also focus on the impact of pollution on the extraction of natural resources in developing countries. In particular, Bruederle and Hodler (2019) study the causal effects of oil spills on infant mortality in Nigeria, providing some evidence for negative health effects of nearby oil spills on children. Aragón and Rud (2016) provide evidence that the expansion of large-scale gold mining in Ghana lowers total agricultural productivity in places within twenty kilometers of the mines. In contrast with this last paper, I assess the consequences of unexpected events related to the transport of oil on agricultural output, considering that the effects do not disappear in a single period. Jayanchadran (2009) also investigates forest fires originated by palm oil producers and logging companies which burn out of control and affect all of Indonesia. She finds a strong link between air pollution from forest fires and infant mortality. My paper differs from the above (except for the paper by Bruederle and Hodler (2019)) in that I trust in the plausibly random timing of oil spills at locations that were affected at some point during the period from January 2006 to December 2018.

The rest of the paper is organized as follows. Section 2 reviews the background to oil spills and pollution in Nigeria, and their links with agricultural output, and presents the model related to this framework. Section 3 describes the methods, covering the data and the empirical strategy. Section 4 presents the main results and several robustness checks. Section 5 shows alternative specifications, and Section 6 deals with mechanisms. Section 7 concludes.

4.2 Background

4.2.1 Oil Spill and Pollution

"Oil spill" means any spill of crude oil or distilled products such as diesel or jet fuel, gasoline, kerosene, Stoddard solvent, hydraulic oils, hydraulic oils, and lubricating oils.[7] "Oil-spill pollution" means the negative effect of oil spills on the environment and living organisms. When an oil-spill event occurs, location is an important predictor of its impact. Onshore spills close to human populations have a greater economic impact. The spillage rate and the number of oil leaks are also decisive determinants of the severity of the consequences (Chang, et al. 2014).

The effect of crude oil pollution on wetland soil, which is what most of the Niger Delta area comprises, is to lower soil fertility by increasing soil PH up to 80%, thus reducing available phosphorus (AP). These effects can alkalinize marsh soil, affecting soil fertility and causing deterioration on wetlands (Wang, et al. 2013). Oil spills often also lead to fires, which release respirable particulate matter (PM from now on) into the air (Bruederle and Hodler, 2019). These air pollutants can be carried over long distances and deposited on the ground as acid rain, or directly absorbed by plants (Aragon and Rud, 2016).

4.2.2 Oil Spills in Nigeria and Agricultural Output

My empirical analysis deals with pollution from oil spills in Nigeria. Nigeria is a West African country in the Gulf of Guinea with a surface area of 923,773 km2 (Zabbey et al, 2017) and a population estimated at close to 201 million in 2019. The Niger Delta area in Nigeria comprises diverse ecosystems of large forests, freshwater, mangrove, and swamps, which are characterized by continual salt-water-inundations. It is the largest wetland in Africa (Okonofua, 2011).[8] The Niger Delta basin has been studied in depth because of its vast deposits of petroleum resources. Oil operations were started there in the 1930s by the Royal/Dutch-Shell Company, operating under the name Shell Petroleum Development Company (SPDC) (Madu et al, 2018). The first oil was produced in December 1957, and the petroleum sector shaped the Nigerian economy in the early

[7] "Crude oil and its derivatives include various individual hydrocarbons. Hydrocarbons are constituted "[...] from carbon and hydrogen atoms that bind together in various ways, resulting in paraffins (or normal alkanes), isoparaffins (isoalkanes), aromatics (such as benzene or various PAHs), cycloalkanes and unsaturated alkanes (alkenes and alkynes)" `https://www.environmentalpollutioncenters.org/oil-spill/`. Other components are sulfur, nitrogen, and/or oxygen atoms.

[8] According to the United Nations Development Program Report (UNDP, 2006), most of the people in the area depend on the natural environment for their livelihood. Good agricultural lands, fisheries, and well-developed industries are part of the abundant resources in the region.

70s, leading to a rapid accumulation of capital, declining total factor productivity, and contracting utilization of capacity.

The increasing dependence of the Nigerian economy on hydrocarbon extraction has placed severe pressure on components of the environment as a result of incidental and accidental discharges of hydrocarbon components into the environment. "[..]The oil companies operate over 5,284 oil wells and thousands of miles of oil pipelines networks though the Niger Delta region" (Madu et al. 2018, pg. 79). The main environmental challenge is that of oil spills. This is a common issue in many developing oil-producing countries. However, in most cases spills are associated with operational or mechanism failures,[9] but in Nigeria they are also the result of oil theft, sabotage, and pipeline vandalism.[10]

The 2011 United National Environmental Program (UNEP) report looks in depth at the consequences of oil spills in Ogoniland, (River State, Niger Delta), finding "[..]oil contamination severely impacting many components of the environment". In addition, Ogoniland frequently has high rainfall, and when oil spills are not properly cleaned up, oil has been found "[..] being washed away, traversing farmland and almost always ending up in the creeks" (UNEP report, 2011, p. 9). The report also focuses attention on the importance of land/resource use policies in the Niger Delta, and the importance of corporate social responsibility programs, including clean-up programs in the area.

Agriculture has traditionally been the dominant economic activity in Nigeria. In 1985, crop farming and fishing accounted for approximately 90% of all activity in the Niger Delta area. The active labor force linked to these activities accounted for around 50%-68% of the total. More than 90% of farmers are subsistence farmers, working with

[9]Many pipelines are old and subject to corrosion. The estimated safe life span of a pipeline is fifteen years, but in numerous places in the Niger Delta it is possible to find pipelines 20 or 25 years old. These pipelines are thus prone to rupture and are major fire hazards (Nriagu, 2019).

[10]There are varying socio-political factors related to pipeline vandalism. One important problem associated with unrest in the Niger Delta which results in the destruction of oil pipelines, and consequently oil spills in the area, is who controls oil revenues. Since 1999, the federal government has paid out 13% of the revenues derived from oil to oil-producing states. The federal government uses a revenue allocation formula to distribute these tax revenues to states. The quest for self-determination of young people in the Niger Delta area and a failure to consider the interests of host communities are associated with the control of these rents. This has led to an increase in civil unrest and often to the sabotaging of oil pipelines, thus causing oil spills in the area. (Madu et al. 2018).

traditional techniques and basic tools. Land is still farmed using the bush fallow system or land rotation. These organic farming techniques are very susceptible to environmental changes that affect water or soil, and therefore lead to deforestation. This high level of resource utilization based on land and labor-intensive methods makes the area more susceptible to oil pollution.

I link oil pollution with agricultural productivity here through the impact of pollutants on crop yields and health, soil quality, and human capital. Once crude oil and petroleum products leak directly into the environment, different compounds are absorbed by the soil, entering ground and surface water or evaporating in the air depending on their physical characteristics (Bruederle and Hodler, 2019). These pollutants lead to a rapid deterioration in the soil, a reduction in crop yield and, hence, to a fall in agricultural output. Evidence from biological science (for example Maggs et al, 1995; Marshall et al, 1997 between others) finds a "[..] reduction of around 20-60% in the yield of crops such as rice, wheat, and beans". In particular, a case study of the effect of oil pollution on soil properties and growth of tree crops[11] showed that seedling germination and plant heights are significantly affected at high levels of pollution (Uquetan, U. et al. 2017). Besides, the effects on ground pollution could be cumulative and long-lived. In fact, although the Nigerian crude oil has rapid evaporation loss of around 50%, a study carried out about nineteen years after a major 1970 oil spill at Ebubu, Ogoni, found that "[...]vegetation in areas downstream of the spill was still being degraded due to a slow seepage of crude oil from the spill site" (Nriagu, 2019, pg. 761). Consequently, agricultural productivity could be affected not just in the period when the spill occurs but also via a persistent effect that can continue to impact the agricultural cycle years after the events.

Finally, agricultural output could also fall because of a drop in labor productivity. There may be direct adverse health effects on workers through PM inhalation or indirect effects through damage to livelihood resources, such as the quality of foods from degraded lands and fishing grounds. In any case, a drop in labor productivity or labor supply

[11] Specifically, cocoa, cashew, pawpaw and mango.

could result, leading to a decrease in agricultural output.

4.2.3 Analytical Framework

This subsection develops a simple framework for understanding how oil-spill pollution could result in adjustments in the optimal behavior of households. I follow the simple agricultural standard model of consumer-producer households used in development literature as per Aragón and Rud (2016), who extend the framework set out by Benjamin (1992). Oil spills can impact directly on land plots, or may have occurred some periods before and soil could receive filtration that still affects agricultural total factor productivity. Also, there may be no direct impact on plots, but indirect pollution through air or water pollution that leads to changes in soil quality, biomass, and human health.

I assume that farmers (households) are both consumers and producers of an agricultural good with a price of $p = 1$. Households have a productive parameter A and use land, X, and labor, L to produce the agricultural good $Y = F(A, X, L)$. F is a concave production function. Farmers have certain endowments (E^X, E^L), which represent land and household endowments, respectively. Endowments are used as inputs on the farm or can be sold at a local input market (X^s, L^s), as land and labor supply at prices r and w. Labor endowments also can be used as leisure. In addition, farmers can buy an additional quantity of land and labor (hired labor) when there are producers in line with land and labor demand: (X^b, L^b).

The problem of farmers consists of maximizing household utility $U(C, l)$ over consumption, C, and leisure, l, subject to the budget constraint $C = F(A, X, L) - r(X^b - X^s) - w(L^b - L^s)$. Endowment constraints are $X = E^X + X^b - X^s$, and $L = E^L + L^b - L^s - l$.

In the context of the Nigerian agricultural market,[12] I assume that households are

[12] Even though agriculture is the main system of livelihood for Nigerian, the sector is characterized by poor access to input markets. For example, "[..] an outdated land tenure system that constrains access to land (1.8 ha/farming household), a very low level of irrigation development (less than 1 percent of cropped land under irrigation), limited adoption of research findings and technologies, high cost

not homogeneous in their access to input markets. [13] In particular, there are two types of farmer: Unconstrained farmers, who participate in competitive input markets, and fully constrained farmers, who neither buy nor sell inputs. In the first case, if input markets exist and work well it is possible to study production and consumption decisions separately, and there is trade. Households maximize their profits and, given the optimal profit, choose between consumption and leisure levels. Thus, the optimal levels of output and inputs, $Y^*(A,w,r)$, $X^*(A,w,r)$, and $L^*(A,w,r)$, depend only on the value of A, which means total factor productivity, and on input prices.

For fully constrained farmers, endowments shape the optimal decisions on inputs. Farmers use all their land in the planting season $X^* = E^X$ given that the opportunity cost of land is zero. Given that there is no labor market, $L^s = L^b = 0$, and the optimal level of labor depends on a trade-off between income and leisure. In this simplified framework, the farmer's problem is:

$$\begin{gathered}\text{Max U(C,l)}\\ \text{s.a}\\ \text{C=F(A, E}^X, L)\\ \text{L=E}^L - l\end{gathered} \tag{4.1}$$

of farm inputs, poor access to credit, inefficient fertilizer procurement and distribution, inadequate storage facilities and poor access to markets have all combined to keep agricultural productivity low (average of 1.2 metric tons of cereals/ha) with high post-harvest losses and waste" (FAO in Nigeria `http://www.fao.org/nigeria/fao-in-nigeria/nigeria-at-a-glance/en/)`

[13] Land acquisition is bound by the Land Use Act of 1978. There are three types of land market: 1) Formal land markets, where the government allocates a certificate of occupancy; 2) combined formal and informal markets where there is a certificate of occupancy in the transfer of land rights; and 3) informal markets. The titles owned do not entail a certificate of occupancy because the bulk of the transactions are not documented. Nevertheless, an estimated 95% of agricultural land in Nigeria is not titled (Oluwatayo et al., 2019).

The first order condition becomes: $U_c F_L = U_l$. Thus, the optimal level of labor is a function that depends on both the level of total factor productivity and input endowments, $L^*(A, E^X, E^L)$.[14]

If oil spills directly impact plots in the growing season, the agricultural good that has been planted is lost. In terms of the model, this can be interpreted as a reduction of land endowment, leading to a diminishing land supply. However, there are two indirect channels through which oil-spill pollution affects agricultural output and hence household consumption. As described above, most oil spills are located in the Niger Delta, and are most likely to occur in the pipeline networks close to oil wells. Thus, oil companies that operate in this zone could have a demand for local inputs (land and labor), leading to an increase in input prices, which would reduce input use and consequently, agricultural output among unconstrained farmers. This channel also could reduce the supply of inputs through government expropriation of land for oil extraction and infrastructure access, and through population displacement. There would be no effect on total factor productivity A.[15]

Moreover, oil pollution affects the quality of inputs, as discussed in the previous section, and soil quality, crop yields, health, and labor productivity all decrease. This argument is linked to a drop in the total productivity factor, which unambiguously causes a decrease in agricultural output and household consumption, although input uses may not change. It might also lead to a reduction in input uses. For unconstrained farmers, this might mean a reduction in labor and land uses because input prices do not change. Among constrained farmers, the drop in total factor productivity leads to labor being replaced by leisure, while the use of land does not change.

In short, this model highlights the importance of studying the impact of oil-spill pollution through its indirect effects on agricultural total factor productivity. Other outcomes, such us input uses and agricultural output, may not be very informative about the channels that determine a drop in agricultural output.

[14] Agricultural employment for a wage is relatively infrequent in Nigeria. GHS-Nigerian data shows that only 3.5% of men and 1.4% of women are wage workers.

[15] I also explore the use of other inputs such as fertilizers, improved seeds, etc, later in my analysis.

However, the unobservable heterogeneity in A could also impact input uses and the engagement of the econometric identification of total factor productivity. Thus, in my empirical approach, I follow the model prediction that relies on household endowments as a key for determining input uses in the presence of imperfect input markets. This assumption leads to consistent estimates of the parameters of the production function

4.3 Methods

4.3.1 Data

I merge geo-referenced household surveys containing agricultural, socioeconomic, and weather variables from the Nigerian General Household Survey (GHS-Panel) (waves 1, 2, 3, and 4) with data from oil spills also geo-referenced from The Nigerian Oil Spill Monitor[16] to construct a final dataset of around 6,000 observations for my main analysis.

Agricultural output and inputs

My main data source is a repeated cross-section from the Nigeria General Household Survey Panel (GHS-Panel).[17] It is collected by the National Bureau of Statistics in collaboration with the World Bank's program on Living Standards Measurement Surveys - Integrated Surveys for Agriculture (LSMS-ISA). This program was revised in 2010 to include a panel component (GHS-Panel). The GHS-Panel is a national survey of 5,000 households, which are also representative of geopolitical zones (at urban and rural levels). Households were interviewed in 2010-2011 (Wave 1), 2012-2013 (Wave 2), 2015-2016 (Wave 3), and 2018-2019 (Wave 4). The Nigeria GHS-Panel is part of a larger, regional project in Sub-Saharan Africa that involves eight countries and seeks to obtain better agricultural statistics. The surveys collect data on agricultural activities, other household income activities, household expenditure, and consumption. The finest level is that of enumeration areas (EA), which approximately match neighborhoods (urban areas) and villages (rural areas). In Wave 4, the GHS-sample was partially refreshed to

[16] `https://oilspillmonitor.ng`

[17] I cannot estimate a panel dataset because at the time of writing the longitudinal weights were still being prepared. However, cross-section weights are available for each round.

maintain the representativeness and integrity of the sample. A new set of 360 random enumeration areas were incorporated into the sample, which meant 3600 new households. Thus, a subsample of 1425 families from previous rounds was interviewed. Farmers are located in 423 local government areas (LGAs), 37 states, and six Zones: North-Central, North-East, North-West, South-East, South-West, and South-South. Figure B.2 in the Appendix C shows a map of the six geographical zones of Nigeria.

Each wave consists of two visits to each household:[18] A post-planting visit just after the planting period to collect information on inputs used, planting preparation, labor used for planting, and other information relating to the period; and a post-harvest visit after the harvest season to collect information on crops harvested, labor used for harvesting, and other variables related to the harvest cycle. I focus on the farming household as a production unit in a period (the year) that represents a season-round pair. A farmer may operate one or more plots of land, so I aggregate any information at the plot level to household level. The GHS panel also provides a set of geospatial variables using household locations and geo-referenced plots together with various geospatial databases that are available to the survey team. Specifically, the geo-coordinates of clusters (or an average of household GPS locations by EA in GHS-Panel) are reported but slightly displaced within a specified range determined by an urban/rural classification. The displacement is done randomly in terms of direction and distance up to 5 km for the rural clusters, and 2 km for urban clusters. A 10 km distance-up is applied for one percent of rural areas.[19]

To measure the real agricultural output (Y), I construct a Laspeyres index of production that aggregates the quantity produced of main cash and staple crops crops (cassava, maize, yam, beans, cocoyam, millet, oil palm, and rice) produced by household farms using proxies of prices in 2010 as weights. I also identify the other, minor crops grown under a category named "other crops". I use unit values as proxies of prices. To calculate these proxies, I follow Aragón et al. (2019) and divide the value of sales by the

[18]The post-planting and post-harvest visit calendars are shown in the Appendix C.
[19]The reason for this modification of coordinates is to meet user interest in geo-referenced locations while preserving the confidentiality of sample households and communities.

quantity of each crop. I then calculate the median unit value of each crop at national level.

For the main agricultural inputs, I construct land input by adding up the size of plots harvested by households. Labor input is estimated by adding hired worked days to the number of days that all members of the household spend working on the household farm. I use the endowment of each household as an instrumental variable, following the methodology of Benjamin (1992). Available land is the sum of the area of all plots to which a farmer has access, either by the distribution of the community or family, outright purchase, renting, or use free of charge. Labor endowment is the number of equivalent adults in households.

The survey also provides information on household characteristics and agricultural practices (age of head of household, literacy, an indicator of whether households own their land, use of fertilizers, herbicides, pesticides, and improved seeds).[20] I use these as control variables in my main specification and robustness analysis.[21] In the robustness analysis, I also supplement household and agricultural practices data with a set of geospatial variables that help to control for other characteristics that could also affect the total agricultural productivity channel. These include long distances to main points (federal roads, main towns, main markets, state capitals, and border posts), mean rainfall levels and temperatures, soil characteristics (landscape type, level of toxicity, excess salt, workability, nutrient retention and availability, and oxygen availability to roots).

Table C.1 in the Appendix C presents summary statistics of the agricultural characteristics, households variables, and weather and terrain conditions. There are several relevant observations for my analysis. First, farmers have small scale operations with no substantial differences between the plot areas harvested and their total plots (the average total land harvested is 3.77 hectares and the average total plot size is 4.05 hectares, giving a figure of around 93%). Second, farmers use practices that

[20] In the database, there is also information on additional shocks that impact farms. There is not any oil spill in the dataset.

[21] `https://microdata.worldbank.org/index.php/catalog/1002`

can be described as subsistence farming, e.g. limited use of pesticides and herbicides. Table C.2 presents summary statistics from the dataset which are not only restricted to agricultural workers (rural or urban, population, sex, age). Some of these variables may explain a drop in agricultural total productivity not associated with oil-spill pollution (dummy variables if an individual, male or female, is employed, semi-employed or hired in domestic production, works in agriculture, migration, literacy, secondary education, and own business). I also present some household variables that help me to explain a drop in labor productivity (dummy variable if any individual reports being ill in the last four weeks, number of days for which an individual reports ceasing to engage in any usual activity, number of total hours worked, and real employment income).

The oil spills dataset

The second database used is The Nigerian Oil Spill Monitor, which provides geo-referenced data from January 2006 to December 2018 on oil spills registered by the National Oil Spill Detection and Response Agency (NOSDRA), the Nigerian environmental regulator. The Nigerian Oil Spills Monitor visualizes oil spills on an online map and allows data to be downloaded in a table.[22] The data prior to 2013 is not entirely well-referenced. In most cases, only the site location is provided. In these cases, I use the geocoding[23] tool from the geographical information system (QGIS)[24] to obtain their geographical coordinates. NOSDRA calls on the public to report oil spills by email or via a hotline, but relies on voluntary engagement and on the support of oil companies to provide data. The dataset reports some supplementary information, such as the estimated quantity of oil spilt, the cause, the area covered, and the quantity recovered among other items. However, not all oil spills are supported by this information. Oil companies may be willing to provide information if oil spills are caused by sabotage or theft, or through their own fault (as in the cases of pipeline corrosion, maintenance, human operational errors, and equipment failures). There are 11,981 oil spills recorded

[22] The dataset of oil spills used in this paper was downloaded in January 2019.

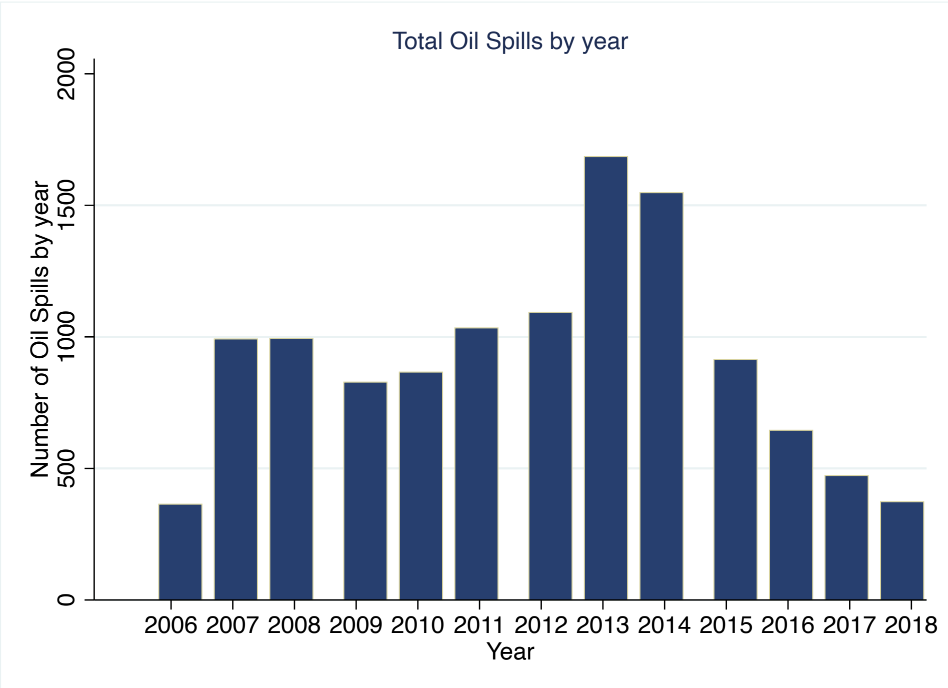
[23] Specifically, I use the Geocode tool to geo-reference the exact site.

[24] QGIS is a user-friendly Open Source Geographic Information System (GIS) licensed under the GNU General Public License. QGIS is an official project of the Open Source Geospatial Foundation (OSGeo). It runs on Linux, Unix, Mac OSX, Windows and Android and supports numerous vector, raster, and database formats and functionalities. `https://www.qgis.org/es/site/about/index.html`

for the period analyzed, around 68% of them attributed to sabotage. Most of these oil spills are concentrated on pipelines close to onshore oil and gas fields in the South-south zone of Nigeria

Figure 4.1 illustrates the total number of oil spills per annum over my sample period. There are no suitable references for oil spills before 2006. The figure shows a steady increase in oil spills in 2013 but a sharp decrease in 2015. This last evidence is consistent with the drop in oil prices in Nigeria[25] from that year onwards, suggesting that one reason for this decrease in oil spills could be a decrease in the sabotaging of pipelines to steal oil.

Figure 4.1: Number of oil spills per year. Years: January 2006- December 2018.



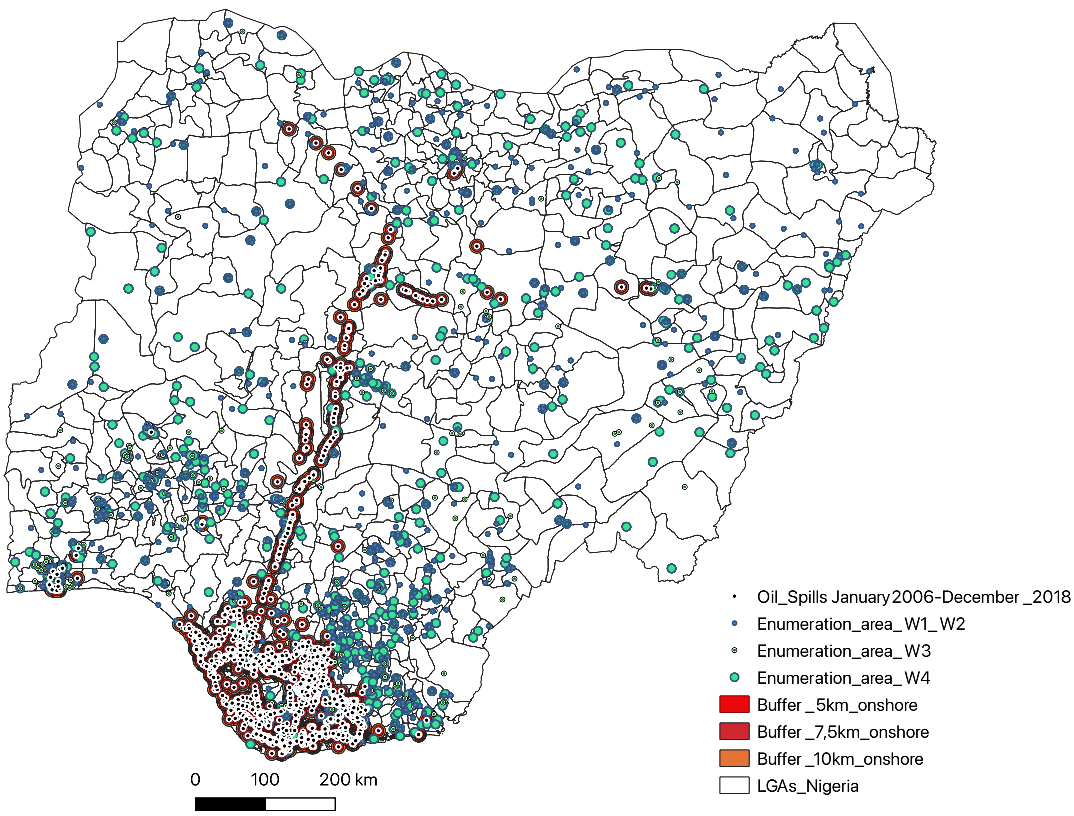
Sources: Own work based on Nigerian Oil Spill Monitor *NOSDRA*.data

To link oil spills and household data, I use the QGIS program mentioned above. Thus, I obtain the geographical coordinates for both oil spills and enumeration areas on a map. On average, each enumeration area contains ten households. I focus on the

[25] See `https://www.cbn.gov.ng/rates/crudeoil.asp`, the Central Bank of Nigeria for historical oil prices in Nigeria.

enumeration areas located near oil spills. Thus, I create buffers around oil spills that define proximity to them.[26] [27] Figure 4.2 is a map of Nigeria showing the location of oil spills and the enumeration areas for each wave. The shaded areas are the union of all buffers within radii of 5, 7.5, and 10 kilometers of all oil spills in my dataset.

Figure 4.2: Location of total onshore oil spills, enumeration areas, and buffers at 5km, 7.5km and 10km.



Sources: Own work based on Nigerian GHS-PANEL data and Nigerian Oil Spill Monitor *NOSDRA*.data

[26]I present results up to 5 km in the main text and 7.5 km in the Appendix C. Recall that the coordinate modification strategy in the Nigeria GHS-panel surveys means that up to 99% of households are located within a buffer zone of 5 km from the reported coordinates.

[27]Bruederle and Holder (2019) focus on mothers who live in clusters provided by the DHS survey at a reported distance of less than 10 km from the closest oil spill. According to Aragóon and Rud (2016), p. 1982 "[..]..using satellite imagery it is found that the concentration of (NO2), an indicator of air pollutant, is higher in locations near mines and declines with distance". They define buffer zones of 20 km from mine sites as the mining area. Nevertheless, oil spill pollution differs from that caused by mines, and Nigerian oil is very light in chemical composition with high levels of evaporation. Thus, I begin my analysis with the nearby locations. In a robustness analysis, I also consider longer distances (20km to 50 km).

Conflict Data

I also use spatially explicit data from The Armed Conflict Location and Event Dataset (ACLED Dataset) (Raleigh et al., 2017). These data cover different countries and periods. Events are collected from various sources, including humanitarian agencies, research publications, and local, regional, and international press. In each dataset, the unit of observation is the event. They contain latitude and longitude coordinates and the exact day (in most cases) of conflict events. I construct a dummy variable that indicates whether any conflict event causing at least one fatality took place within 25 kilometers[28] of the reported enumeration area during the sample period of the Nigeria GHS-Panel, i.e. from January 2009 to December 2018.

4.3.2 Empirical Strategy

The objective of my empirical analysis is to determine the extent of the effects of oil-spill pollution on agricultural activity. To that end, I estimate a production function and assess the impact of oil spills that occurred in zones near farms on total factor productivity A.

I follow the empirical implementation method set out in Aragón and Rud (2016), who study the expansion of mining activities in Ghana, for two reasons: First, pollutants affect agricultural total factor productivity similarly in both cases; and second, their impact may be higher on the areas near the main sources of pollution. However, in Aragón and Rud (2016), the pollution comes from mines, which are in fixed locations and pollute the air continuously. In this paper, oil spills are rare events on pipelines that might recur over time,[29]and their effects are also persistent in the environment.

I also assume the following agricultural production function:[30]

[28] I follow the approach of Bruederle and Hodler (2019).

[29] An examination of the oil spills in the dataset shows several spills in nearby geographic coordinates and in the same year, which hence affect the same farms. Thus, my oil spill pollution variable reflects the number of oil spills near a given location and year.

[30] I am assuming Cobb-Douglas technology for the sake of simplicity and because I follow the methodology of Aragón and Rud, 2016; and Restuccia et al. 2006.

$$Y_{i,e,t} = A_{i,e,t} X_{i,t}^{\alpha} L_{i,t}^{\beta} e^{\epsilon_{it}} \tag{4.2}$$

where Y is the agricultural output of farmer i, in enumeration area e, in time period t. $A_{i,e,t}$ is total factor productivity, $X_{i,t}$ and $L_{i,t}$ are the actual land and labor inputs. $e^{\epsilon_{it}}$ captures unanticipated shocks not related to oil spills, which are by definition uncorrelated with input decisions by farmers. Finally, α and β are the input shares of land and labor respectively. Farmers may need other inputs for production, such as fertilizers, herbicides, animals, etc., but these are not commonly used so, following Aragón and Rud (2016), I decided to exclude them from the benchmark model, though I do include them later in my robustness analysis.

Total factor productivity $A_{i,e,t}$ is composed of three factors: O_{et} a function of the total number of oil spills in the proximity of enumeration area e before time t; the heterogeneity of farmers ($\chi_{i,t}$) and time-invariant environmental conditions and the local economy (ν_e). Hence, $A_{i,e,t}$=exp($\delta O_{et}+\chi_i+\nu_e$). The parameter of interest is δ. If $\delta < 0$, oil spills are affecting total factor productivity, but if $\delta = 0$, the effect of oil spills could be transmitted via the input competition channel through prices or availability of inputs.

A limitation arises when I only approximate accumulated pollution via the number of oil spills. The amount of oil spilled and the spillage rate are key determinants of the severity of the consequences (Chang et al. 2014). Madu et al. (2017) find no correlation between these variables, but the estimated volume of the oil spills variable reported by NOSDRA[31] is incomplete for all events and implies an observation loss of approximately one-third. Thus, I decided not to consider this variable in my main model, although the volume spilled could be key in quantifying the damage to the environment.[32] However, a histogram of the variable shows that the density of its probability is concentrated in a small quantity of oil spills: There are few medium or large oil spills.[33]

[31]NOSDRA gives the amount in barrels reported as spilled by each company. However, the time-series data of both the estimated quantity of oil lost and the estimated quantity of oil recovered in each location are incomplete.

[32]I present additional results with this variable in my robustness analysis.

[33]See Figure C.3 in the Appendix C.

There are also some empirical challenges: Places around the pipelines, and hence locations near oil spills could have permanent differences in productivity. In particular, the sharp increase in oil spill data in 2013 could indicate that data from previous oil spills was not fully reported.[34] As Aragón and Rud (2016) point out, when I estimate the coefficient of interest, this omitted variables problem may lead to endogeneity issues.[35] To avoid such issues, I unify the buffer zones around oil spills as defined above to create an oil spill area.[36] I also use time variation in the repeated cross-section to compare differences in productivity in oil-spill and non-oil-spill areas. As highlighted by the aforesaid authors, this is basically a difference-in-difference methodology with continuous treatment. In this case, proximity to oil spills defines the control group and the intensity of treatment is the proxy for the estimated quantity of oil lost. Taking this approximation, I assume that the trend in output in both areas would have been similar without the presence of oil spills. In fact, most pipelines and oil spills are concentrated in the Niger Delta, a specific area where oil exploration has impacted the entire ecosystem.[37] Assuming this empirical strategy, the variable O_{et} takes the value of 0 in the enumeration areas farthest from the defined oil spill area.

Second, in estimating my production function, both agricultural output and input choice could be affected by productivity being simultaneously determined. In this case, unobserved heterogeneity in productivity is reflected in the error term, creating an endogeneity problem in the estimation of input coefficients.

I address these issues in several ways. First at all, I use variables such as observable characteristics of farmers as proxies for heterogeneity, χ_i and I take LGAs fixed effects to capture differences in average output due to heterogeneity in the local economy. Taking

[34]See Bruederle and Hodler (2019).

[35]Zabbey et al. (2007) pg. 3, recall that "[..] An estimated 10 m to 13 m tons of hydrocarbons have been reportedly spilled into the Niger Delta over the last 50 year. During this period over 77% of spilled hydrocarbons are not recovery". Thus, I can assume that the number of oil spills is greater than reported.

[36]See Figures A4 and A5 in the Appendix C.

[37]Many activities associated with oil extraction have affected the Delta area negatively. In particular, building infrastructures for oil exploration (such as access roads and canals, resulting in deforestation), laying pipes and gas flaring seriously damage the environment. For instance, gas flaring introduces toxic pollutants (such as PAHs and toxic metals, especially vanadium) into the air. In the Niger Delta, gas flaring facilities are often close to local communities with no protection, leading to a high level of exposure to pollutants among households (Nriagu, 2011).

logs in the agricultural production function, I estimate the following equation:

$$y_{i,e,d,t} = \alpha x_{i,t} + \beta l_{i,t} + \delta O_{et} + \nu Z_i + \kappa Oilspillarea_e + \mu_d + \theta_t + \varepsilon_{i,e,t} \tag{4.3}$$

where $y_{i,e,d,t}$ represents the log of the agricultural output of farmer i, in enumeration area (village or urban neighborhood) e, in LGAs d, in period t, $\mathrm{x}_{i,t}$ and $l_{i,t}$, are the log of land and labor for household i in period time t, respectively. The variable Z_i is a set of farmer's control set, O_{et} is the proxy for cumulative oil pollution in the proximity of the enumeration area; $Oilspillarea_e$ is a dummy that determines whether the land is within 5 kilometers of an oil spill, μ_d is a set of LGAs fixed effects, and θ_t is a set of time fixed effects. Finally, $\varepsilon_{i,e,t}$ is the corresponding disturbance term.

The above identification assumption means exploring the presence of some constrained farmers too. I estimate a standard IV model using input endowments as instruments for my observed use of inputs. As mentioned above, traditional farming is the main source of livelihood in Nigeria, which means that most farmers could have constrained access to the inputs market. As Benjamin (1992) points out, the greater the proportion of constrained farmers, the closer the correlation between household endowments and input uses. However, I can only use this approach in cases where correlation is strong enough and endowment affect output only through input uses and not through the productivity parameter A. That means that endowments are not conditionally correlated with the residual unobserved heterogeneity term, $\varepsilon_{i,e,t}$, which corresponds to the error term, $e_{i,t}$, heterogeneity in locations, and unaccounted farmers. Under this assumption, I can estimate my model with OLS regression. [38]

[38]In a robustness analysis in the Appendix C, following Aragón and Rud (2016), I also consider the possibility that endowments may be correlated with the error term, $\varepsilon_{i,e,t}$. In that case, the exogeneity assumption in the IV strategy does not entirely apply. That situation emerges for more productive farmers who have systematically larger plots or households. To solve this issue, I apply the partial identification strategy used by Nevo and Rosen (2012), which implements an imperfect instrumental variables (IIV) strategy to identify a set of parameter values instead of point values. Recall that IV strategy relies on identifying point values. IV permits partial correlation with the error term. In particular, this approach implies that "[..] (i) the correlation between the instrument and the error term has the same sign as the correlation between the endogenous regressor and the error term, and (ii) that the instrument is less correlated with the error term than is the endogenous regressor" (Nevo and Rosen, 2012, p. 659). Given that I use the same instrumental variables as previous literature, I carry out the same exercise to check the validity of my instrument variables.

Finally, changes in agricultural productivity could be driven by other events that correlate in time and space with oil spills. Oil spills are likely to occur simultaneously with other events specific to oil production. Thus, following Bruederle and Hodler (2019), I use total factor productivity to compare the effect on agricultural output in the oil-producing states in the Niger Delta with the effect for agricultural output elsewhere. Oil spills are often also the result of vandalism. Sometimes military groups attack pipelines, which entails violence against civilians (U.S. Energy Information Administration, 2016). I use total factor productivity to compare the effect of oil spills on agricultural output for household farms close to conflict areas and households far from conflict areas.

Oil spills location and the oil spills pollution function

Oil-spill pollution is measured based on the location of oil spills near to households and, hence, near cultivated plots. As a proxy of oil-spill pollution, I use a function of the number of oil spills until period t. It is plausible that the enumeration areas near oil spills may receive the greatest impact both directly or indirectly through air and water contamination, because of the proximity of wetlands. As mentioned above, I consider the survey enumeration areas at a reported distance of less than 10 kilometers from the closest oil spill as my treatment group.[39] However, the effect on total agricultural productivity could fade away over time. In particular, I define the total oil spill function as follows:

$$O_{e,t} = \sum_{n=0}^{a_t} g(n) * Total\_oilspill_{e,t-n} \tag{4.4}$$

where $Total\_oilspill_{e,t-n}$ is the number of oil spills close to an enumeration area e, t is the period of the wave, n is the number of years before each wave, and a_t is the total number of years before each wave. [40] The persistent effect is defined by $g(n)$.

[39]The results show that the best specification in this case is to choose buffer zones of up to 5km. Taking enumeration areas up to 10 kilometers from oil spills is not significant.

[40]In particular, a_t could be $a_{2011} = 5$, $a_{2013} = 7$, $a_{2016} = 10$, $a_{2018} = 12$.

This function takes different specifications depending on how persistent is the effect of oil spills on soil quality and human capital is. In particular, in my benchmark model, $g(n) = exp^{-n}$.

With this formulation, I consider the possibility that oil spill incidents during the period of the wave have the most impact on total factor productivity. That means that contemporaneous oil spills impact agricultural output strongly in present crop seasons. I also consider that productivity depends on previous oil spills that may have impacted both the quality of soil and human capital. However, these impacts decline exponentially over n years. The main processes that influence the degradation of oil spills include evaporation, auto-oxidation, and microbial degradation. The first known model to describe a process of decomposition of organic matter is the simple exponential model, which was initially proposed by Jenny et al. (1949) and discussed in detail by Olson (1963). I decided to take this approximation to create my oil spills pollution variable, given that the oil would affect soil quality at a lower rate over time. In particular, the original function is: $X = X_0 e^{-kt}$, where X is the amount of litter remaining at the time t from an initial amount X_0. For the sake of simplicity, I consider the value of k to be 1. To the best of my knowledge, there are no previous studies that determine how many years this effect will persist in the soil.[41] It probably depends on the degree of evaporation, the chemical composition of the hydrocarbon contaminants, the physical characteristics of the terrain, weather issues, other environmental factors (including PH and soil aeration), and clean-up aspects. To the best of my knowledge, there is no way of determining how the process works or how long chemicals of these types can affect the quality of land. Thus, I consider all oil spills up to the last day of the harvest survey for each wave as a cumulative, persistent effect on total factor productivity. Nevertheless, I also use different measurements in the robustness analysis. For example, oil spills may have the same impact on soil independently of the year when they happen. Thus $g(n) = 1 \to \forall n$.[42] Another approach is to identify the number of oil spills that affect

[41] The UNEP report (2011) concludes that contamination persists for many years.

[42] In my analysis, the biota of soil quality could be lost for many years because of pollution. Another reason may be that oil spills could affect labor productivity permanently through chronic diseases suffered by the labor force. Thus, I decided to do a robustness analysis with no degrading effect.

land from the beginning of the planting period to the end of the harvest period given by each survey.

$$g(n)=\begin{cases} 1 & \text{si } n=0 \\ 0 & \text{si } n>0 \end{cases}$$

In this case, the effect is not persistent over time. Finally, I consider oil spills that occurred up to five years before the planting period. In this last case, I apply the same number of years to each wave. Thus, $g(n)=\begin{cases} exp^{-n} & \text{si } n=0, 1,.....,5 \\ 0 & \text{si } n>5 \end{cases}$

In short, my cumulative oil spills function depends on the total number of oil spills near location e and on the year of each spill. Effects are always greater if oil spills occur during the year of each survey, given that they could affect both agricultural productivity and input uses in that year directly or indirectly. However, if there are events before each survey, agricultural productivity may probably be affected by their persistent effects on the quality of soil and human capital. The extent of that persistence over time will depend on how I parameterize the function g(n).[43][44]

Table 4.1 presents a simplified difference-in-difference estimation of the main variables, comparing mean values in all waves for farmers located in oil-spill and non-oil spill areas. The first observation is that in both areas the log of agricultural output decreases in 2012-2013 and in 2018-2019. However, the impact is stronger for oil-spill areas in 2012-2013. In that period the number of oil spills increased. In fact, there is a stronger significant difference in this variable when the two zones are compared. There is also a clearly significant difference in the use of labor input. Land harvested is slightly significant at 10%, but labor is negative and significant at 1%, suggesting an adjustment of this input in the spill area. Concerning household characteristics, I find clear evidence that less land is owned by farmers who live near oil spills. The head of the family also tends to be younger, but careful examination of this variable reveals that the significant impact may be due to the inclusion of new households in wave 4.

[43]See Table C.3 in the Appendix C for summary statistics of the oil-spill pollution variables.

[44]See Table C.4 in the Appendix C for data on collection dates of surveys and oil-spill incidents considered for each period for the main analysis and the second approach.

However, these differences disappear in both cases when I control for other household characteristics. Finally, the greater use of fertilizer may suggest that farmers take action because of the pollution perceived on their land.

Table 4.1: Mean of main variables, by wave and location

VARIABLE	Within 5 km of oil spill				More than 5 km from oil spill				Diff. columns
	2010-2011	2012-2013	2015-2016	2017-2018	2010-2011	2012-2013	2015-2016	2018-2019	(4-3-2-1)-(8-7-6-5)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Cumulative Oil Spill	1.065	2.619	1.128	7.042	—	—	—	—	—
Ln Real Agricultural Output	10.193	9.529	10.554	7.428	10.370	10.158	10.577	6.896	-0.02***
									(0.005)
Land harvested (hectares)	0.783	0.920	1.177	1.027	7.233	3.596	3.121	1.311	0.08*
									(0.042)
labor (days)	154.870	78.335	299.809	708.565	215.904	218.284	381.436	725.299	-7.378***
									(2.542)
N^o members in household	2.758	3.823	5.175	3.416	2.929	3.497	4.460	3.527	-0.023
									(0.024)
Owner-occupied farmland (%)	82.185	80.539	66.212	72.868	81.483	75.596	75.820	75.906	-0.01***
									(0.003)
Age of head of family (years)	48.384	60.368	56.135	45.632	50.649	53.123	54.416	49.604	-0.18**
									(0.071)
Literacy (%)	75.361	50.913	58.035	80.670	52.353	58.207	55.509	69.329	0.000
									(0.001)
Fertilizers	0.429	0.155	0.218	0.400	0.442	0.459	0.599	0.483	0.00**
									(0.001)
Improved_Seed	1	0.952	0.989	1	0.977	0.958	0.977	1	-0.00
									(0.000)
Small Business	0.699	0.346	0.428	0.472	0.524	0.444	0.469	0.539	-0.01
									(0.005)
Observation	38	54	156	188	1,639	1,235	1,757	1,881	

Notes: Columns 1-8 report mean values for the sub-samples of farmers less and more than 5 kilometers from an oil spill for each wave of the Nigerian GHS. Means are estimated using simple weights. Column 9 displays the coefficient of the regression estimate for each variable. This is obtained by regressing each variable on Cumulative Oil Spill and a dummy for being 5 kilometers from an oil spill. As in the baseline regressions, standard errors are clustered at LGA level. Fixed effects are included, but no control variables. By definition, Cumulative Oil Spills more than 5km from an oil spill are zero in all periods. The total number of observations is 5,998. *** p<0.01, ** p<0.05, * p<0.1. The standard errors are in parentheses.

4.4 Main Results

4.4.1 Effect on Agricultural Productivity

This section provides the results for the main hypothesis, evidencing that oil spills near farmers are associated with significant reductions in agricultural productivity. I start with the baseline specification using the total cumulative oil-spill function in locations up to 5 kilometers from the oil spill.

Table 4.2 presents the main results. Column 1 examines the link between agricultural output and the proxy for total accumulated oil-spill pollution in nearby locations, without controlling for input use. I find that link to be negative and significant, and consistent with oil spills affecting agricultural output through both pollution and

Table 4.2: Oil spill pollution and Agricultural Productivity.

VARIABLES	Ln Agricultural Output			LnYield	LnYield_Cas	LnYield_Maize
	(1)	(2)	(3)	(4)	(5)	(6)
Cumulative_OilSpill	-0.0236*	-0.0234***	-0.0273***	-0.0288***	-0.0373*	-0.0152
	(0.013)	(0.006)	(0.007)	(0.010)	(0.022)	(0.019)
LnLand		0.2572***	0.5384***			
		(0.024)	(0.171)			
Lnlabor_days		0.2001***	0.2954*			
		(0.025)	(0.153)			
Estimation	OLS	OLS	2SLS	OLS	OLS	OLS
Observations	6390	6130	6114	9051	1177	2564
R-squared	0.612	0.640	0.618	0.308	0.300	0.294
Waves dummies	YES	YES	YES	YES	YES	YES
LGAs fixed effects	YES	YES	YES	YES	YES	YES

Notes: Robust standard errors in parentheses. Standard errors are clustered at LGA level. All regressions include a dummy for being 5 kilometers from an oil spill. Controls on farmers: columns 2 to 4 and column 6 give household head age and literacy and an indicator of whether farms are owner-occupied. Denotes significance at *** p<0.01, ** p<0.05, * p<0.1 Column 3 is estimated using 2SLS. Column 3 is estimated using 2SLS. The instruments excluded are the log of the area of land managed and the log of the number of equivalent adults in the household.

input competition as the model developed by Aragón and Rud (2016) suggests. Next, I explore the channels likely to be driving the link. Column 2 estimates the agricultural production function defined in (1) with the OLS model, while column 3 estimates the 2SLS regression using input endowments. [45] All regressions include a set of controls for farmers, wave dummies, and LGA fixed effects. All specifications use cluster errors at LGA level and sample weights to account for both autocorrelation spatial patterns and sample design.

Results suggest a negative link between the presence of nearby oil spills and agricultural output once input use is controlled for.[46] Following the identification strategy, I interpret these results as evidence of a reduction in agricultural productivity. Thus, oil-spill pollution affects the agricultural sector negatively in the areas affected. To further quantify the results in column 3, following the standard procedure in the literature, I find that an increase of one unit of the accumulated total number of oil spills leads to a decrease in agricultural production of around 2.73%; alternatively, an

[45]The results of the First Stage show a positive, significant correlation between inputs and input endowments. See Table C.5 in the Appendix C. As a further check, in Figure C.7 and Table C.6 in the Appendix C I present the estimations using the imperfect instrumental variable (IIV) approach. Figure C.7 shows that the effect on residual productivity is negative in more than 96% of all combinations.

[46]Using the 2SLS estimation in column 3, the results of α and β do not reject the null hypothesis of constant returns to scale at 5%.

increase of one standard deviation in the measuring of accumulated oil spills is associated with a reduction of almost 8% in agricultural productivity. [47]

Columns 4 to 6 show the effect of oil spills on crop yield, which is defined as physical output per unit of land. Column 4 shows the sum of the yields from cassava, maize, and yam; column 5 those from cassava; and column 6 those from maize. These are the main crops in both oil-spill and non-oil spill areas. Crop yield is a standard measurement of agricultural productivity that abstracts from deflation and output aggregation issues. However, it gives no information about whether changes in agricultural productivity are generated by changes in inputs or in total factor productivity, A. In all cases, I estimate an OLS regression that includes controls for farmers and fixed effects. As expected, the results are negative, suggesting again that the effect of oil spills on agricultural productivity is negative and significant.

Spatial disaggregation

Recall that I consider areas within 5 kilometers of oil spills as being hit harder.[48] I now disaggregate the effects by distances between oil spills and farming plots. Specifically, I focus on how spatial proximity to oil spills affects the extent of their effect. To that end, I construct indicator variables for the geographical distance between the reported enumeration area and the closest oil spill. Thus, I replace $O_{e,t}$ by a linear spline of the main variable included in each distance bracket b.

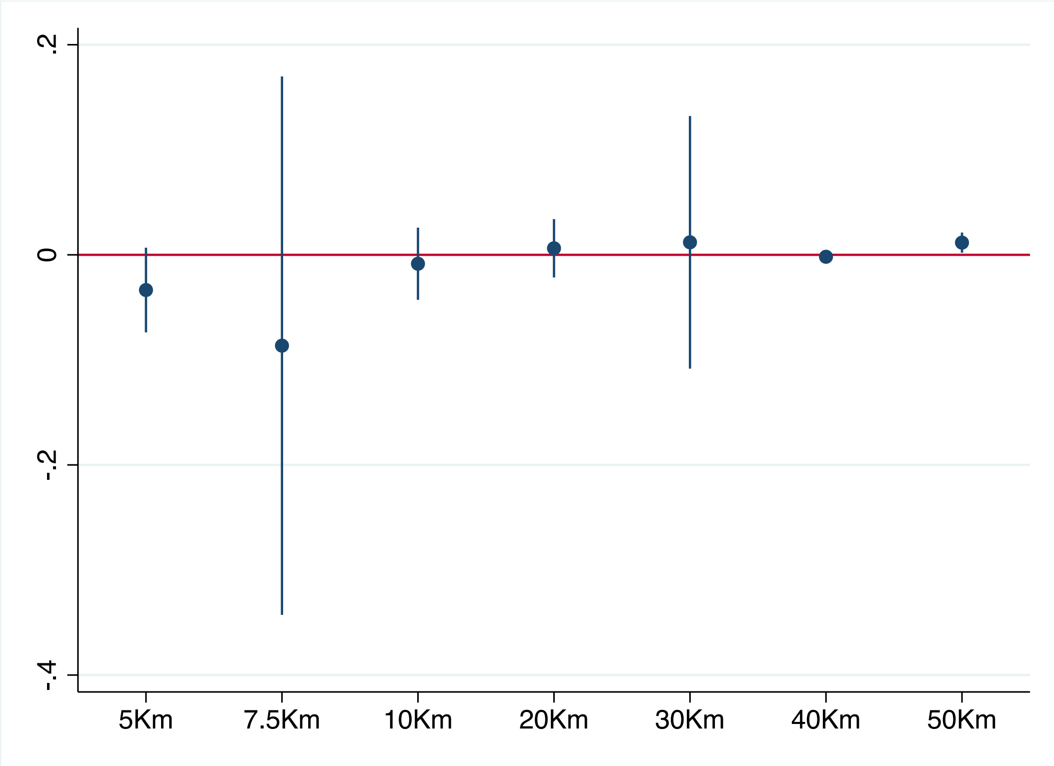
In particular, it is replaced by: $\sum_b \gamma^{p,k} \sum_{n=0}^{a_t} exp^{-n} * Total\_oilspill_{e,t-n}^{p,k}$. This refers to the sum total of oil spills close to enumeration area e, within the distance brackets with lower and upper limit p, and k, respectively,[49] allowing for previous total oil spills in exponential decay. The estimates of $\gamma^{p,k}$ are presented in Table C.7 and Figure 4.3.

[47] The impact is computed as marginal effects as follows. It is given by the standard deviation times the estimated coefficient multiplied by 100.

[48] Remember that the effect of pollution is located in places near oil spills, although it could spread through water and filtration into the ground through rivers, and by air through the fires caused by oil spills.

[49] The distances are the following: 0-5km, 5-7.5km, 7.5-10km, 10-20km, 20-30km, 30-40km, 40-50km.

Figure 4.3: The Effect of Oil-Spill Pollution on Agricultural Productivity measured in Distances from Oil Spills.



Notes: This figure shows the estimates of $\gamma^{p,k}$ for the following values of p and k: 0-5km, 5-7.5km, 7.5-10km, 10-20km, 20-30km, 30-40km, 40-50km. Circles represent point estimates, while lines indicate the 95 percent confidence interval.

The effect of oil spills on total agricultural productivity is greatest for oil spills that occurred less than 7.5 km from the cluster location. The loss of productivity becomes smaller and positive in locations more than 10km from an oil spill. However, the confidence intervals are large, given that the number of enumeration areas considered is much lower for each individual treatment than for the combined treatment. Because of the larger decrease in total agricultural productivity in the 5km to 7.5 km interval,[50] I also include enumeration areas up to 7.5 km away as a focus for my treatment. I present the results in Table C.8 in the Appendix C. The table is organized in the same way as Table 4.2. The results show that the effect of cumulative, persistent oil pollution on locations within 7.5 km are still significant in most cases. However, the effect is not so

[50] Columns 1 to 4 of Table C.7 show a large decrease in total agricultural productivity in areas between 5 and 7.5 km away, but that difference disappears once additional variables are introduced into the model.

strong as the previous choice. This could also be due to the random displacement of 1% of clusters, so I take this as a validation of the idea that I should focus on locations within 5 km of oil spills.[51] I repeat the exercise in Table C.9 with locations 10, 20, 30, 40, and 50 km from oil spills. Surprisingly, I find that the effect is again negative and significant only at locations up to 30 km from oil spills. Thus, these results should be interpreted with caution because most oil spills occur closer to wetland areas, and the oil spilled could flush over the surface of the water and affect large areas. The design of the analysis with distanced buffer zones around oil spills may not be the best choice, and other types of analysis such as the closest household to oil spills along river courses could be studied.

4.4.2 Robustness

Additional Control Variables

Table 4.3 presents several checks on the robustness of the main model. First, following Benjamin (1992), I introduce variables to control for additional heterogeneity that could bias my results. First, I estimate OLS without land and labor variables but including controls for whether a farm uses fertilizers, pesticides, herbicides, and improved seeds. The prices of these inputs have a significant effect on labor demand, suggesting that they could be a substitute for this input (Benjamin, 1992). In Column 2 I also reintroduce the main input variables. Column 3 expands these specifications by adding an array of heterogenous trends to the enumeration area level. Specifically, I add indicators of distance trends (nearest federal road, nearest major market, border post on the main road, major towns, distance to the capital of the state of residence). In column 4 I also introduce variables that affect total productivity and could capture other confounding factors for productivity and quality of plots. In particular, I use mean temperature and rainfall, rooting, slope, nutrient retention, excess salt, oxygen supply to roots, toxicity, and workability. These last characteristics are important to control for the quality of plots independently of oil-spill shocks. All my results show that the

[51] I do likewise with locations within 10 km. The results are not significant in any specification. These additional tables are available on request.

negative effect of cumulative oil-spill pollution plus real agricultural production is still significant when possible confounding factors are included.[52]

Alternative Measurements of Oil Pollution

As mentioned above, my oil pollution measurement is based on the hypothesis that the impact of pollution on agricultural productivity is greater in the present crop season. The variable is also cumulative and persistent, although it fades over time with exponential decay. I also use the total number of oil spills rather than the estimated quantity of oil spilt in terms of barrels lost to formulate my proxy of cumulative, persistent oil pollution. My findings, however, may be affected by these choices. Therefore, as an additional robustness check, I examine the extent to which the above results depend on the definition of oil spill pollution used to construct the main variable in the model.

First, I consider the three additional specifications for my function $g(n)$, in order to formulate $O_{e,t}$, present in the above section. Figure C.8 and Table C.11 in the Appendix C present the results for each additional measure. As can be seen, all results are negative and significant in OLS estimates on the agricultural output. Results show that the consequences of oil pollution are greater during the crop seasons for each wave. However, the effect is also persistent over time.

As a second approach, I reformulate all the oil pollution proxies used[53] with the estimated quantity of oil split, measured in barrels.[54] Figure C.9 and Table C.12 present

[52] In the Appendix C, I present the results using a 2SLS estimator. The results are very similar to the OLS estimation. See Table C.10.

[53] Recall that the volume of oil lost is an important indicator of environmental damage, but one third of the data for the variable is missing, which could bias my results.

[54] Specifically, the cumulative oil pollution proxy is formulated as follows:

$$O_{e,t} = \sum_{n=0}^{a_t} g(n) * Total\_estimated\_quantity\_barrels_{e,t-n} (4.5)$$

where $Total\_estimated\_quantity\_barrels_{e,t-n}$ is the estimated quantity number of barrels spills close to enumeration area e, t is the year of the wave, n is the number of years before each wave, and a_t is total number of years after each wave. For this variable, $g(n) = exp^{-n}$. In addition, I construct the following oil pollution measurements: Volumen of OilSpill (barrels) measures the estimated number of barrels lost nearby a location in the year of each wave. Thus, $g(n) = \begin{cases} 1 & \text{si } n = 0 \\ 0 & \text{si } n > 0 \end{cases}$. FCum_Volumen of OilSpill

Table 4.3: Additional checks

VARIABLES	Ln Agricultural Output				
	(1)	(2)	(3)	(4)	(5)
Cumulative_OilSpill	-0.0249*	-0.0238***	-0.0260***	-0.0224***	-0.0244***
	(0.013)	(0.006)	(0.006)	(0.007)	(0.007)
LnLand		0.2466***	0.2459***	0.2566***	0.2463***
		(0.024)	(0.024)	(0.024)	(0.024)
Lnlabor_days		0.1904***	0.1911***	0.1978***	0.1876***
		(0.025)	(0.025)	(0.024)	(0.024)
Fertilizers	0.3272***	0.2611***	0.2638***		0.2734***
	(0.079)	(0.076)	(0.075)		(0.074)
Pesticides	0.3404***	0.2196***	0.2156***		0.2102***
	(0.069)	(0.066)	(0.067)		(0.066)
Herbicides	0.1845*	0.0955	0.1067		0.1099
	(0.099)	(0.095)	(0.095)		(0.094)
Improved_Seeds	0.2547	0.1516	0.1612		0.1496
	(0.353)	(0.274)	(0.274)		(0.272)
Rooting				0.4526*	0.4450*
				(0.262)	(0.248)
Oxygen to roots				-0.0432	-0.0149
				(0.191)	(0.195)
Toxicity				0.5825	0.3611
				(0.548)	(0.558)
Excess salt				-0.5637	-0.4103
				(0.469)	(0.481)
Workability				-0.4470*	-0.4433*
				(0.246)	(0.237)
Nutrient_Retention				0.2565	0.2816
				(0.253)	(0.248)
Nutrient_Availability				-0.2581	-0.2556
				(0.222)	(0.218)
Mean temperature				0.0137	0.0173
				(0.015)	(0.015)
Mean rainfall				-0.0001	0.0001
				(0.000)	(0.000)
Slope				0.0123	0.0103
				(0.017)	(0.017)
Estimation	OLS	OLS	OLS	OLS	OLS
Observations	6324	6076	6076	6130	6076
R-squared	0.618	0.643	0.643	0.641	0.644
Waves dummies	YES	YES	YES	YES	YES
LGA fixed effects	YES	YES	YES	YES	YES

Notes: Robust standard errors are in parentheses. Standard errors are clustered at LGA level. All regressions include a dummy for being within 5 kilometers of an oil spill. Controls for farmers are as follows: columns 1 and 2 show age of head of household and literacy (an indicator of whether a household owns its farm plot). Columns 3 to 5 show indicators from time trends with distances to federal road, main towns, main markets, states capitals, and border posts on the main road. Significance levels are denoted as follows *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

the estimation results with different measurements of oil pollution based on this variable. In qualitative terms, the results are quite similar to those presented in Figure C.8 and Table C.11. The effect of cumulative oil pollution on both agricultural production and crop yields is negative in all regressions. However, if I only consider the estimated number of barrels lost in the year of each wave, the variable is insignificant in all cases.

4.5 Possible Confounders and Alternative Explanations

I interpret the above findings as a credible channel through which oil-spill pollution has affected agricultural productivity. In this section, I explore two possible confounders and four plausible alternative explanations.

4.5.1 Possible Confounders

I test whether the loss of productivity could be caused by events in just one part of the country. The General Household Survey divides Nigeria into six geopolitical zones.[55] In all zones, surveys report enumeration areas affected by oil-spill events. In the Niger Delta area there could be events linked to oil operations and extractions that drive this loss of productivity but are not exclusively oil-spills per se. [56] Moreover, violent events could also lead to a loss of agricultural output, affecting both agricultural total factor productivity and labor use. Specifically, I take the approach in Bruederle and Hodler (2019) by considering cluster locations within 25 km of conflict events that involve at least one fatality during the period.[57]

First, I rerun my main regression six times dropping these geographical zones one by one. Columns 1 to 6 in Table C.14 and Figure C.11 present the coefficient estimates. My oil spill pollution measurement remains negative and statistically significant in five

(barrels) measures cumulative oil spills that persist for only five years, $g(n) = \begin{cases} exp^{-n} & \text{si } n = 0, 1, \ldots, 5 \\ 0 & \text{si } n > 5 \end{cases}$. TCum_Volumen of OilSpil (barrels) is the total estimated number of barrels spilt near locations up to the last day of the harvest survey for each wave, g(n)=1.

[55]Recall that Figure C.2 in the Appendix C gives a map of Nigeria showing its boundaries and geopolitical zones.

[56]Figure C.10 in the Appendix C gives a map of the Niger Delta region.

[57]Figure C.12 in the Appendix C gives a map of conflicts and buffer zones within 25 km of conflicts.

specifications, the exception being when I exclude the South-South zone, which covers most of the Niger Delta. Column 7 in Table C.14 shows the results when I restrict the data to just the Niger Delta area. The effect of oil pollution there is greater than when I analyze oil spills throughout the country.

These results may indicate that productivity losses could be driven by events in one specific zone. However, this interpretation should be taken with caution. The percentage of farmers who have suffered an oil-spill event is around 25% in the Niger Delta, but just 4% elsewhere. To clarify these results, I also conduct an additional test to examine whether oil spills outside the Niger Delta area have not impacted agricultural output. I address this issue by relaxing the baseline specification and comparing the effects of oil spills on agricultural productivity in and outside the Niger Delta region. [58] The results in column 8 of Table C.14 and in Figure 4.4, confirm that oil spills pollution affects both the Niger Delta and other regions. However, the effect is greater in the Niger Delta area, where both the number and the persistence of oil spills are higher.[59]

Second, I explore whether my results could be driven by violent conflicts. 91 percent of the enumeration areas have suffered both oil spills and violent conflict. Columns 1 and 2 of Table C.15 show the figures for oil-spill pollution with the database constrained to conflict areas and non-conflict areas, respectively.[60] In both estimates, the results are negative and significant, confirming that oil-spill pollution is a channel that reduces agricultural productivity. Column 3 of Table C.15 estimates the main specification in the same way as column 8 of Table C.14, to compare the effects of oil-spill pollution in conflict and non-conflict areas. The result, which is also presented in Figure 4.4, shows that the effect of cumulative oil-spill pollution is far greater for farms outside

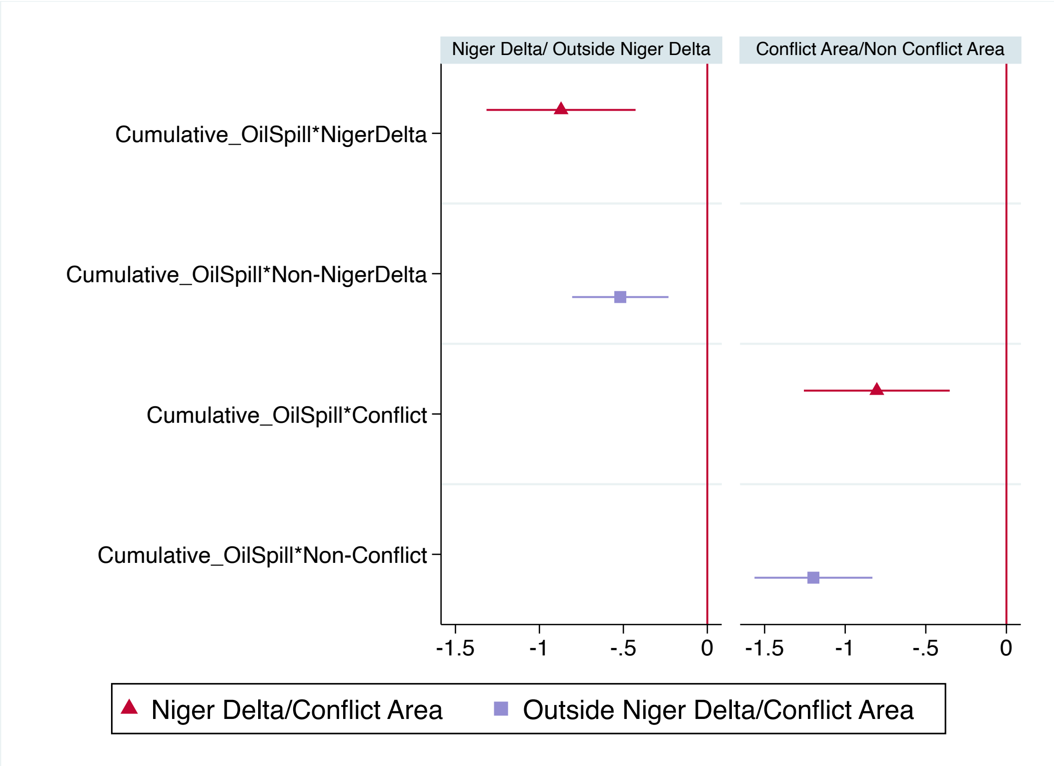
[58]To that end, I estimate my model with panel data from wave 1 to wave 3, which enables me to control for enumeration area time trends in the main specification. The inclusion of enumeration area time trends enables me to check that local economic, social or political developments are not driving the consequences of this difference between locations. Recall that I use a repeated cross-section in my analysis because longitudinal weight, which includes wave 4, is not currently available, which means that I cannot apply enumeration area time trends.

[59]Column 8 also displays the p-value of the test of equivalence.

[60]In both estimations, I decided to drop the North-East geographical zone because the Boko Haram crisis, which is located in this area, could bias the results. Boko Haram, led by Abubakar Shekau, is West Africa's most active and lethal actor. Since 2009, events involving it have numbered more than 2,350 and it has been linked to more than 27,000 fatalities. See also Figure C.12. For more information, see the ACLED website: https://acleddata.com/crisis-profile/boko-haram-crisis/.

conflict areas. This difference is however not statistically significant at 5%.[61] I therefore conclude that loss of total agricultural productivity in farms close to oil spills is not only a result of violent conflict.

Figure 4.4: Results for possible confounders: Niger Delta area and Violent Events.



Notes: The left panel shows the coefficient estimates from a linear regression of agricultural output on the interaction terms: $Cumulative\_OilSpill * NigerDelta\_area$, and $Cumulative\_OilSpill * Non - NigerDelta\_area$, controlling for LGAs, year time effects and ea-specific time trends. The right panel shows the coefficient estimates from a linear regression of the agricultural output on the interactions terms: $Cumulative\_OilSpill * Conflict\_area$, and $Cumulative\_OilSpill * Non - Conflict\_area$, controlling for LGAs and year fixed effects and ea-specific time trendss. The sample is the same as in the main specification (Table 4.2, column (4)). Geometric figures represent point estimates, while the horizontal lines represent 95% confidence intervals. Standard errors are adjusted for clustering at the LGAs level.

4.5.2 Alternative Explanations

My next step is to consider alternative explanations for the drop in total factor productivity following the approach in Aragón and Rud (2016). As mentioned above,

[61] Column 3 also displays the p-value of the test of equivalence.

oil and gas companies may demand local inputs (land or labor) for oil operations. For example, extractive companies could appropriate farmland to build additional infrastructures. In my estimations, I disregard all households that have been displaced. It is not possible to determine why these families decided to migrate, so farm reallocation could be a reason. Thus, this is not a plausible channel for explaining the drop in agricultural output.

Second, the fall in agricultural productivity might merely reflect changes in the composition of agricultural workers. For example, if the effect of oil pollution is permanent, members of the household could look for additional income by working in other sectors. Thus, Table 4.4 shows whether oil-spills are related to changes in various perceptible population characteristics. Columns 1 and 2 look at the probability of a working-age individual (male or female) being employed, semi-employed or hired in domestic production. Column 3 examines the probability of a worker being employed in agriculture. I would expect a negative correlation if there is an occupational shift towards non-agriculture activities. Columns 4 and 5 look at the demographics of agricultural workers and short-term mobility. Column 4 shows the probability of a worker being a prime-age male (20-40 years), while column 5 proxies the variable of migration with an indicator of whether any member of a household has been away for more than 30 days. Finally, columns 6 and 7 examine approximate measurements of the human capital of agricultural workers, such as literacy and having completed secondary school. These last measurements are informative because I am assuming that farming ability is positively correlated with education level. In Table 4.2 literacy is associated with an increase in total factor productivity and agricultural output. However, in Table 4.4, I find no significant evidence of any change in population characteristics except in the first and the fourth columns at the 10% level.

Another alternative reason that may explain a drop in agricultural productivity is related to weak property rights in Nigeria and the Land Use Act of 1978. The LUA replaced the previous plural land tenure system in Nigeria, with the idea of bringing consistency to the Nigerian land system. However, the risk of expropriation did not

Table 4.4: Population Characteristics

VARIABLES	AnyWork	AnyWork	Works in agriculture	Male_prime_age	Migration	Literacy	Secondary
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Cumulative_OilSpill	-0.0058*	0.0056	-0.0036	0.0278*	-0.0184	-0.0220	-0.0138
	(0.003)	(0.005)	(0.003)	(0.015)	(0.018)	(0.016)	(0.028)
Sample	Males in working age	Female in working age	All workers	Agricultural workers	Agricultural workers	Agricultural workers	Agricultural workers
Estimation	OLS	OLS	OLS	OLS	OLS	OLS	OLS
Observations	16878	18204	35112	6976	11728	11776	7399
R-squared	0.428	0.323	0.293	0.300	0.093	0.245	0.152
Waves dummies	YES	YES	YES	YES	YES	YES	YES
LGA fixed effects	YES	YES	YES	YES	YES	YES	YES

Notes: Robust standard errors are shown in parentheses. Standard errors are clustered at LGA level. All regressions include a dummy for being within 5 kilometers of an oil spills, an indicator or ecological zone and urban area. "Any Work" is a dummy variable that takes a value of one if an individual (male or female) is employed, semi-employed or hired in domestic production and 0 otherwise. Working age is between 15-65 years. "Works in agriculture" is a dummy with a value of one if an individual works in agriculture as a producer or laborer and 0 otherwise. "Male of prime age" is a dummy that takes a value of one if an individual is a male between 20 and 40 years old. "Migration" is a dummy variable with a value of one if any member of a family has been away for more than 30 days and 0 otherwise. "Literacy" is a dummy denoting whether an individual has literacy skills. "Secondary" is a dummy variable that denotes whether an individual has completed secondary schooling. Farmer controls include: age of head of household and literacy, and an indicator of whether the household owns its farm plot. Columns 1 to 3 include additional controls: age, age^2, literacy, and household size. Significance is denoted as follows: *** p<0.01, ** p<0.05, * p<0.1.

disappear under this legislation, and failure to provide compensation for oil pipeline failures is an important issue in this area. Thus, I first check whether there is a change in land ownership to examine property rights. Households could make less agricultural investments in rented farms. Moreover, farmers who have suffered oil spills before or who are located close to pipelines could use fertilizers or improved seed to minimize the effects of oil-spill pollution.

Finally, other channels could also be important in accounting for falls in agricultural output. For instance, a local oil operation boom may change the composition of workers, and the non-farming sector is also gaining significance in Nigeria (for example, in the South West region household enterprises account for half of all jobs (World Bank, 2015)). I am unable to examine the first channel directly due to lack of data, but I analyze the second by looking at whether any member of the family owns or manages a non-farm enterprise at least one year before the post-harvest visit for each wave.

Table 4.5 shows the results. Firstly, I find that changes in land ownership are concentrated significantly in locations near oil spills. Thus, there could be a risk of expropriation in locations near pipelines, which could partly explain lower agricultural productivity. Concerning agricultural practices, I find a significant increase in the use of fertilizers that may suggest actions taken by farmers to offset the negative effects of oil pollution on land. However, this contrasts with my finding that the coefficient

Table 4.5: Agriculture Land Tenure and Practices. Small Business

VARIABLES	Owns_farm (1)	Fertilizers (2)	Improved_Seeds (3)	Own_Business (4)
Cumulative_OilSpill	-0.0141***	0.0025**	-0.0007*	-0.0034
	(0.002)	(0.001)	(0.000)	(0.005)
Observations	6704	6340	6328	6369
R-squared	0.304	0.569	0.393	0.266
Waves dummies	YES	YES	YES	YES
LGA fixed effects	YES	YES	YES	YES

Notes: Robust standard errors are shown in parentheses. Standard errors are clustered at LGA level. All regressions include a dummy for being 5 kilometers from an oil spill. "Owns_farm" is a dummy that takes value of one if the household owns land and 0 otherwise. "Fertilizers" and "Improved_Seeds" are dummies that take a value of one if farmers use chemical fertilizers or improved seeds and 0 otherwise. "Own_ Business" is a dummy with a value of one if any member of the household owns or manages a non-farm enterprise and 0 otherwise. Farmer controls in columns 2, 3, and 4 include the age of the head of landowning households, literacy, and an indicator of whether a household owns its land. Significance is denoted as follows: *** p<0.01, ** p<0.05, * p<0.1

for improved seeds is again negative. Finally, I find no change in non-farm businesses, suggesting that there is no incentive to make additional efforts outside the farm in the treatment group.

The findings discussed above are far from conclusive, but they suggest that oil-spill pollution could be a plausible channel for explaining the decline in agricultural productivity in locations near oil spills. The effects of oil-spill pollution are found to be very local at first approximation, and the pollution caused by spills may explain this drop well. Authors such as Bruederle and Holder (2019) also remark on the significance of oil spills in the loss of health among children and adults. These findings are closely related to a drop in labor productivity.

4.6 Mechanisms

Section 2, above describes the mechanisms by which oil-spill pollution affects the total agricultural productivity factor. In particular, I consider three plausible channels: First, oil-spill pollution affects crop yields and health directly. Second, oil pollution deteriorates the quality of the soil and hence affects agricultural output. Third, oil spills affect human health, and hence labor productivity. In this section, following Aragón and Rud (2016), I discuss these arguments with the following augmented Cobb-Douglas production function:

$$Y = q_C(q_X X)^{\alpha}(q_L L)^{\beta} \tag{4.6}$$

where Y is agricultural output and X and L are the observable quantities of land and labor. q_X and q_L are input-specific quantity shifters, which capture factors such as quality of soil and labor productivity. q_C captures all other unobservable factors such as the crop health and yields. Thus, as analyzed above, oil-spill pollution might affect any of these factors.

In this framework, total factor productivity $A = q_C q_X^{\alpha} q_L^{\beta}$. That is the residual that I observe when I estimate agricultural output. My empirical analysis shows that the effect of oil spills reduces A but, as Aragón and Rud (2016) pointed out "[..]with the data at hand we cannot identify its effect on each component as this would require data on quality of soil, crop's health and labor productivity". Previous studies have demonstrated that oil pollution has a significant influence on soil properties and crop growth (Uquetan et al. 2017). Studies in the Niger Delta area find high prevalence rates for symptoms in human heath which are associated with oil spills in other parts of the world, including abnormalities in hematologic, hepatic, respiratory, renal, and neurologic functions (Nriagu, 2011). In any case, I can assume that not all the reduction in A is driven by a drop in labor productivity, q_L, but I cannot then identify the effects on soil quality or crop health, so I follow Aragón and Rud (2016); and conduct the same exercises that they do to assess the impact of pollution on labor productivity with additional tests.

First, I examine worker health indicators. I use self-reported data on the incidence of illness and cessation of usual activities from the Nigerian GHS-Panel data[62] to examine

[62] Specifically, the questions on household surveys are the following:

1. During the last four weeks, have you suffered any illness or injury?

2. For how many days did you stop your usual activities?

In both cases, I center on illness, not injury.

the link between these health measurements and my main oil pollution variable. I focus on working-age individuals (15-65) and splits between urban and rural populations.

Table 4.6: Oil Spill Pollution and Self-reported Illness

Variable	Ill in previous four weeks			Ln (Number of days off work)		
	(1)	(2)	(3)	(4)	(5)	(6)
Cumulative_OilSpill	-0.0062	-0.0092	-0.0006	-0.0017	-0.0034	-0.0026
	(0.005)	(0.006)	(0.004)	(0.003)	(0.003)	(0.007)
Sample	All	Urban	Rural	All	Urban	Rural
Observations	36675	9498	26196	23001	5916	16491
R-squared	0.070	0.055	0.080	0.225	0.178	0.252
Waves dummies	YES	YES	YES	YES	YES	YES
LGA fixed effects	YES	YES	YES	YES	YES	YES

Notes: Robust standard errors are shown in parentheses. Standard errors are clustered at LGA level. All regressions include a dummy for being 5 kilometers from an oil spill, and individual controls such as age, age^2, gender, an indicator of ecological zone and rural area. "Ill in previous four weeks" is an indicator that takes a value of 1 if an individual reports being ill during the last four weeks and 0 otherwise. This does not include injures. "Ln (Number of days off work)" is the log of number of days than an individual reports having ceased his/her usual activity. Significance is denoted as follows *** p<0.01, ** p<0.05, * p<0.1

Table 4.6 displays the results. In no case is there any evidence of an increase in the probability of being ill, or in the length of time for which activities are halted. I repeat the analysis with the total oil spills in the year of the wave, given that the survey reports short-term questions. Table C.16 in the Appendix C shows the results. In this case, column 3 reveals a positive link between being ill and oil-spill pollution among workers in rural areas. Thus, a spill during the year may affect workers in rural areas, reducing their health and hence their labor productivity. This result is consistent with those of Bruederle and Hodler, 2019.

Second, I also examine the effect of oil-spill pollution on non-agricultural urban workers through the total number of hours worked and income from employment. If the effect of oil-spill pollution is transmitted through a reduction in labor productivity, drops in these variables could be observed. This group includes both employed and self-employed workers, and I assume the following: first, labor demand for urban workers depends on their productivity; and second, oil operations arising from oil spills neither increase labor demand in urban areas nor affect the urban labor supply.

These last assumptions are plausible in the Nigerian employment marker. Given the capital-intensive nature of extractive sectors, their link with the rest of the economy is small, as is their contribution to job creation. Indirect jobs tend to be high-value-added jobs in the main urban areas, but this is probably not related to the issue at hand. (World Bank, 2015).

Table 4.7: Oil Spill Pollution and labor Outcomes for urban workers

Variable	Ln(Total hours worked)		Ln(Real Employment Income)	
	(1)	(2)	(3)	(4)
Cumulative_OilSpill	-0.0054	-0.0042	-0.0509***	-0.0552***
	(0.004)	(0.003)	(0.015)	(0.015)
Sample	All urban workers	Urban non-agric. workers	All urban workers	Urban non-agric. workers
Observations	4782	4369	2846	2788
R-squared	0.240	0.130	0.391	0.381
Waves dummies	YES	YES	YES	YES
LGA fixed effects	YES	YES	YES	YES

Notes: : Robust standard errors are shown in parentheses. Standard errors are clustered at LGA level. All regressions include a dummy for being 5 kilometers from an oil spill and industrial dummies. Columns 1 and 2 include individual controls such as age,age^2, literacy, and household size. Columns 3 and 4 add additional controls in the form of the log of the total number of hours worked. All regressions exclude oil industry workers. Significance is denoted as follows *** p<0.01, ** p<0.05, * p<0.1

Table 4.7 presents the results. Although the no significant change is observed in the number of hours, there is a significant drop in income from employment that relates to a loss of labor productivity. In particular, an increase of one standard deviation in cumulative oil-spill pollution is associated with a reduction of around 11% in employment income in urban areas less than 5km from oil spills. I repeat the estimations in Table C.17 with the oil-spill pollution variable during each wave (Oil spill). In this case there is clear evidence in both the total number of hours and employment income that confirms the link between the presence of oil spills near the locations and a drop in labor productivity.

4.7 Conclusions

This paper examines how oil-spill pollution affects total productivity and agricultural output. This is a type of externality that polluting industries impose on agricultural zones. Using geo-referenced data from the Nigerian Oil Spill Monitor and The Nigerian General Household Survey (GHS), I apply a difference-in-difference approach following the methodology in Aragón and Rud (2016). Previous literature has found that oil spills mean high levels of pollution in the affected regions, but that literature has not so far considered the cumulative, long-lasting effects of oil pollution on agricultural output through total factor productivity. I build up a novel variable that reflects this effect and obtain many interesting results. First, I find evidence that onshore oil spills near certain locations reduce their total factor productivity and agricultural output compared to other locations in the same LGAs but further from the spills. The effect for farmers is economically significant: there is a decline of approximately 2.73% in total factor productivity when an oil spill occurs nearby. Second, I show evidence that the effect does not disappear in the period studied. The empirical evidence suggests that the loss of productivity is also significant when only oil spills occurring in the year of the relevant wave are considered, but consequences are also persistent over time. Third, I find evidence that farmers are less likely to own their own land, and the drop in labor productivity leads to a decrease in both the health of workers in rural areas and employment income in urban areas. The number of oil spills recorded by the Nigerian Oil Monitor has fallen since 2014, but the results still indicate that it is necessary to pay attention to oil spills and their effects on nearby farmland. On the policy side, these results could be interpreted in terms of a need not only to prevent new oil spills but also to stress the effective clean-up of contaminated land, including surrounding environments. A system of compensation with community hosts for the economic losses suffered by farmers close to oil-spills is also required. The effects are long-lasting in time, so the system should offset these losses.

The main limitation of this paper is that I cannot exactly assess the relative importance of the various mechanisms through which oil-spill pollution may affect productivity, such as changes in soil quality. However, previous literature confirms effects on crop health. Moreover, although I find evidence of a decrease in labor productivity, I cannot properly estimate the effect on the input competition channel or quantify the changes in input uses because of data limitations. These issues lie beyond the scope of this study, but examining them is a matter for further research. Distance is a logical indicator of the damage to soil quality caused by oil spills. However, most pipelines are very close to wetlands and oil pollution effects may spread to farms through rivers. In this case, an alternative empirical strategy based on the distance from oil spills to households along river courses may improve the study. Further research could consider such an analysis.

Chapter 5

Conclusions

This thesis applies novel empirical methodologies to analyze several causes and consequences of conflict. A key aspect of the research is the considering of spatial patterns and the use of geo-located data to find the direction of causality. This framework helps to understand the processes underlying globalization and its effect on conflict, with a view to finding policy tools to deal with this challenge. The main conclusions of the studies reported are provided at the end of each chapter, but in this section, I review the stand-out results from each chapter and describe future research approaches.

Chapter 2 addresses the potential endogeneity of globalization variables, which is particularly important in establishing a causal link between globalization and civil conflict. Unlike previous literature, which relates several dimensions of globalization and conflict, my co-adviser Roberto Ezcurra and I have sought to address the inherent causality between the two phenomena. To that end, we introduce country fixed effects to tackle omitted variables. However, finding instrumental variables for each dimension of globalization to resolve the endogeneity issue was not an easy task. Once we observed how trade and financial flows, cultural exchanges, and political issues spread around the world, we decided that these phenomena followed a spatial pattern. Thus, each dimension of the KOF index is related to the neighboring one, following the theories of geography and spatial interdependence from theoretical models of the so-called "New Economic Geography" (Krugman, 1998). This led us to create instrumental variables that associate each index of globalization of a country with the globalization indexes for the rest of the countries, applying an exogenous geographical distance matrix between them. These variables (the KOF index and the variable for each dimension) open up a way to resolve any endogeneity issue related to globalization.

One of the key implications of this chapter is that the non-statistical association between globalization and civil war does not necessarily imply that the processes of economic, social, or political globalization do not lead to conflict. Rather, it might mean that there is no direct link because of the complexity of the interactions between the different actors involved in the process. This conclusion drives us to wonder what factors might indirectly connect globalization to conflict. We thus consider two implications of our results: First, the need to isolate and quantify different transmission channels that could link the two phenomena; and second, the idea that country-level analysis might not be the best choice for studying certain causes of conflict. The results show that there is no direct association at country level. But, the effect could be local, and it could depend on factors such as spatial inequality, geography, ethnicity, cultural and historical issues, and the quality of governance, among others.

For these reasons, I decided to study the role of external commodity prices as a proxy of income shocks and their effect on conflict (which depends on ethnic characteristics) using a micro-level analysis. The novel use of geo-located data has given us the chance to apply the cell level to study conflict, which has ensured exogeneity to conflict events. Using this approach, we have been able to match several geo-referenced databases, thus providing a more detailed picture of the characteristics of each location.

The main contribution of Chapter 3, drawn up along with Fidel Pérez-Sebastián and Miguel Angel Campo-Bescós, is to argue that the effect of ethnicity on conflict is indirect. This proposition arose from the idea that the causes of conflict might not be homogeneous and might depend on local characteristics such as political and ethnic diversity. Several interesting conclusions emerge from the results of the chapter. For instance, after an income shock that leads to violence, discriminating between kinds of conflict is always preferable. We find it necessary to distinguish between organized armed-force conflict and non-organized violence to establish the correct mechanisms behind acts of violence. In addition, interaction with ethnic political variables leads us to suggest that weak governments are less able to benefit from the rebellion-repressing capability offered by positive income shocks. And the sense of grievance in some ethnic groups is certainly more important in their becoming temporary rioters than soldiers. From a policy perspective, these results hold the main lesson. We demonstrate that agricultural price fluctuations lead to conflict at local level. An agricultural price-stabilization mechanism might therefore needed, but addressing the right policy also depends on the nature of the ethnic diversity and the type of violence. In line with these findings, the analysis by Esteban and Ray (2017) shows that income inequality is closely attached to ethnic identity, particularly in sub-Saharan Africa. Following that approximation, ethnicity in our case acts indirectly in terms of how the distribution of capital gains and economic rents among the population after a positive shock could lead to conflict. Alesina (2016) points out that what it is most important for development is the economic differences between ethnic groups that coexist in the same country. This issue is more significant than the percentage of ethnic diversity in a given location. This chapter demonstrates that this conclusion can be extended to conflict at local level.

Finally, the case of Nigeria is noteworthy. Nigeria is an example of failing to convert oil windfalls into development. Oil exploration has also led to an increase in oil pollution in the country, especially in the Niger Delta area. Some ethnic groups located in this area have been particularly hard hit by the negative impact of pollution from both oil operations and oil spills. Oil spills constitute a major ecological disaster that has resulted in environmental, social, and economic problems. Most oil spills are caused by sabotage motivated by issues of self-determination, grievance protests over the dangerous impact of oil exploitation, and theft.

For these reasons, Chapter 4, examines the effect of oil spills on agricultural productivity. The aforementioned conflicts have impoverished farmers close to pipelines. The displacement of farmers from rural areas due to continuous environmental degradation has trapped a significant percentage of local inhabitants in cyclical poverty and penury. To determine the effect of oil spills on agricultural productivity, I also use novel geo-located data on oil spills and on the location of farmers within specific local government areas (LGAs). I apply a difference-in-difference methodology to properly identify the effect of oil spills on agricultural productivity. I consider all types of oil-spill events since their effect on agricultural productivity is indifferent to their causes. That said, most are caused by sabotage.

I find that the effects of oil spills on agricultural productivity are concentrated on farms less than 10 kilometers from the oil spills and are persistent over time. I also develop an oil-spills pollution measurement that takes into consideration both the number of oil spills at farms and their degradation in an exponential decay pattern. From a policy viewpoint, this result suggests that a policy for preventing new oil spills should be implemented and the need of effective clean-up of polluted land on both affected farms and surrounding lands must be stressed. A compensation formula in host communities affected by past and present oil spills is also needed. Given that most pipelines are close to wetlands, and with a view to finding a suitable radius of action around oil spills, future research could incorporate an empirical strategy based on the distance from oil spills to households along river courses.

Concerning future lines of research, finding ways to properly identify the role of income inequality in conflict might be a logical continuation of this dissertation. Future studies might consider the effect of spatial inequality on conflict, in particular using the new income inequality variable, e.g. the spatial Gini index per capita calculated with the average nighttime light emission from the DMSP-OLS Nighttime Lights Time Series dataset, and population data from the World Pop geospatial open database. This could be an area for future research into the link between inequality and conflict, using geo-localized data. Another relevant point that has been overlooked in most research on civil conflict is that conflicts are correlated in space and time. Internal conflicts and wars are likely to be contagious, given that refugee flows, poaching, disease, lawlessness, and the illicit trades in drugs, weapons, and minerals may generate spillover effects in regions close to conflict zones. These findings regarding the role of space suggest that such interdependence needs to be factored into the modeling process and that an explicit accounting for spatial effects is required, using spatial econometric models.

Understanding the causes and consequences of conflict is a task of first-order importance for development and environmental economists. This thesis contributes to this goal by presenting two specific examples of causes of conflict and a certain environmental consequence derived from violence with a view to facilitating appropriate political actions.

Appendix A

Appendix Chapter 1

Table A.1: Components of the KOF index of globalization.

Indices and Variables	*Weights*
Economic Globalization	*[36%]*
Actual flows	[50%]
Trade (percent of GDP)	(21%)
Foreign direct investment, stocks (percent of GDP)	(28%)
Portfolio investment (percent of GDP)	(24%)
Income payments to foreign nationals (percent of GDP)	(27%)
Restrictions	[50%]
Hidden import barriers	(24%)
Mean tariff rate	(27%)
Taxes on international trade (percent of current revenue)	(26%)
Capital account testrictions	(23%)
Social Globalization	*[37%]*
Data on personal contacts	[34%]
Telephone traffic	(25%)
Transfers (% of GDP)	(4%)
International tourism	(26%)
Foreign population (percent of total population)	(21%)
International letters (per capita)	(25%)
Data on information flows	[35%]
Internet users (per 1000 people)	(33%)
Television (per 1000 people)	(36%)
Trade in newspapers (percent of GDP)	(32%)
Data on cultural proximity	[31%]
Number of McDonald's restaurants (per capita)	(44%)
Number of Ikea (per capita)	(45%)
Trade in books (% of GDP)	(11%)
Political globalization	*[26%]*
Embassies in country	(25%)
Membership in international organizations	(28%)
Participation in UN Security Council Missions	(22%)
International treaties	(25%)

Source: http://globalization.kof.ethz.ch/

Table A.2: Correlation coefficients between the various dimensions of globalization.

	Overall globalization	Economic globalization	Social globalization	Political globalization
Overall globalization	1.000			
Economic globalization	0.858	1.000		
Social globalization	0.947	0.772	1.000	
Political globalization	0.587	0.218	0.417	1.000

Notes: Data for 148 countries in 2009. All the correlation coefficients are statistically significant at the 1% level.

Table A.3: Descriptive statistics.

Variable	Mean	Std. Dev.	Min	Max
Conflict incidence: PRIO25	0.17	0.38	0	1
Conflict incidence: PRIOCW	0.13	0.34	0	1
Conflict incidence: PRIOWAR	0.05	0.21	0	1
Conflict onset (PRIO25)	0.02	0.15	0	1
Overall globalization	47.18	18.26	12.26	92.84
Economic globalization	49.60	19.42	9.42	97.52
Social globalization	38.66	21.45	6.01	93.25
Political globalization	57.95	21.81	4.28	98.56
GDP per capita (log)	8.30	1.30	4.76	11.92
Economic growth	0.02	0.07	-0.97	0.80
Democracy	0.44	0.50	0	1
Anocracy	0.23	0.42	0	1
Natural resources	9.02	15.22	0	214.49
Overall globalization in neighbouring countries	42.33	13.68	8.66	83.82
Economic global. in neighbouring countries	46.55	14.09	14.92	86.25
Social globalization in neighbouring countries	36.42	14.30	8.62	80.45
Political globalization in neighbouring countries	49.25	14.90	7.15	89.35
Conflict in neighbouring countries	0.15	0.13	0.01	0.78

Table A.4: Robustness analysis: Effect of different groups of countries.

	FE-2SLS (1)	FE-2SLS (2)	FE-2SLS (3)	FE-2SLS (4)	FE-2SLS (5)	FE-2SLS (6)	FE-2SLS (7)	FE-2SLS (8)	FE-2SLS (9)	FE-2SLS (10)
Overall globalization	0.000					-0.003				
	(0.002)					(0.003)				
Economic globalization		0.002			0.006		-0.002			-0.009
		(0.002)			(0.010)		(0.002)			(0.016)
Social globalization			-0.000		-0.004			-0.002		0.006
			(0.002)		(0.007)			(0.002)		(0.013)
Political globalization				0.001	0.001				0.001	0.002
				(0.002)	(0.003)				(0.002)	(0.003)
GDP per capita (log)	0.041	0.025	0.044*	0.036	0.0382	0.03	0.013	0.029	0.015	-0.006
	(0.026)	(0.026)	(0.026)	(0.030)	(0.046)	(0.023)	(0.026)	(0.023)	(0.020)	(0.040)
Economic growth	-0.079	-0.059	-0.080	-0.082	-0.112	0.036	0.051	0.028	0.040	0.085
	(0.067)	(0.077)	(0.066)	(0.066)	(0.124)	(0.080)	(0.091)	(0.081)	(0.081)	(0.142)
Democracy	0.005	-0.002	0.005	0.002	-0.016	0.012	0.012	0.009	0.006	0.013
	(0.025)	(0.024)	(0.024)	(0.025)	(0.030)	(0.020)	(0.020)	(0.021)	(0.021)	(0.026)
Anocracy	0.039	0.036	0.039	0.038	0.031	0.048**	0.047**	0.045**	0.049**	0.048*
	(0.024)	(0.025)	(0.025)	(0.025)	(0.028)	(0.022)	(0.022)	(0.023)	(0.022)	(0.027)
Natural resources	-0.000	0.000	-0.001	-0.000	-0.000	-0.001	0.001	-0.001	-0.000	0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Omitted countries	Sub-Saharan Africa	Sub-Saharan Africa	Sub-Saharan Africa	Sub-Saharan Africa	Sub-Saharan Africa	Asia	Asia	Asia	Asia	Asia
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Root mean square error	0.180	0.178	0.179	0.180	0.181	0.203	0.200	0.203	0.350	0.210
Countries	114	100	114	114	100	132	120	132	133	120
Observations	3,325	3,067	3,325	3,325	3,067	4,145	3,838	4,145	4,165	3,838

Notes: The dependent variable is a binary variable that takes a value of one for conflicts with 25 or more battle-related deaths in a year, zero otherwise (Prio25). Robust standard errors clustered at the country level in parentheses. * Significant at 10% level, ** significant at 5% level, *** significant at 1% level.

Table A.4: Robustness analysis: Effect of different groups of countries (continuation).

	FE-2SLS (1)	FE-2SLS (2)	FE-2SLS (3)	FE-2SLS (4)	FE-2SLS (5)	FE-2SLS (6)	FE-2SLS (7)	FE-2SLS (8)	FE-2SLS (9)	FE-2SLS (10)
Overall globalization	-0.002					-0.008				
	(0.003)					(0.007)				
Economic globalization		0.000			0.058		-0.004			-0.103
		(0.002)			(0.427)		(0.007)			(2.800)
Social globalization			-0.003		-0.056			-0.006		0.102
			(0.002)		(0.405)			(0.005)		(2.864)
Political globalization				0.003	-0.021				0.001	-0.013
				(0.005)	(0.173)				(0.004)	(0.381)
GDP per capita (log)	0.013	-0.018	0.018	-0.198	-0.109	0.053	0.015	0.050	0.007	-0.066
	(0.021)	(0.020)	(0.021)	(5.620)	(0.519)	(0.037)	(0.029)	(0.035)	(0.036)	(1.056)
Economic growth	0.024	0.050	0.0156	-0.1019	0.0258	0.0329	0.0834	0.0225	0.0449	0.2311
	(0.068)	(0.094)	(0.068)	(3.810)	(0.301)	(0.071)	(0.098)	(0.073)	(0.073)	(2.202)
Democracy	0.004	-0.003	-0.002	-0.329	-0.086	0.004	0.002	-0.002	-0.005	0.050
	(0.021)	(0.020)	(0.020)	(9.396)	(0.216)	(0.023)	(0.024)	(0.022)	(0.024)	(0.747)
Anocracy	0.035	0.033	0.028	-0.120	0.003	0.041*	0.038*	0.036	0.042*	0.057
	(0.022)	(0.022)	(0.024)	(4.457)	(0.065)	(0.022)	(0.022)	(0.023)	(0.024)	(0.333)
Natural resources	-0.000	0.001	-0.001	0.003	0.003	-0.000	0.001	-0.000	-0.000	0.006
	(0.001)	(0.001)	(0.001)	(0.095)	(0.015)	(0.001)	(0.001)	(0.001)	(0.001)	(0.060)
Omitted countries	Latin America & Caribbean	Latin America & Caribbean	Latin America & Caribbean	Latin America & Caribbean	Latin America & Caribbean	High income countries	High-income countries	High-income countries	High-income countries	High-income countries
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Root mean square error	0.212	0.207	0.213	0.472	0.231	0.237	0.232	0.236	0.238	0.280
Countries	136	117	136	137	117	112	95	112	113	95
Observations	4,009	3,614	4,009	4,029	3,614	3,359	3,001	3,359	3,379	3,001

Notes: The dependent variable is a binary variable that takes a value of one for conflicts with 25 or more battle-related deaths in a year, zero otherwise (Prio25). Robust standard errors clustered at the country level in parentheses. * Significant at 10% level, ** significant at 5% level, *** significant at 1% level.

Table A.5: Robustness analysis: The impact of cross-border conflict spillovers (alternative definition).

	FE-OLS (1)	FE-2SLS (2)	FE-OLS (3)	FE-2SLS (4)	FE-OLS (5)	FE-2SLS (6)	FE-OLS (7)	FE-2SLS (8)	FE-OLS (9)	FE-2SLS (10))
Lagged conflict	0.597***	0.596***	0.618***	0.618***	0.597***	0.596***	0.597***	0.599***	0.618***	0.619***
	(0.039)	(0.039)	(0.040)	(0.040)	(0.039)	(0.039)	(0.038)	(0.039)	(0.040)	(0.042)
Overall globalization	-0.001	-0.002								
	(0.001)	(0.003)								
Economic globalization			-0.000	-0.000					-0.000	0.001
			(0.001)	(0.002)					(0.001)	(0.012)
Social globalization					-0.001	-0.002			-0.001	-0.004
					(0.001)	(0.002)			(0.001)	(0.012)
Political globalization							-0.000	0.001	-0.000	0.002
							(0.001)	(0.002)	(0.001)	(0.002)
GDP per capita (log)	0.029	0.032	0.017	0.017	0.030	0.033	0.024	0.020	0.022	0.015
	(0.018)	(0.022)	(0.022)	(0.024)	(0.019)	(0.022)	(0.018)	(0.021)	(0.022)	(0.042)
Economic growth	0.021	0.021	0.045	0.044	0.019	0.017	0.029	0.030	0.041	0.035
	(0.077)	(0.077)	(0.087)	(0.088)	(0.077)	(0.078)	(0.077)	(0.078)	(0.087)	(0.134)
Democracy	-0.007	-0.006	-0.008	-0.008	-0.008	-0.009	-0.008	-0.013	-0.009	-0.017
	(0.019)	(0.019)	(0.019)	(0.018)	(0.019)	(0.019)	(0.019)	(0.022)	(0.018)	(0.030)
Anocracy	0.031	0.030	0.030	0.031	0.029	0.028	0.031	0.028	0.028	0.025
	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)	(0.021)	(0.020)	(0.020)	(0.020)	(0.028)
Natural resources	-0.001	-0.001	0.001	0.001	-0.001	-0.001	-0.000	-0.000	0.001	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Conflict in neighbouring countries	0.160**	0.159**	0.144*	0.144*	0.160**	0.159**	0.162**	0.156*	0.144*	0.149
	(0.079)	(0.078)	(0.079)	(0.077)	(0.080)	(0.080)	(0.079)	(0.087)	(0.079)	(0.102)
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Root mean square error	0.205	0.205	0.200	0.200	0.205	0,205	0.206	0.206	0.200	0.200
Countries	158	158	138	138	158	158	159	159	138	138
Observations	4,494	4,494	4,097	4,097	4,494	4,494	4,511	4,511	4,097	4,097

Notes: The dependent variable is a binary variable that takes a value of one for conflicts with 25 or more battle-related deaths in a year, zero otherwise (Prio25). The variable 'Conflict in neighbouring countries' has been constructed as the average incidence of conflict in neighbouring countries over the last five years (see the main text for further details). Robust standard errors clustered at the country level in parentheses. * Significant at 10% level, ** significant at 5% level, *** significant at 1% level.

Table A.6: Robustness analysis: Alternative definitions of conflict incidence.

	FE-2SLS (1)	FE-2SLS (2)	FE-2SLS (3)	FE-2SLS (4)	FE-2SLS (5)	FE-2SLS (6)	FE-2SLS (7)	FE-2SLS (8)	FE-2SLS (9)	FE-2SLS (10)
Dependent variable	PRIOCW	PRIOCW	PRIOCW	PRIOCW	PRIOCW	PRIOWAR	PRIOWAR	PRIOWAR	PRIOWAR	PRIOWAR
Lagged conflict	0.715***	0.727***	0.715***	0.718***	0.726***	0.545***	0.559***	0.545***	0.543***	0.561***
	(0.034)	(0.035)	(0.034)	(0.033)	(0.035)	(0.045)	(0.046)	(0.045)	(0.044)	(0.046)
Overall globalization	-0.001					-0.001				
	(0.002)					(0.002)				
Economic globalization		-0.000			-0.004		-0.000			0.003
		(0.002)			(0.010)		(0.002)			(0.007)
Social globalization			-0.000		0.003			-0.001		-0.003
			(0.001)		(0.008)			(0.001)		(0.005)
Political globalization				0.000	0.001				0.000	0.000
				(0.002)	(0.002)				(0.001)	(0.001)
GDP per capita (log)	0.015	0.007	0.013	0.009	-0.011	0.013	0.011	0.012	0.006	0.022
	(0.015)	(0.016)	(0.015)	(0.013)	(0.033)	(0.010)	(0.014)	(0.010)	(0.009)	(0.022)
Economic growth	0.056	0.040	0.055	0.060	0.070	-0.001	-0.055	-0.004	0.002	-0.078
	(0.075)	(0.080)	(0.075)	(0.075)	(0.114)	(0.050)	(0.056)	(0.050)	(0.050)	(0.072)
Democracy	-0.001	-0.003	-0.002	-0.004	0.003	-0.003	-0.003	-0.004	-0.005	-0.010
	(0.012)	(0.012)	(0.013)	(0.013)	(0.022)	(0.012)	(0.012)	(0.011)	(0.012)	(0.019)
Anocracy	0.023*	0.018	0.024*	0.023*	0.022	0.005	0.007	0.004	0.006	0.003
	(0.013)	(0.014)	(0.014)	(0.013)	(0.017)	(0.012)	(0.013)	(0.012)	(0.013)	(0.014)
Natural resources	-0.000	0.001	-0.000	-0.000	0.001	-0.000	-0.000	-0.000	-0.000	-0.001
	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Root mean square error	0.154	0.152	0.154	0.154	0.153	0.146	0.148	0.146	0. 148	0.149
Countries	159	139	159	160	139	159	139	159	160	139
Observations	4,864	4,431	4,864	4,884	4,431	4,864	4,431	4,864	4,884	4,431

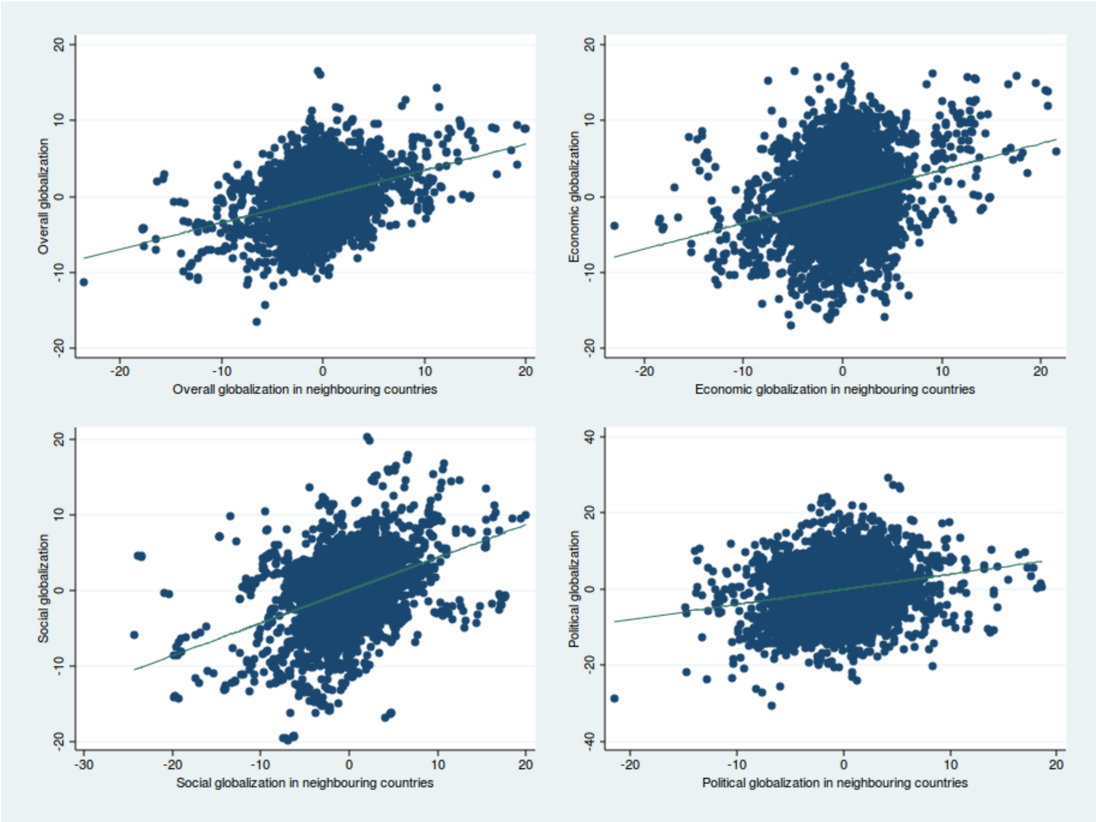
Notes: Robust standard errors clustered at the country level in parentheses. * Significant at 10% level, ** significant at 5% level, *** significant at 1% level.

Table A.7: Robustness analysis: Globalization and conflict onset.

	FE-2SLS (1)	FE-2SLS (2)	FE-2SLS (3)	FE-2SLS (4)	FE-2SLS (5)
Dependent variable	Onset	Onset	Onset	Onset	Onset
Overall globalization	-0.003				
	(0.002)				
Economic globalization		-0.001			0.010
		(0.001)			-0.012
Social globalization			-0.003*		-0.010
			(-0.001)		(0.010)
Political globalization				0.000	0.001
				(0.001)	(0.002)
GDP per capita (log)	0.024*	0.013	0.028**	0.011	0.054
	(0.012)	(0.013)	(0.013)	(0.009)	(0.044)
Economic growth	0.008	0.037	-0.002	0.008	-0.054
	(0.028)	(0.036)	(0.028)	(0.028)	(0.102)
Democracy	0.012	0.014	0.007	0.008	-0.012
	(0.011)	(0.011)	(0.011)	(0.011)	(0.03)
Anocracy	0.015	0.020*	0.010	0.018*	0.0061
	(0.011)	(0.011)	(0.012)	(0.011)	(0.019)
Natural resources	-0.000	0.001	-0.000	-0.000	-0.001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.002)
Country fixed effects	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes
Root mean square error	0.142	0.137	0.141	0.142	0.148
Countries	159	139	159	160	139
Observations	4,864	4,431	4,864	4,884	4,431

Notes: Robust standard errors clustered at the country level in parentheses. * Significant at 10% level, ** significant at 5% level, *** significant at 1% level.

Figure A.1: First stage regressions: Partial regression plots.



Appendix B

Appendix Chapter 2

B.1 Data Description and Sources

1.1 Structure of the dataset. Our baseline unit of analysis is a full grid of Africa divided into sub-national units of 0.5 x 0.5 grades latitude and longitude (which corresponds to a cell of roughly 55 x 55 kilometers at the equator). This is the result of intersecting grid cells provided by the PRIO-GRID[1] structure, with a map of the entire Africa and their national political borders provided by The Global Administrative Unit Layers (2010), a project from the United Nations Food and Agricultural Organization (FAO). The use of the PRIO-GRID allows us to easily include cell specific data from this dataset. All conflict events are aggregate at the level of the cell. Administrative boundaries are taken at the end of our sample period. The country which stands for the largest share of a cell's area is assigned to this cell.

1.2 Conflict events. We make use of two different datasets containing the geo-location of conflict events in Africa: the UCDP-Georeferenced Event Dataset (UCDP-GED), version 5.0 (Croicu and Sundberg, 2016), and the Armed Conflict Location and Event Dataset (ACLED Dataset) (Raleigh et al., 2017). These data cover different countries and time periods. The events are collected from various sources, including humanitarian agents, research publications, and local, regional or international press news. In each dataset the unit of observation is the event. They contain latitude and longitude information, and the precise day (in most cases) of conflict events. UCDP defines an event as an incident where armed force was used by an organised actor against another organized actor, or against civilians, resulting in at least 1 direct death at a specific location and a specific date. In addition, only events linkable to a UCDP/PRIO Armed Conflict (or State Conflict), a UCDP Non-State Conflict or a UCDP One-Sided Violence instance are included are recorded separately. Events are included for the entire period of consecutive years during which conflicts were active as long as at least one of those years have crossed the 25 battle related deaths threshold.

[1]http://www.prio.no/Data/PRIO-GRID/

Meanwhile, the ACLED Dataset registers “a range of violent and non-violent actions by political agents, including governments, rebels, militias, communal groups, political parties, rioters, protesters and civilians”. In a broader perspective, ACLED records violent activity both within and outside the context of a civil war. To that end, there is not specifically a battle-related deaths threshold.

More specifically, we consider the following dependent variables:

- **UCDP incidence.** We aggregate to the cell-year level, coding the variable as one if any conflict from UCDP data took place, zero otherwise.
- **ACLED riots.** We aggregate to the cell-year level, coding the variable as one if conflicts from ACLED data took place defined as “a protest [that] describes a non-violent, group public demonstration, often against a government institution”, and zero otherwise.
- **ACLED violence against civilians.** We aggregate to the cell-year level, coding the variable as one if conflicts from ACLED data took place defined as “violence against civilians [that] occurs when any armed/violent group attacks civilians”, and zero otherwise. “By definition, civilians are unarmed and not engaged in political violence. Rebels, governments, militias, rioters can all commit violence against civilians.”
- **ACLED battles.** We aggregate to the cell-year level, coding the variable as one if conflicts from ACLED data took place defined as “battle-no change of territory”, “battle-non-state actor overtakes territory” and “battle-government regains territory”, and zero otherwise.

1.3 Crop cover data.

- **Agricultural commodities: FAO-GAEZ.** Following the approximation of Berman and Couttenier (2015), we consider as our main crop database the FAO’s Global Agro-Ecological Zones (GAEZ). Specifically, the “GAEZ modeling framework for crop potential assessment using detailed agronomic-based knowledge to assess land suitability, potential attainable yields and potential production of crops for specified management assumptions and input levels, both for rain-fed and irrigated conditions". Suitability is defined as the percentage of potential production capacity that could be attained in each cell.

For our 18 crops, we have considered the data that corresponding to low input levels conditions. Which means that yields are based on the use of traditional ways of farming without any additional mechanical, chemical or irrigation methods (only rain-fed cases). The model is applied considering the average climate conditions of the baseline period 1961-1990. A cell is suitable for crop production if it could achieve at least 40% of its maximum capacity.

- **Alternative crop production database: M3 crops.** Data on the actual production of agricultural crops in each cell is drawn from the M3-Crops dataset by Monfreda et al. (2008).[2] Total production is the crop production in metric tons per hectare of a grid cell. We aggregate the raster information for production at the 5 arc minutes x 5 arc minutes resolution (about 9.2 km x 9.2 km at the equator) at the resolution of our grid structure. Thus, we match the crop maps raster with our grid structure, taking the statistical medium value of each crop on each cell.

1.4 FAO food balance sheets: Consumer prices index. We construct our Consumer Price Index taking the approximation of McGuirk and Burke (2020). In particular, we use country-level data on food consumption patterns from the FAO Balance Sheets. This webpage gives complete information concerning three components of a particular country's food system: "1) Domestic food supply of the food commodities in terms of production, imports, and stock changes. 2) Domestic food utilization which includes feed, seed, processing, waste, export, and other uses. And 3) per capita values for the supply of all food commodities (in kilograms per person per year) and the calories, protein and fat content. Annual food balance sheets show the trends in the

[2] http://www.earthstat.org/

overall national food supply, disclose changes that may have taken place in the types of food consumed, and reveal the extent to which the food supply of the country is adequate in relation to nutritional requirements."[3] For each type of commodity, "the food consumption is constructed as the calorie per person and per day available for human consumption" (McGuirk and Burke, 2020, pg. 23). Besides, we have also followed the methodology of these authors constructing time-invariant consumption shares based on averages of the series 1990-2013 because of possible lack in the quality of the data.

1.5 Climate variables.

- **Drought SPEI growing season.** The variable droughtcrop-speigdm as is cited by PRIO-GRID v.2.0 datasets "gives the proportion of months in the growing season that are part of the longest streak of consecutive months in that growing season with SPEI-I values below -1.5. The growing season is the growing season for the cell's main crop, defined in the MIRCA2000 dataset v.1.1. For growing seasons that cross 1 January, we define the whole season to belong to the year in which the season ended. Thus, a year with two consecutive months below -1.5 during the growing season that started in September the previous year and ended in March in the current year, is given a value of 2/7. Each year only has defined one growing season."

  SPEIbase is based on precipitation and potential evapotranspiration PET) from the Climatic Research Unit (CRU) of the University of East Anglia CRU v.3.22. The PET estimation used by CRU is the Penman-Montheith method, considered to be better than the Thornthwaite estimation. Source: Standardized Precipitation and Evapotranspiration Index SPEIbase v.2.3 from the SPEI Global Drought Monitor.

- **Drought SEPI.** The variable droughtyr-speigdm from PRIO-GRID v.2.0 datasets "gives the proportion of months out of 12 months that are part of the

[3]This is an original text from http://www.fao.org/economic/ess/fbs/en/.

longest streak of consecutive months ending in the given year with SPEI-I values below -1.5. For a year where the longest consecutive streak of months below -1.5 is three, the cell will be given a value of $3/12 = 0.25$. When the longest streak starts in the previous year, it is only counted and included in the year in which the streak ended. Theoretically, the proportion can become higher than 1". The original source is SPEI Global Drought Monitor.

- **Temperature.** Temperature is also taken from PRIO-GRID v.2.0 datasets and "gives the yearly mean temperature (in degrees Celsius) in the cell, based on monthly meteorological statistics from GHCN/CAMS, developed at the Climate Prediction Center, NOAA/National Weather Service". It is based on Y. Fan and H. van den Dool (2008): A global monthly land surface air temperature analysis for 1948-present, Journal of Geophysical Research, 113, D01103, doi:10.1029/2007JD008470.

- **Rainfall.** "Rainfall gives the yearly total amount of precipitation (in millimeter) in the cell, based on monthly meteorological statistics from the GPCP v.2.2 Combined Precipitation Data Set. Since the original data only reported the daily average for each month, the authors multiplied the daily average by the number of days in each month in order to obtain approximate monthly totals, from which yearly totals were estimated". Definition provided by PRIO-GRID v.2.0 based on G.J. Huffman, D.T. Bolvin and R.F. Adler (2012): Estimating climatological bias errors for the Global Precipitation Climatology Project (GPCP), Journal of Applied Meteorology and Climatology, 51, 84-99. Last updated 2012: GPCP Version 2.2 SG Combined Precipitation Data Set. WDC-A, NCDC, Asheville, NC. Dataset accessed 26.06.2015 at ftp://precip.gsfc.nasa.gov/pub/gpcp-v2.2/psg/

1.6 Ethnicity

- **Political status.**

- **Excluded.** Excluded accounts for the quantity of excluded groups that are settled in the grid cell for the year 1997. This variable is provided in PRIO-GRID v.2.o and derived from the GeoEPR/EPR 2014 update 2 datasets. The excluded variable "counts the number of excluded groups (discriminated or powerless)". Powerless means "that elite representatives hold no political power at either national or the regional level without being explicitly discriminated against". On the other hand, discrimination means "that group members are subjected to active, intentional, and targeted discrimination, with the intent of excluding them from both regional and national power. Such active discrimination can be either formal or informal". See Cederman, Wimmer and Min (2010).

- **Monopoly.** It is a dummy variable which means that a monopoly group is settled in the grid cell for the year 1997. This variable is built matching the settlement areas from Ethnic Power Relations (EPR) Dataset Core 2014 with the grid structure provided in PRIO-GRID v.2.0. Monopoly means "that elite members hold monopoly power in the executive to the exclusion of members of other ethnic groups". See Cederman, Wimmer and Min (2010).

• **Spatial ethnic diversity** We use data form Geo-referencing Ethnic Power Relation (GeoEPR 2014) from M. Vogt, N.C Bormann, S. Rüegger, L.E. Cederman, P. Hunziker and L. Girardin (2015), Integrating data on ethnicity, geography, and conflict: The ethnic power relations data set family, Journal of Conflict Resolution, 59(7), 1327-1342. It "codes the settlement patterns of politically relevant ethnic groups in independent states with more than 500,000 inhabitants from 1946-2009 based on the group list in the Ethnic Power Relations dataset version 2014". For each grid cell, we construct two diverse types of measures of ethnic diversity: Ethnic Fractionalization and Ethnic Polarization in 1997.

- **Spacial ethnic fractionalization and polarization.** The Spatial Ethnic

Fractionalization index (EF_i) is based on the standard Herfindahl-Hirschman index of ethnic diversity or fractionalization and equals:

EF$_i$= 1-$\sum_{j=1}^{N} \pi_j^2 = \sum_{j=1}^{N} \pi_j (1 - \pi_j)$; (B.1)where π_j is the proportion of area that belongs to ethnic group j.

The spatial ethnolinguistic polarization index (EP), on the other side, equals

EP$_i$= 4$\sum_{j=1}^{N} \pi_j^2 (1 - \pi_j)$.(B.2)

1.7 Natural resources and local commodity price indices. In each cell-year, we merge information on Natural Resources from PRIO-GRID v.1.2 and v.2.0 with the U.S. Geological Survey (USGS) dataset. We construct our indexes of Petrol Prices and Mineral Prices with this information.

Specifically, the construction of the local commodity price index for oil and gas uses geocoded data of the localization of oil and gas fields in Africa from PRIO-GRID v.1.2. This information is employed to build a time-invariant dummy variable (e_{ij}) coded as 1 if oil ($j = 1$) or gas ($j = 2$) or oil and gas (($j = 3$)) are present in a cell at any time during the period 1990-2013. Finally, we combine the dummy with the IMF data on world oil and gas annual prices to estimate a price index for cell i and time t (PI_{jt}^E) as follows:

$$PI_{it}^E = \sum_{j=1}^{3} e_{ij} P_{jt}^E; \tag{B.3}$$

where e_{ci} is a gas or/and oil dummy variable for cell i; and P_{it}^E is the annual price for oil if $i = 1$, for gas if $i = 2$, and the average of P_{1t}^E and P_{2t}^E if both oil and gas are found in the cell. The index is normalized to 1 in the year 1990.

A similar methodology is employed to compute the mineral-commodity price index

(PI^M_{ct}). We use the information from the Mineral Resources Data System provided by the USGS. Following Berman et al. (2017), we define a mineral-specific dummy variable coded as 1 in cells where at least one mine has been registered as active in the period 1990-2013 after its discovery or known production, and 0 otherwise. Because we no not have data on international commodity prices of gems and diamonds, the dummy variables only capture the presence of other mines. Specifically, we cover the following minerals: bauxite (aluminum), coal, copper, diammonium phosphate, gold, iron ore, lead, nickel, manganese, phosphate, potash, silver, tin, uranium, and zinc. We combine the time-invariant dummies with price series from the IMF and the Global Economic Monitor (GEM) Commodities dataset, provided by the World Bank (WB), as follows:

$$PI^M_{it} = \sum_{j=1}^{n} m_{ij} P^M_{jt}; \tag{B.4}$$

where m_{ij} is the dummy variable of mineral-j mine-presence in cell i; and P^M_{jt} is the annual price for minerals produced in the mine j normalized to 1 in the year 1990. If we have more than one mineral mine-presence, m_{ij} equals 1 divided by the number of mines in the cell.

1.8 Urban area. Source: PRIO-GRID v. 2.0. "To measure the coverage of urban areas the dataset includes the percentage of urban areas in a cell extracted from the Integrated Science Assessment Model-Historical Database of the Global Environment (ISAM-HYDE)." In PRIO-GRID, this indicator is available for the years 1950, 1960, 1970, 1980, 1990, 2000, and 2010. We interpolate these values to build our percentage of urban area in a cell.

B.2 Robustness Analysis

Here, we perform several robustness checks. Each of them proposes a modification of the basic regression specification. All the tables containing the results are located below, in the Tables section of this appendix.

First, we study how results change if the dependent variable is conflict intensity, instead of conflict incidence. The intensity data comes from the same sources than incidence. Tables B.15 to B.17 show how the results in Tables B.10, B.12 and B.13 change when the dependent variable is the number of events related to UCDP-GED organized armed-conflict, ACLED riots and ACLED violence against civilians, respectively. In general, our main findings hold in terms of sign or sign and significance. An interesting difference, though, is the negative significant signs shown by the CP index for riots (Table B.16) and the interaction between consumer prices and excluded groups in the factor conflict (Table B.15) and riots regressions. As explained previously, this time the only force that can be behind the sign is an increase in state capacity to control insurgence, especially in areas where the government is relatively strong, shown by its capacity to exclude certain ethnic groups from politics.

Second, Tables B.18 to B.20 revise the same conflict-incidence tables (B.10, B.12 and B.13) when, instead of the GAEZ suitability and potential yield information, actual crop yields from the M3-Crop database (Monfreda et al., 2008) are employed to calculate the crop weights in the APP and CP indices.[4] Given the strong endogeneity concerns that surround the relationship between actual crop yields and conflict, numbers for year 2000 are employed to compute a time-invariant share for each crop in each cell, and the regressions are estimated for the years between 2001 and 2013 to try to diminish those problems. In this occasion we find some differences compared to our benchmark results. The main one being that the interactions of the price indices and the ethnic monopoly-group variable show sometimes the opposite signs than before.

Third, we change the source of the measure of factor conflict. It could be thought that the UCDP-GED is a very specific and non-exhaustive dataset, because it contains only certain large conflicts. To address this potential issue, Table B.21 adopts the category Battles from ACLED, which assesses violent interaction between two politically organized armed groups. Recall that, unlike UCDP-GED, ACLED does not have a lower bound requirement of at least 25 battle-related deaths in at least one year. Compared

[4]The M3-Crop database is available at https://mygeohub.org/groups/drinet/cropdata.

to the Table B.10, the main difference is that monopoly groups and the CP index show stronger importance as determinants of factor conflict. Nevertheless, the signs of all significant coefficients are the same that were estimated in Table B.10, and the interpretation of the results can follow the same logic as in the previous subsection.

Fourth, we consider spillover effects from income shocks in neighboring cells. This type of effects are important on their own and have been emphasized by previous literature, like HF in the case of droughts and MB for agricultural prices, because of their potential correlation over space and time. The shocks can spill over bordering cells directly, through changes in food-prices and climate conditions, or indirectly, through changes in conflict incidence triggered by income shocks. Given that the spillovers can persist over time, we follow MB and re-estimate the regressions including as explanatory variables the contemporaneous value and two lags of the APP index and the drought index averages across the 1- and 2-degree neighboring cells.[5] Results are presented in Table B.22. This table shares the same structure with Tables B.23 to B.28. Columns (1) to (3), (4) to (6) and (7) to (9) must be compared to Tables B10, B12 and B13, respectively; and in particular, to the results in columns (2), (10) and (12). Table B.22 shows that our main findings again hold in terms of sign and significance, because spillovers do not show any power to explain conflict.

Fifth, in the main analysis, we have allowed for location-specific 5-year-lag serial correlation and cross-sectional spatial correlation in a radius of 110 km. Now, Table B.23 considers spatial kernels of 55 and 1000 km and serial correlations of 2 lags and 100,000 years. Results are robust to these modifications.

Sixth, we address the modifiable areal unit problem by enlarging the cell surface. In particular, we consider cells of 110 km x 110 km and 220 km x 220 km and present the findings in Tables B.24 and B.25, respectively. When the areal unit is 110 km x 110 km (Table B.24), results are robust in terms of sign and many times significance. Moving

[5]Estimation of the effects derived from the CP index cannot be implemented because it is a country-level aggregate. Notice also that we do not include the realizations of the outcome variable in bordering cells in this spillover regressions. As argued by Berman et al. (2017) and MB, among others, the reason is that the identification of spillovers is problematic, and introducing spatial lags of the dependent variable can generate a clear simultaneity bias due to its temporal persistence.

now to Table B.25, where the areal unit is 220 km x 220 km, we see that using a larger cell as unit of the analysis substantially modifies the results. The difference possibly comes from a greater degree of coexistence of food-producing and food-consuming areas in the same cell as its surface is enlarged; which makes more difficult separate the effects of the APP and CP indices. We can see that the significance of many coefficients vanishes. For example, only five coefficients remain strongly significant in columns (3), (6) and (9); importantly, out of those, most are consistent with our main results.

Seventh, we extend the number of lags of all the variables included in the regression from two to five (Table B.26). As we can see, our main results are generally robust: the estimated coefficient signs are maintained and many times their significance. Interestingly, we find again a negative and significant sign for the CP index in the riots regression as we did in our first robustness test that adds evidence in favor of state capacity as a way to control rebellion.[6]

Eighth, an alternative estimation method for binary dependent variables is employed, namely, a conditional fixed-effect logit model (Table B.27). Results are most of the time robust in terms of signs, but coefficients many times are not significant. This loss of significance is not surprising, because the conditional logit only uses observations that show an incidence equal to one for the estimation, and then the number of observations is reduced from about 140,000 in the main analysis to around 20,000 with the logit.

Finally, the annual average SPEI indicator along with the variables temperature and rainfall are added to our benchmark regressions (Table B.28). As we can see, our main results are robust to this modification.

[6]When urban area and its interaction with the CP index are introduced in the riots regression, the CP index maintains its negative sign and CP*Urban shows a positive sign, and both are significant. This occurs with the intensity and 5-lags specifications.

B.3 Tables

Table B.1: Conflict Variables Statistics

Variable	N	Mean	Std. Dev.	Min	Max
UCDP _Incidence	170112	0.025	0.157	0	1
Riots and Violence against civilians	170112	0.061	0.240	0	1
ACLED_Riots	170112	0.025	0.157	0	1
ACLED_Violence	170112	0.040	0.197	0	1
ACLED_Battles	170112	0.039	0.193	0	1
events UCDP _Incidence	170112	0.110	1.699	0	245
events ACLED_Riots	170112	0.104	2.473	0	779
events ACLED_Violence	170112	0.147	1.903	0	222

Table B.2: Independent Variables

Variable	Obs	Mean	Std. Dev.	Min	Max
Ln(APP Index)	170112	1.392	2.029	0	5.918
Drought SPEI GS	170112	0.050	0.565	-8.382	3.272
Ln(CP Index)	141801	0.231	0.373	-0.380	0.970
Excluded groups	132960	0.494	0.666	0	5
Monopoly groups	132960	0.059	.236	0	1
Fractionalization Index	169488	0.164	0.221	0	0.823
Polarization Index	169488	0.300	0.393	0	1
Urban (% cell)	164704	0.127	0.66	0	23.905
Ln(Mine Price Index)	170112	0.016	0.238	-1.920	6.455
Ln(Petrol&Gas Index)	170112	0.056	0.258	-0.564	1.653
SPEIbase	164144	0.059	0.079	0	0.833
Precipitation	170112	682.84	612.294	0.123	3275.409

Note: From FAO-GAEZ, PRIO-GRID, GeoEPR/EPR 2014, USGS and author's elaboration

Table B.3: Summary UCDP-GED Sample

Country	N	# events	Max. # events	Country	N	# events	Max. # events
Algeria	13936	2573	72	Libya	10448	230	63
Angola	6960	744	44	Madagascar	4064	42	11
Benin	640	7	5	Malawi	624	0	0
Botswana	3280	1	1	Mali	6816	161	13
Burkina Faso	1392	14	9	Mauritania	5888	12	1
Burundi	176	1139	104	Morocco	4480	5	2
Cameroon	2496	26	4	Mozambique	4816	16	3
Central African Republic	3232	344	31	Namibia	4912	13	5
Chad	6256	184	10	Niger	6432	52	5
Congo	1792	192	36	Nigeria	4992	1505	123
Congo DRC	12208	1942	87	Rwanda	144	182	40
Djibouti	128	11	4	Senegal	1200	125	11
Egypt	6304	0	0	Sierra Leone	480	639	79
Equatorial Guinea	192	0	0	Somalia	3872	2630	245
Eritrea	816	39	5	South Africa	7728	45	13
Ethiopia	5952	1347	18	South Sudan	615	270	28
Gabon	1488	0	0	Sudan	12825	1641	36
Gambia	48	14	4	Swaziland	80	0	0
Ghana	1360	2	1	Tanzania	4960	12	3
Guinea	1360	75	12	Togo	304	90	47
Guinea-Bissau	208	35	10	Tunisia	1168	13	3
Ivory Coast	1808	268	67	Uganda	1280	1404	48
Kenya	3072	420	23	Zambia	4000	5	2
Lesotho	192	2	2	Zimbabwe	2160	49	7
Liberia	592	130	28				

Period 1998-2013. N: Number of observations by country. # events: total number of UCDP events in the country over the sample period. Max. # events:: maximum number of yearly UCDP events in the country over the sample period.

Table B.4: Summary ACLED RIOTS Sample

Country	N	# events	Max. # events	Country	N	# events	Max. # events
Algeria	13936	535	46	Libya	10448	313	62
Angola	6960	119	19	Madagascar	4064	299	72
Benin	640	59	11	Malawi	624	129	8
Botswana	3280	25	5	Mali 6816	175	37	
Burkina Faso	1392	158	23	Mauritania	5888	33	4
Burundi	176	67	7	Morocco	4480	401	41
Cameroon	2496	68	6	Mozambique	4816	161	17
Central African Republic	3232	23	4	Namibia	4912	285	44
Chad	6256	14	2	Niger	6432	90	8
Congo	1792	95	26	Nigeria	4992	1061	33
Congo DRC	12208	528	45	Rwanda	144	63	12
Djibouti	128	23	6	Senegal	1200	206	35
Egypt	6304	2648	779	Sierra Leone	480	23	5
Equatorial Guinea	192	1	1	Somalia	3872	669	31
Eritrea	816	5	4	South Africa	7728	3830	102
Ethiopia	5952	223	19	South Sudan	615	32	5
Gabon	1488	59	21	Sudan	12825	472	54
Gambia	48	9	4	Swaziland	80	93	31
Ghana	1360	74	7	Tanzania	4960	100	6
Guinea	1360	213	57	Togo	304	142	39
Guinea-Bissau	208	44	7	Tunisia	1168	754	164
Ivory Coast	1808	372	29	Uganda	1280	479	56
Kenya	3072	1363	71	Zambia	4000	478	48
Lesotho	192	3	1	Zimbabwe	2160	587	51
Liberia	592	145	27				

Period 1998-2013. N: Number of observations by country. # events: total number of ACLED riots events in the country over the sample period. Max. # events:: maximum number of yearly riots events in the country over the sample period.

Table B.5: Summary ACLED VIOLENCE Sample

Country	N	# events	Max. # events	Country	N	# events	Max. # events
Algeria	13936	397	12	Libya	10448	244	45
Angola	6960	513	32	Madagascar	4064	108	16
Benin	640	14	2	Malawi	624	82	6
Botswana	3280	5	1	Mali	6816	192	24
Burkina Faso	1392	31	4	Mauritania	5888	8	1
Burundi	176	1235	78	Morocco	4480	81	15
Cameroon	2496	81	7	Mozambique	4816	151	11
Central African Republic	232	483	28	Namibia	4912	73	5
Chad	6256	202	7	Niger	6432	54	7
Congo	1792	135	21	Nigeria	4992	1818	67
Congo DRC	12208	2375	71	Rwanda	144	417	102
Djibouti	128	11	2	Senegal	1200	136	11
Egypt	6304	413	89	Sierra Leone	480	837	98
Equatorial Guinea	192	3	1	Somalia	3872	3065	222
Eritrea	816	88	8	South Africa	7728	713	28
Ethiopia	5952	432	27	South Sudan	615	284	41
Gabon	1488	13	3	Sudan	12825	1832	64
Gambia	48	22	7	Swaziland	80	26	5
Ghana	1360	73	7	Tanzania	4960	148	12
Guinea	1360	177	20	Togo	304	22	3
Guinea-Bissau	208	41	7	Tunisia	1168	90	15
Ivory Coast	1808	434	74	Uganda	1280	1669	63
Kenya	3072	1477	42	Zambia	4000	249	33
Lesotho	192	10	2	Zimbabwe	2160	3813	163
Liberia	592	229	21				

Period 1998-2013. N: Number of observations by country. # events: total number of ACLED violence events in the country over the sample period. Max. # events:: maximum number of yearly riots violence in the country over the sample period.

Table B.6: Commodity Prices. CROPS. Serie 1990-2014

Variable	Obs	Mean	Std. Dev.	Min	Max
bananas	25	1.148	0.374	0.691	1.820
barley	25	1.509	0.615	0.893	2.981
cocoa	25	1.420	0.542	0.713	2.469
coconut oil	25	2.196	0.985	0.945	5.141
coffe	25	1.403	0.598	0.677	3.065
cotton	25	0.893	0.277	0.560	1.873
groundnuts	25	1.017	0.426	0.609	2.172
maize	25	1.326	0.581	0.807	2.731
olive oil	25	1.175	0.283	0.830	1.857
oranges	25	1.283	0.432	0.684	2.085
palm oil	25	2.198	0.995	0.995	4.495
rice	25	1.283	0.536	0.638	2.587
soybeans	25	1.333	0.527	0.770	2.454
sugar	25	0.974	0.207	0.714	1.633
sunflower oil	25	1.380	0.628	0.628	2.806
tea	25	1.140	0.260	0.808	1.717
tobacco	25	1.002	0.203	0.779	1.471
wheat	25	1.271	0.437	0.725	2.117
AgPrices	25	24.718	41.168	0	371.57

Table B.7: Average over series of Food Crops: 1990-2013

Variable	Obs	Mean	Std. Dev.	Min	Max
Average_Bananas	14205	2.265	22.78	0	488.792
Average_Barley	14205	1.109	14.579	0	311.417
Average_Cocoa	14205	0.153	0.940	0	12.417
Average_Coconut	14205	0.836	14.325	0	345.625
Average_Coffee	14205	0.052	0.300	0	3.917
Average_Maize	14205	24.810	124.52	0	1339.75
Average_Nuts	14205	0.564	3.620	0	41.708
Average_OilPalm	14205	4.755	25.320	0	313.208
Average_OliveOil	14205	0.401	4.805	0	93.958
Average_Rice	14205	20.716	106.605	0	1004.875
Average_Sorghum	14205	7.903	48.666	0	679.591
Average_Soybean	14205	0.234	1.769	0	25.750
Average_Sugar	14205	11.461	48.369	0	365.417
Average_Sunflower	14205	1.452	10.997	0	154.625
Average_Tea	14205	0.029	0.181	0	2.167
Average_Wheat	14205	23.93	134.325	0	1611.875
Average_Food	14205	32158.23	11267.66	2353	60640
Consumer_Price	14205	1.286	0.071	0.0985	1.934

Food Balance Sheets. Old methodology. Author's elaboration

Table B.10: Factor Conflict: Agricultural Producer Prices, Drought SPEI Growing Season and Consumer Prices.

UCDP FACTOR CONFLICT	Incidence (1)	Incidence (2)	Incidence (3)	Incidence (4)	Incidence (5)	Incidence (6)	Incidence (7)	Incidence (8)	Incidence (9)	Incidence (10)	Incidence (11)	Incidence (12)
APP Index	-0.0200***	-0.0181***	-0.0096***	-0.0086**	-0.0170***	-0.0190***	-0.0175***	-0.0186***	0.0108***	-0.0140***	-0.0110***	-0.0138***
	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.004)	(0.005)
Drought SPEI GS	0.0039***	0.0030***	0.0025**	0.0005	0.0040***	0.0033***	0.0039***	0.0033***	0.0029***	0.0011	0.0028**	0.0008
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)
CP Index		0.0250**		0.0360***		0.0235**		0.0231**		0.0348***		0.0344***
		(0.011)		(0.013)		(0.011)		(0.011)		(0.013)		(0.013)
APP Index x Excluded groups			-0.0223***	-0.0226***					-0.0237***	-0.0269***	-0.0236***	-0.0265***
			(0.004)	(0.008)					(0.005)	(0.008)	(0.005)	(0.008)
Drought SPEI GS x Excluded groups			0.0048***	0.0073***					0.0054***	0.0076***	0.0053***	0.0076***
			(0.002)	(0.002)					(0.002)	(0.002)	(0.002)	(0.002)
CP Index x Excluded groups				-0.0024						-0.0030		-0.0029
				(0.004)						(0.004)		(0.004)
APP Index x Monopoly groups			-0.0607*	-0.0879**					-0.0608*	-0.0885**	-0.0609*	-0.0887**
			(0.033)	(0.038)					(0.033)	(0.038)	(0.033)	(0.038)
Drought SPEI GS x Monopoly groups			-0.0041**	-0.0017					-0.0040**	-0.0019	-0.0040**	-0.0019
			(0.002)	(0.004)					(0.002)	(0.004)	(0.002)	(0.004)
CP Index x Monopoly groups				0.0260**						0.0245**		0.0245**
				(0.011)						(0.011)		(0.011)
APP Index x Ethnic Fraction.					-0.0162*	0.0051			0.0110	0.0379**		
					(0.010)	(0.014)			(0.011)	(0.015)		
Drought SPEI GS x Ethnic Fraction.					-0.0010	-0.0028			-0.0047	-0.0039		
					(0.004)	(0.003)			(0.004)	(0.004)		
CP Index x Ethnic Fraction.						0.0107				0.0108		
						(0.008)				(0.008)		
APP Index x Ethnic Polariz.							-0.0075	0.0014			0.0063	0.0195**
							(0.006)	(0.008)			(0.006)	(0.008)
Drought SPEI GS x Ethnic Polariz.							-0.0003	-0.0012			-0.0021	-0.0014
							(0.002)	(0.002)			(0.002)	(0.002)
CP Index x Ethnic Polariz.								0.0070*				0.0066
								(0.004)				(0.004)
Observations	170,112	139,136	170,112	110,000	169,488	138,592	169,488	138,592	169,488	109,968	169,488	109,968
Unconditional_Probability_FConflict %	2.530%	2.168%	2.530%	2.435%	2.539%	2.176%	2.539%	2.176%	2.539%	2.434%	2.517%	2.434%
Cell FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	NON	YES	NON	YES	NON	YES	NON	YES	NON	YES	NON	YES
Country x year FE	YES	NON	YES	NON	YES	NON	YES	NON	YES	NON	YES	NON
Country-specific time trend	NON	YES	NON	YES	NON	YES	NON	YES	NON	YES	NON	YES

Notes: The dependent variable is a binary variable that takes a value of one for conflicts following the definition of UCDP incidence database (INCIDENCE). The Agricultural price Index (APP Index), the drought SPEI growing season, and the Consumer Price Index (CP Index) coefficients displayed capture the sum of price impacts at t, t-1, and t-2. LPM estimations. Conley (2008) standard errors in parentheses, allowing the for spatial correlation within a 110km radius and for five periods of correlation. p-values for the linear combination are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Control variables include interactions between the log of oil prices and oil dummy indicating the presence of an oil field in a given cell, and the interaction between the log of the price for the main mineral produced in a cell following the approximation of Berman et al. (2017), in both cases at t, t-1 and t-2.

Table B.11: Output Conflict: Agricultural Producer Prices, Drought SPEI Growing Season and Consumer Prices.

ACLED CONFLICT	Riots&Violence	Riots&Violence	Riots&Violence	Riots&Violence	Riots&Violence	Riots&Violence	Riots&Violence	Riots&Violence	Riots&Violence	Riots&Violence	Riots&Violence	Riots&Violence
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
APP Index	0.0070	0.0113**	0.0162***	0.0166**	-0.0007	0.0062	0.0003	0.0079	0.0074	0.0054	0.0082	0.0065
	(0.005)	(0.005)	(0.005)	(0.007)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.008)	(0.006)	(0.007)
Drought SPEI GS	0.0027**	0.0038***	0.0028*	0.0030	0.0039***	0.0059***	0.0038***	0.0056***	0.0038**	0.0046*	0.0037**	0.0041*
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
CP Index		0.00004		0.0251		-0.0051		-0.0054		0.0249		0.0251
		(0.014)		(0.016)		(0.014)		(0.014)		(0.016)		(0.015)
APP Index x Excluded groups			-0.0171***	-0.0078					-0.0275***	-0.0159	-0.0251***	-0.0144
			(0.006)	(0.011)					(0.006)	(0.011)	(0.006)	(0.011)
Drought SPEI GS x Excluded groups			0.0001	0.0018					0.0011	0.0023	0.0009	0.0022
			(0.002)	(0.002)					(0.002)	(0.003)	(0.002)	(0.003)
CP Index x Excluded groups				0.0152***						0.0122**		0.0127**
				(0.005)						(0.006)		(0.006)
APP Index x Monopoly groups			-0.1725***	-0.2179***					-0.1745***	-0.2147***	-0.1746***	-0.2148***
			(0.040)	(0.051)					(0.043)	(0.051)	(0.043)	(0.051)
Drought SPEI GS x Monopoly groups			-0.0015	0.0280					-0.0013	0.0296	-0.0013	0.0297
			(0.006)	(0.029)					(0.006)	(0.029)	(0.006)	(0.029)
CP Index x Monopoly groups				0.0808***						0.0747***		0.0753***
				(0.017)						(0.017)		(0.017)
APP Index x Ethnic Fraction.					0.0415***	0.0386*			0.0733***	0.0778***		
					(0.016)	(0.022)			(0.017)	(0.024)		
Drought SPEI GS x Ethnic Fraction.					-0.0092**	-0.0146***			-0.0105**	-0.0105*		
					(0.005)	(0.005)			(0.005)	(0.005)		
CP Index x Ethnic Fraction.						0.0457***				0.0113		
						(0.011)				(0.012)		
APP Index x Ethnic Polariz.							0.0199**	0.0156			0.0349***	0.0376***
							(0.009)	(0.012)			(0.009)	(0.013)
Drought SPEI GS x Ethnic Polariz.							-0.0045**	-0.0067***			-0.0050**	-0.0039
							(0.002)	(0.003)			(0.002)	(0.003)
CP Index x Ethnic Polariz.								0.0248***				0.0042
								(0.006)				(0.006)
Observations	170,112	139,136	170,112	110,000	169,488	138,592	169,488	138,592	169,488	109,968	169,488	109,968
Unconditional_Probability_R&V %	6.138%	5.904%	6.138%	6.669%	6.156%	5.920%	6.156%	5.920%	6.156%	6.669%	6.156%	6.669%
Cell FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	NON	YES	NON	YES	NON	YES	NON	YES	NON	YES	NON	YES
Country x year FE	YES	NON	YES	NON	YES	NON	YES	NON	YES	NON	YES	NON
Country-specific time trend	NON	YES	NON	YES	NON	YES	NON	YES	NON	YES	NON	YES

Notes: The dependent variable is a binary variable that takes a value of one for conflicts following the definition of ACLED riots and violence database (Riots &Violence), The Agricultural price Index (APP Index), the SPEI growing season, and the Consumer Price Index (CP Index) coefficients displayed capture the sum of price impacts at t, t-1, and t-2. LPM estimations. Conley (2008) standard errors in parentheses, allowing for spatial correlation within a 110km radius and for five periods of correlation. p-values for the linear combination are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Control variables include the interactions between the log of oil prices and oil dummy indicating the presence of an oil field in a given cell, and the interaction between the log of the price for the main mineral produced in a cell following the approximation of Berman et al. (2017), in both cases at t, t-1 and t-2.

Table B.12: Output Conflict: Agricultural Producer Prices, Drought SPEI Growing Season and Consumer Prices.

ACLED CONFLICTS	Riots (1)	Riots (2)	Riots (3)	Riots (4)	Riots (5)	Riots (6)	Riots (7)	Riots (8)	Riots (9)	Riots (10)	Riots (11)	Riots (12)
APP Index	0.0224***	0.0272***	0.0248***	0.0329***	0.0208***	0.0299***	0.0206***	0.0296***	0.0228***	0.0343***	0.0226***	0.0338***
	(0.003)	(0.004)	(0.004)	(0.005)	(0.004)	(0.004)	(0.004)	(0.005)	(0.004)	(0.006)	(0.004)	(0.006)
Drought SPEI GS	0.0015*	0.0028***	0.0024**	0.0028*	0.0028***	0.0057***	0.0026**	0.0054***	0.0033***	0.0055***	0.0032***	0.0050***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)
CP Index		-0.0247***		-0.0072		-0.0029***		-0.0293***		-0.0099		-0.0135
		(0.010)		(0.011)		(0.010)		(0.010)		(0.011)		(0.010)
APP Index x Excluded groups			-0.0050	-0.0088					-0.0074	-0.0086	-0.0071*	-0.0095
			(0.004)	(0.007)					(0.004)	(0.008)	(0.004)	(0.011)
Drought SPEI GS x Excluded groups			-0.0017	-0.0008					-0.0009	-0.0007	-0.0011	-0.0008
			(0.001)	(0.002)					(0.001)	(0.002)	(0.001)	(0.002)
CP Index x Excluded groups				0.0021						0.0006		0.0010
				(0.004)						(0.004)		(0.004)
APP Index x Monopoly groups			-0.0205	-0.0546***					-0.0211	-0.0512**	-0.0212	-0.0509**
			(0.020)	(0.021)					(0.020)	(0.021)	(0.020)	(0.021)
Drought SPEI GS x Monopoly groups			-0.0052	0.0010					-0.0050	0.0028	-0.0050	0.0030
			(0.005)	(0.028)					(0.006)	(0.028)	(0.006)	(0.028)
CP Index x Monopoly groups				0.0419***						0.0371***		0.0372***
				(0.011)						(0.011)		(0.011)
APP Index x Ethnic Fraction.					0.0080	-0.0198			0.0162	-0.0087		
					(0.011)	(0.016)			(0.013)	(0.018)		
Drought SPEI GS x Ethnic Fraction.					-0.0098***	-0.0199***			-0.0091***	-0.0153***		
					(0.003)	(0.004)			(0.004)	(0.004)		
CP Index x Ethnic Fraction.						0.0350***				0.0207**		
						(0.008)				(0.009)		
APP Index x Ethnic Polariz.							0.0048	-0.0099			0.0089	-0.0031
							(0.006)	(0.008)			(0.007)	(0.010)
Drought SPEI GS x Ethnic Polariz.							-0.0044**	-0.0097***			-0.0041**	-0.0068***
							(0.002)	(0.002)			(0.002)	(0.002)
CP Index x Ethnic Polariz.								0.1805***				0.0093**
								(0.004)				(0.005)
Observations	170,112	139,136	170,112	110,000	169,488	138,592	169,488	138,592	169,488	109,968	169,488	109,968
Unconditional_Probability_Riots %	2.540%	2.696%	2.540%	3.100%	2.547%	2.704%	2.547%	2.704%	2.547%	3.100%	2.547%	3.100%
Cell FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	NON	YES	NON	YES	NON	YES	NON	YES	NON	YES	NON	YES
Country x year FE	YES	NON	YES	NON	YES	NON	YES	NON	YES	NON	YES	NON
Country-specific time trend	NON	YES	NON	YES	NON	YES	NON	YES	NON	YES	NON	YES

Notes: The dependent variable is a binary variable that takes a value of one for conflicts following the definition of of ACLED riots database (Riots), The Agricultural price Index (APP Index), the drought SPEI growing season, and the Consumer Price Index (CP Index) coefficients displayed capture the sum of price impacts at t, t-1, and t-2. LPM estimations. Conley (2008) standard errors in parentheses, allowing for spatial correlation within a 110km radius and for five periods of correlation. p-values for the linear combination are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Control variables include the interactions between the log of oil prices and oil dummy indicating the presence of an oil field in a given cell, and the interaction between the log of the price for the main mineral produced in a cell following the approximation of Berman et al. (2017), in both cases at t, t-1 and t-2.

Table B.13: Output Conflict: Agricultural Producer Prices, Drought SPEI Growing Season and Consumer Prices.

ACLED CONFLICT	Violence (1)	Violence (2)	Violence (3)	Violence (4)	Violence (5)	Violence (6)	Violence (7)	Violence (8)	Violence (9)	Violence (10)	Violence (11)	Violence (12)
APP Index	-0.0076*	-0.0059	-0.0001	-0.0057	-0.0134***	-0.0124**	-0.0127***	-0.0115**	-0.0070	-0.0158**	-0.0065	-0.0154**
	(0.004)	(0.005)	(0.005)	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)	(0.005)	(0.006)
Drought SPEI GS	0.0004	0.0011	-0.0006	-0.0021	0.0007	0.0012	0.0009	0.0014	-0.0001	-0.0030	0.0001	-0.0029
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)
CP Index		0.0176		0.0300**		0.0146		0.0147		0.0316**		0.0322**
		(0.012)		(0.013)		(0.012)		(0.012)		(0.013)		(0.013)
APP Index x Excluded groups			-0.0148***	-0.0041					-0.0228***	-0.0111	-0.0210***	-0.0101
			(0.005)	(0.009)					(0.005)	(0.009)	(0.005)	(0.009)
Drought SPEI GS x Excluded groups			0.0037**	0.0066***					0.0044***	0.0068***	0.0044***	0.0067***
			(0.002)	(0.002)					(0.002)	(0.002)	(0.002)	(0.002)
CP Index x Excluded groups				0.0157***						0.0154***		0.0158***
				(0.005)						(0.005)		(0.005)
APP Index x Monopoly groups			-0.1150***	-0.1558***					-0.1164***	-0.1549***	-0.1166***	-0.1553***
			(0.037)	(0.044)					(0.037)	(0.044)	(0.037)	(0.044)
Drought SPEI GS x Monopoly groups			-0.0060	0.0417*					-0.0059	0.0423*	-0.0059	0.0422*
			(0.004)	(0.022)					(0.004)	(0.022)	(0.004)	(0.022)
CP Index x Monopoly groups				0.0827***						0.0798***		0.0805***
				(0.015)						(0.015)		(0.015)
APP Index x Ethnic Fraction.					0.0304**	0.0368**			0.0568***	0.0699***		
					(0.013)	(0.018)			(0.015)	(0.020)		
Drought SPEI GS x Ethnic Fraction.					-0.0024	-0.0015			-0.0058	0.0041		
					(0.004)	(0.004)			(0.004)	(0.004)		
CP Index x Ethnic Fraction.						0.0247***				-0.0035		
						(0.009)				(0.009)		
APP Index x Ethnic Polariz.							0.0148**	0.0174*			0.0274***	0.0362***
							(0.007)	(0.010)			(0.008)	(0.011)
Drought SPEI GS x Ethnic Polariz.							-0.0022	-0.0013			-0.0039**	0.0020
							(0.002)	(0.002)			(0.002)	(0.002)
CP Index x Ethnic Polariz.								-0.0002				-0.0046
								(0.005)				(0.005)
Observations	170,112	139,136	170,112	110,000	169,488	138,592	169,488	138,592	169,488	109,968	169,488	109,968
Unconditional_Probability_Violence %	4.030%	3.743%	4.030%	4.235%	4.044%	3.757%	4.044%	3.757%	4.044%	4.235%	4.044%	4.235%
Cell FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	NON	YES	NON	YES	NON	YES	NON	YES	NON	YES	NON	YES
Country x year FE	YES	NON	YES	NON	YES	NON	YES	NON	YES	NON	YES	NON
Country-specific time trend	NON	YES	NON	YES	NON	YES	NON	YES	NON	YES	NON	YES

Notes: The dependent variable is a binary variable that takes a value of one for conflicts following the definition of of ACLED violence database (VIOLENCE), The Agricultural price Index (APP Index), the drought SPEI growing season, and the Consumer Price Index (CP Index) coefficients displayed capture the sum of price impacts at t, t-1, and t-2. LPM estimations. Conley (2008) standard errors in parentheses, allowing for spatial correlation within a 110km radius and for five periods of correlation. p-values for the linear combination are reported in parentheses. *** p<0.01, **p<0.05, * p<0.1. Control variables include the interactions between the log of oil prices and oil dummy indicating the presence of an oil field in a given cell, and the interaction between the log of the price for the main mineral produced in a cell following the approximation of Berman et al. (2017), in both cases at t, t-1 and t-2.

Table B.14: Agricultural Producer Prices, Drought SPEI Growing Season and Consumer Prices.: URBAN CONFLICTS

Type of CONFLICT	UCDP_Incidence	UCDP_Incidence	UCDP_Incidence	UCDP_Incidence	ACLED_Riots	ACLED_Riots	ACLED_Riots	ACLED_Riots	ACLED_Violence	ACLED_Violence	ACLED_Violence	ACLED_Violence
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
APP Index	-0.0189***	-0.0189***	-0.0151**	-0.0150***	0.0275***	0.0223***	0.0298***	0.0293***	-0.0070	-0.0108**	-0.0197***	-0.0193***
	(0.004)	(0.004)	(0.005)	(0.005)	(0.004)	(0.004)	(0.006)	(0.006)	(0.005)	(0.005)	(0.007)	(0.007)
Drought SPEI GS	0.0038***	0.0038***	0.0024	0.0023	0.0035***	0.0036***	0.0073***	0.0068***	0.0026***	0.0026***	0.0005	0.0007
	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)
CP Index	0.0247**	0.0246**	0.0330***	0.0330**	-0.0224**	-0.0267***	-0.0106	-0.0114	0.0179***	0.0157***	0.0307***	0.0311***
	(0.011)	(0.011)	(0.013)	(0.013)	(0.010)	(0.010)	(0.011)	(0.011)	(0.012)	(0.012)	(0.014)	(0.014)
Urban	-0.0106**	-0.0131	-0.0103	-0.0104	0.0498***	-0.1418***	-0.1329***	-0.1333***	0.0421***	-0.0925***	-0.0816***	-0.0817***
	(0.005)	(0.008)	(0.008)	(0.008)	(0.010)	(0.022)	(0.021)	(0.021)	(0.010)	(0.021)	(0.021)	(0.021)
CP Index x Urban		0.0007	-0.0001	-0.0000		0.0704***	0.0627***	0.0628***		0.0518***	0.0454***	0.0455***
		(0.003)	(0.003)	(0.003)		(0.007)	(0.007)	(0.007)		(0.007)	(0.007)	(0.007)
APP Index x Excluded groups			-0.0302***	-0.0298***			-0.0099	-0.0103			-0.0108	-0.0099
			(0.008)	(0.008)			(0.008)	(0.008)			(0.009)	(0.009)
Drought SPEI GS x Excluded groups			0.0074***	0.0073***			-0.0018	-0.0019			0.0040**	0.0040*
			(0.002)	(0.002)			(0.002)	(0.002)			(0.002)	(0.002)
CP Index x Excluded groups			-0.0011	0.0009			0.0013	0.0016			0.0173***	0.0176***
			(0.004)	(0.004)			(0.004)	(0.004)			(0.005)	(0.005)
APP Index x Monopoly groups			-0.0878**	-0.0880**			-0.0346*	-0.0344			-0.1435***	-0.1439***
			(0.038)	(0.038)			(0.021)	(0.021)			(0.044)	(0.044)
Drought SPEI GS x Monopoly groups			-0.0056	-0.0055			-0.0127	-0.0124			0.0320	0.0320
			(0.005)	(0.005)			(0.029)	(0.029)			(0.022)	(0.022)
CP Index x Monopoly groups			0.0240**	0.0241**			0.0236**	0.0236**			0.0707***	0.0712***
			(0.011)	(0.011)			(0.011)	(0.011)			(0.015)	(0.015)
APP Index x Ethnic Fraction.			0.0456***				-0.0076				0.0655***	
			(0.015)				(0.018)				(0.020)	
Drought SPEI GS x Ethnic Fraction.			-0.0063				-0.0168***				0.0006	
			(0.004)				(0.004)				(0.004)	
CP Index x Ethnic Fraction.			0.0116				0.0176**				-0.0045	
			(0.008)				(0.009)				(0.009)	
APP Index x Ethnic Polariz				0.0240***.				-0.0024				0.0336***
				(0.008)				(0.010)				(0.011)
Drought SPEI GS x Ethnic Polariz.				-0.0030				-0.0077***				0.0003
				(0.002)				(0.002)				(0.002)
CP Index x Ethnic Polariz				0.0068*				0.0086*				-0.0045
				(0.004)				(0.005)				(0.005)
Observations	134,672	134,672	107,488	107,488	134,672	134,672	107,488	107,488	134,672	134,672	107,488	107,488
Unconditional_Probability_Conflict %	2.180%	2.180%	2.420%	2.420%	2.618%	2.618%	2.985%	2.985%	3.740%	3.740%	4.192%	4.192%
Cell FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Country-specific time trend	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Notes: The dependent variable is a binary variable that takes a value of one for conflicts following the definition of UCDP-GED datase (UCDP_INCIDENCE) and ACLED riots (RIOTS), and violence against civilians (VIOLENCE) database. The Agricultural price Index (APP Index), the drought SPEI growing season, and the Consumer Price Index (CP Index) coefficients displayed capture the sum of price impacts at t, t-1, and t-2. LPM estimations. Conley (2008) standard errors in parentheses, allowing for spatial correlation within a 110km radius and for five periods of correlation. p-values for the linear combination are reported in parentheses. *** p<0.01, ** p<0.05, *p<0.1. Control variables include the interactions between oil prices and oil dummy indicating the presence of an oil field in a given cell, and the interaction between the log of the price for the main mineral produced in a cell following the approximation of Berman et al. (2017), in both cases at t, t-1 and t-2. Urban is the percentage of a given cell area classified as urban by PRIO-GRID database.

Table B.15: Factor Conflict: Agricultural Producer Prices, Drought SPEI Growing Season and Consumer Prices: Conflict INTENSITY

UCDP FACTOR CONFLICT	Intensity (1)	Intensity (2)	Intensity (3)	Intensity (4)	Intensity (5)	Intensity (6)	Intensity (7)	Intensity (8)	Intensity (9)	Intensity (10)	Intensity (11)	Intensity (12)
APP Index	-0.1531***	-0.1286***	-0.1144***	-0.1048***	-0.1794***	-0.1672***	-0.1776***	-0.1609***	-0.1491***	-0.1727***	-0.1474***	-0.1678***
	(0.029)	(0.031)	(0.028)	(0.040)	(0.031)	(0.034)	(0.034)	(0.032)	(0.030)	(0.042)	(0.029)	(0.042)
Drought SPEI GS	0.0148	0.0060	0.0126	-0.0130	0.0173*	0.0066	0.0173*	0.0060	0.0157	-0.0141	0.0156	-0.0158
	(0.009)	(0.010)	(0.011)	(0.018)	(0.009)	(0.010)	(0.009)	(0.010)	(0.011)	(0.020)	(0.011)	(0.020)
CP Index		0.3435***		0.4389***		0.3336***		0.3318***		0.4363***		0.4352***
		(0.093)		(0.113)		(0.094)		(0.094)		(0.113)		(0.113)
APP Index x Excluded groups			-0.0916**	-0.1055***					-0.1341***	-0.1542***	-0.1253***	-0.1447***
			(0.028)	(0.052)					(0.035)	(0.057)	(0.034)	(0.057)
Drought SPEI GS x Excluded groups			0.0167	0.0495**					0.0201	0.0515***	0.0197	0.0513**
			(0.014)	(0.019)					(0.014)	(0.019)	(0.014)	(0.019)
CP Index x Excluded groups				-0.0536*						-0.0592**		-0.0576***
				(0.029)						(0.028)		(0.028)
APP Index x Monopoly groups			0.3592*	-0.0972					0.3506	-0.1008	0.3494	-0.1026
			(0.213)	(0.166)					(0.213)	(0.165)	(0.213)	(0.166)
Drought SPEI GS x Monopoly groups			-0.0671***	0.0340					-0.0666***	0.0340	-0.0665***	0.0340
			(0.025)	(0.025)					(0.025)	(0.026)	(0.026)	(0.026)
CP Index x Monopoly groups				0.0542						0.0401		0.0422
				(0.066)						(0.067)		(0.067)
APP Index x Ethnic Fraction.					0.1512**	0.2285**			0.3023***	0.4753***		
					(0.062)	(0.098)			(0.082)	(0.122)		
Drought SPEI GS x Ethnic Fraction.					-0.0195	-0.0085			-0.0318	-0.0001		
					(0.025)	(0.018)			(0.021)	(0.023)		
CP Index x Ethnic Fraction.						0.0894*				0.0536		
						(0.089)				(0.051)		
APP Index x Ethnic Polariz.							0.0776**	0.1039***			0.1492***	0.2361***
							(0.036)	(0.054)			(0.046)	0.067)
Drought SPEI GS x Ethnic Polariz.							-0.0103	-0.0020			-0.0161	0.0514
							(0.011)	(0.009)			(0.011)	(0.012)
CP Index x Ethnic Polariz.								0.0515**				0.0262
							(0.024)				(0.026)	
Observations	170,112	139,136	170,112	110,000	169,488	138,592	169,488	138,592	169,488	109,968	169,488	109,968
Unconditional_mean _events	0.109	0.086	0.109	0.101	0.113	0.086	0.110	0.086	0.110	0.101	0.110	0.101
Cell FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	NON	YES	NON	YES	NON	YES	NON	YES	NON	YES	NON	YES
Country x year FE	YES	NON	YES	NON	YES	NON	YES	NON	YES	NON	YES	NON
Country-specific time trend	NON	YES	NON	YES	NON	YES	NON	YES	NON	YES	NON	YES

Notes: The dependent variable is the number of events observed in a cell during a given year, following the definition of UCDP conflict database (#EVENTS INTENSITY), The Agricultural price Index (APP Index), the SPEI growing season, and the Consumer Price Index (CP Index) coefficients displayed capture the sum of price impacts at t, t-1, and t-2. LPM estimations. Conley (2008) standard errors in parentheses, allowing or spatial correlation within a 110km radius and for five periods of correlation. p-values for the linear combination are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Control variables include the interactions between oil prices and oil dummy indicating the presence of an oil field in a given cell, and the interaction between the log of the price for the main mineral produced in a cell following the approximation of Berman et al. (2017) in both cases at t, t-1 and t-2.

Table B.16: Output Conflict: Agricultural Producer Prices, Drought SPEI Growing Season and Consumer Prices: Riots INTENSITY

ACLED CONFLICT	#events Riots (1)	#events Riots (2)	#events Riots (3)	#events Riots (4)	#events Riots (5)	#events Riots (6)	#events Riots (7)	#events Riots (8)	#events Riots (9)	#events Riots (10)	#events Riots (11)	#events Riots (12)
APP Index	0.1140***	0.1472***	0.1404***	0.2049***	0.0479*	0.0862**	0.0523*	0.0898**	0.0805**	0.0666	0.0832**	0.0574
	(0.027)	(0.032)	(0.035)	(0.055)	(0.029)	(0.037)	(0.029)	(0.038)	(0.032)	(0.062)	(0.032)	(0.066)
Drought SPEI GS	0.0234	0.0749**	0.0216	0.0231	0.0367**	0.1103***	0.0371**	0.1104***	0.0321*	0.0298	0.0327*	0.0270
	(0.015)	(0.034)	(0.016)	(0.0223)	(0.017)	(0.042)	(0.017)	(0.042)	(0.017)	(0.023)	(0.017)	(0.022)
CP Index		-0.5700***		-0.4065***		-0.5864***		-0.5854***		-0.3265***		-0.3124***
		(0.1213)		(0.125)		(0.118)		(0.118)		(0.101)		(0.100)
APP Index x Excluded groups			-0.0550**	-0.0117					-0.1276***	-0.0907	-0.1134***	-0.0834
			(0.027)	(0.056)					(0.038)	(0.062)	(0.036)	(0.060)
Drought SPEI GS x Excluded groups			-0.0058	0.0248					0.0031	0.0274	-0.0025	0.0278
			(0.010)	(0.019)					(0.011)	(0.020)	(0.011)	(0.020)
CP Index x Excluded groups				-0.1279**						-0.1051**		-0.1031**
				(0.057)						(0.044)		(0.045)
APP Index x Monopoly groups			-0.1764**	-0.6774*				-0.1950**	-0.5873	-0.1968**	-0.5944	
			(0.075)	(0.378)					(0.077)	(0.360)	(0.077)	(0.361)
Drought SPEI GS x Monopoly groups			0.0680	3.5608**					0.0687	3.6121**	-0.0689	3.6129**
			(0.098)	(1.550)					(0.098)	(1.570)	(0.098)	(1.570)
CP Index x Monopoly groups				1.5961**						1.507**		1.5164**
				(0.772)						(0.749)		(0.753)
APP Index x Ethnic Fraction.					0.3526***	0.3489**			0.4978***	0.9088***		
					(0.093)	(0.156)			(0.123)	(0.319		
Drought SPEI GS x Ethnic Fraction.					-0.0949**	-0.2410***			-0.0651	-0.0954**		
					(0.041)	(0.071)			(0.052)	(0.048)		
CP Index x Ethnic Fraction.						0.1296				-0.4034		
						(0.129)				(0.335)		
APP Index x Ethnic Polariz.							0.1809***	0.1802**			0.2470***	0.5151***
							(0.047)	(0.082)			(0.060)	(0.183)
Drought SPEI GS x Ethnic Polariz.							-0.0518**	-0.1287***			-0.0523**	-0.0263
							(0.022)	(0.037)			(0.023)	(0.030)
CP Index x Ethnic Polariz.								0.0596				-0.2707
								(0.069)				(0.199).
Observations	170,112	139,136	170,112	110,000	169,488	138,592	169,488	138,592	169,488	109,968	169,488	109,968
Unconditional_mean _events	0.104	0.116	0.134	0.134	0.105	0.116	0.105	0.116	0.105	0.134	0.105	0.134
Cell FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	NON	YES	NON	YES	NON	YES	NON	YES	NON	YES	NON	YES
Country x year FE	YES	NON	YES	NON	YES	NON	YES	NON	YES	NON	YES	NON
Country-specific time trend	NON	YES	NON	YES	NON	YES	NON	YES	NON	YES	NON	YES

Notes: The dependent variable is the number of events observed in a cell during a given year, following the definition of ACLED riots database (#EVENTS RIOTS), The Agricultural price Index (APP Index), the SPEI growing season, and the Consumer Price Index (CP Index) coefficients displayed capture the sum of price impacts at t, t-1, and t-2. LPM estimations. Conley (2008) standard errors in parentheses, allowing or spatial correlation within a 110km radius and for five periods of correlation. p-values for the linear combination are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Control variables include the interactions between oil prices and oil dummy indicating the presence of an oil field in a given cell, and the interaction between the log of the price for the main mineral produced in a cell following the approximation of Berman et al. (2017) in both cases at t, t-1 and t-2.

Table B.17: Output Conflict: Agricultural Producer Prices, Drought SPEI Growing Season and Consumer Prices: Violence Against Civilian INTENSITY

ACLED CONFLICT	#events Violence (1)	#events Violence (2)	#events Violence (3)	#events Violence (4)	#events Violence (5)	#events Violence (6)	#events Violence (7)	#events Violence (8)	#events Violence (9)	#events Violence (10)	#events Violence (11)	#events Violence (12)
APP Index	-0.1277***	-0.1275***	-0.0647**	-0.1112***	-0.1814***	-0.1965***	-0.1845***	-0.1984***	-0.1290***	-0.2227***	-0.1312***	-0.2301***
	(0.028)	(0.034)	(0.031)	(0.041)	(0.036)	(0.043)	(0.036)	(0.044)	(0.035)	(0.050)	(0.035)	(0.049)
Drought SPEI GS	-0.0112	0.0014	-0.0128	-0.0114	-0.0071	0.0120	-0.0068	0.0110	-0.0083	-0.0076	-0.0081	-0.0100
	(0.008)	(0.008)	(0.010)	(0.011)	(0.009)	(0.009)	(0.009)	(0.009)	(0.011)	(0.015)	(0.011)	(0.014)
CP Index		0.5992***		0.7623***		0.5653***		0.5688***		0.7537***		0.7609***
		(0.115)		(0.137)		(0.115)		(0.273)		(0.139)		(0.138)
APP Index x Excluded groups			-0.1472***	-0.1191					-0.2260***	-0.1991**	-0.2156***	-0.1944**
			(0.037)	(0.075)					(0.046)	(0.080)	(0.045)	(0.081)
Drought SPEI GS x Excluded groups			0.0134	0.0147					0.0185	0.0174	0.01811**	0.0169
			(0.009)	(0.014)					(0.009)	(0.014)	(0.009)	(0.015)
CP Index x Excluded groups				0.0234						0.0097		0.1739
				(0.048)						(0.046)		(0.0482)
APP Index x Monopoly groups			0.3399	-0.1074					0.3240	-0.1011	0.3207	-0.1048
			(0.281)	(0.132)					(0.281)	(0.131)	(0.281)	(0.131)
Drought SPEI GS x Monopoly groups			-0.0512	0.4437***					-0.0540	0.4450***	-0.0503	0.4508***
			(0.039)	(0.161)					(0.039)	(0.163)	(0.039)	(0.163)
CP Index x Monopoly groups				0.1925**					0.1561		0.1621*	
				(0.098)						(0.097)		(0.097)
APP Index x Ethnic Fraction.					0.3008***	0.3939**			0.5529***	0.7776***		
					(0.103)	(0.159)			(0.128)	(0.191)		
Drought SPEI GS x Ethnic Fraction.					-0.0324	-0.0761***			-0.0484**	-0.0324		
					(0.022)	(0.025)			(0.021)	(0.026)		
CP Index x Ethnic Fraction.						0.2948***				0.1377*		
						(0.794)				(0.835)		
APP Index x Ethnic Polariz.							0.1751***	0.2235***			0.2973***	0.4405***
							(0.060)	(0.082)			(0.072)	(0.102)
Drought SPEI GS x Ethnic Polariz.							-0.01821	-0.0371***			-0.0258**	-0.0102
							(0.012)	(0.012)			(0.011)	(0.013)
CP Index x Ethnic Polariz.								0.1365***				0.3467
								(0.313)				(0.036)
Observations	170,112	139,136	170,112	110,000	169,488	138,592	169,488	138,592	169,488	109,968	169,488	109,968
Unconditional_mean _events	0.147	0.128	0.147	0.145	0.148	0.124	0.148	0.124	0.148	0.145	0.148	0.145
Cell FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	NON	YES	NON	YES	NON	YES	NON	YES	NON	YES	NON	YES
Country x year FE	YES	NON	YES	NON	YES	NON	YES	NON	YES	NON	YES	NON
Country-specific time trend	NON	YES	NON	YES	NON	YES	NON	YES	NON	YES	NON	YES

Notes: The dependent variable is the number of events observed in a cell during a given year, following the definition of ACLED violence database (#events Violence). TheAgricultural price Index (APP Index), the SPEI growing season, and the Consumer Price Index (CP Index) coefficients displayed capture the sum of price impacts at t, t-1, and t-2. LPM estimations. Conley (2008) standard errors in parentheses, allowing or spatial correlation within a 110km radius and for five periods of correlation. p-values for the linear combination are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Control variables include interactions between the log of oil prices and oil dummy indicating the presence of an oil field in a given cell, and the interaction between the log of the price for the main mineral produced in a cell following the approximation of Berman et al. (2017), in both cases at t, t-1 and t-2.

Table B.18: Factor Conflict: Agricultural Producer Prices, Drought SPEI Growing Season and Consumer Prices: Base Crops: M3 DATA.

UCDP FACTOR CONFLICT	Incidence (1)	Incidence (2)	Incidence (3)	Incidence (4)	Incidence (5)	Incidence (6)	Incidence (7)	Incidence (8)	Incidence (9)	Incidence (10)	Incidence (11)	Incidence (12)
APP Index	-0.0047	-0.0078**	0.0009	-0.0073	-0.0059	-0.0168***	-0.0064	-0.0166***	-0.0020	-0.0197***	0.0022	-0.0193***
	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)	(0.005)	(0.007)	(0.005)	(0.007)
Drought SPEI GS	0.0033***	0.0033***	0.0026*	0.0022	0.0035**	0.0027**	0.0034**	0.0026**	0.0029*	0.0018	0.0028*	0.0016
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
CP Index		-0.0127		-0.0029		-0.0077		-0.0081		0.0033		0.0025
		(0.013)		(0.015)		(0.012)		(0.012)		(0.014)		(0.014)
APP Index x Excluded groups			-0.0146***	-0.0079					-0.0173***	-0.0114	-0.0169***	-0.0103
			(0.004)	(0.007)					(0.004)	(0.007)	(0.004)	(0.007)
Drought SPEI GS x Excluded groups			0.0031*	0.0047**					0.0035**	0.0051**	0.0034*	0.0051**
			(0.002)	(0.002)					(0.002)	(0.002)	(0.002)	(0.002)
CP Index x Excluded groups				-0.0054						-0.0053		-0.0056
				(0.005)						(0.005)		(0.005)
APP Index x Monopoly groups			0.0180	0.0372***					0.0163	0.0319**	0.0161	0.0321**
			(0.012)	(0.014)					(0.012)	(0.014)	(0.012)	(0.014)
Drought SPEI GS x Monopoly groups			-0.0040*	-0.0036					-0.0040*	-0.0032	-0.0040*	-0.0032
			(0.002)	(0.004)					(0.002)	(0.004)	(0.002)	(0.004)
CP Index x Monopoly groups				-0.0131						-0.0116		-0.0120
				(0.016)						(0.017)		(0.017)
APP Index x Ethnic Fraction.					0.0079	0.0511***			0.0226**	0.0626***		
					(0.009)	(0.013)			(0.009)	(0.014)		
Drought SPEI GS x Ethnic Fraction.					-0.0011	0.0030			-0.0032	0.0009		
					(0.004)	(0.004)			(0.004)	(0.002)		
CP Index x Ethnic Fraction.						-0.0250***				-0.0092*		
						(0.009)				(0.005)		
APP Index x Ethnic Polariz.							0.0058	0.0275***			0.0126**	0.0324***
							(0.005)	(0.007)			(0.005)	(0.008)
Drought SPEI GS x Ethnic Polariz.							-0.0004	0.0018			-0.0014	0.0002
							(0.002)	(0.002)			(0.002)	(0.002)
CP Index x Ethnic Polariz.								-0.0119**				-0.0090*
								(0.005)				(0.005)
Observations	138,216	113,048	138,216	89,375	137,709	112,606	137,709	112,606	137,709	89,349	137,709	89,349
Unconditional_Probability_FConflict %	2.414%	2.057%	2.414%	2.269%	2.422%	2.065%	2.422%	2.065%	2.422%	2.269%	2.422%	2.269%
Cell FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	NON	YES	NON	YES	NON	YES	NON	YES	NON	YES	NON	YES
Country x year FE	YES	NON	YES	NON	YES	NON	YES	NON	YES	NON	YES	NON
Country-specific time trend	NON	YES	NON	YES	NON	YES	NON	YES	NON	YES	NON	YES

Notes: The dependent variable is a binary variable that takes a value of one for conflicts following the definition of UCDP incidence database (INCIDENCE), The Agricultural price Index (APP Index), the SPEI growing season, and the Consumer Price Index (CP Index) coefficients displayed capture the sum of price impacts at t, t-1, and t-2. LPM estimations. Conley (2008) standard errors in parentheses, allowing for spatial correlation within a 110km radius and for five periods of correlation. p-values for the linear combination are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Control variables include the interactions between oil prices and oil dummy indicating the presence of an oil field in a given cell, and the interaction between the log of the price for the main mineral produced in a cell following the approximation of Berman et al. (2017) in both cases at t, t-1 and t-2. Years: 2001-2013.

Table B.19: Output Conflict: Agricultural Producer Prices, Drought SPEI Growing Season and Consumer Prices: Base Crops: M3 DATA.

ACLED CONFLICT	Riots (1)	Riots (2)	Riots (3)	Riots (4)	Riots (5)	Riots (6)	Riots (7)	Riots (8)	Riots (9)	Riots (10)	Riots (11)	Riots (12)
APP Index	0.0316***	0.0285***	0.0240***	0.0144**	0.0289***	0.0392***	0.0292***	0.0397***	0.0231***	0.0247**	0.0235***	0.0256***
	(0.004)	(0.005)	(0.004)	(0.006)	(0.005)	(0.006)	(0.005)	(0.006)	(0.005)	(0.007)	(0.005)	(0.007)
Drought SPEI GS	0.0033***	0.0044***	0.0010	0.0024	0.0021*	0.0070***	0.0018	0.0067***	0.0018	0.0062***	0.0016	0.0058***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)
CP Index		-0.0480***		-0.0580***		-0.0199		-0.0582***		-0.0180		-0.0185
		(0.017)		(0.015)		(0.016)		(0.015)		(0.016)		(0.016)
APP Index x Excluded groups			0.0067*	0.0010					0.0062	0.0026	0.0065*	0.0023
			(0.004)	(0.007)					(0.004)	(0.007)	(0.004)	(0.007)
Drought SPEI GS x Excluded groups			-0.0001	0.0010					0.0005	0.0005	0.0003	0.0005
			(0.001)	(0.002)					(0.002)	(0.002)	(0.002)	(0.002)
CP Index x Excluded groups.				-0.0020						-0.0028		-0.0031
				(0.005)						(0.005)		(0.005)
APP Index x Monopoly groups			0.1233***	0.2086***					0.1228***	0.2268***	0.1230***	0.2274***
			(0.019)	(0.051)					(0.019)	(0.051)	(0.019)	(0.051)
Drought SPEI GS x Monopoly groups			-0.0024	0.0146					-0.0024	0.0166	-0.0023	0.0168
			(0.006)	(0.031)					(0.006)	(0.031)	(0.006)	(0.031)
CP Index x Monopoly groups				-0.1496***						-0.1699***		-0.1698***
				(0.042)						(0.041)		(0.041)
APP Index x Ethnic Fraction.					0.0131	-0.0662***			0.0044	-0.0540***		
					(0.010)	(0.016)			(0.011)	(0.017)		
Drought SPEI GS x Ethnic Fraction.					-0.0079*	-0.0241***			-0.0073*	-0.0206***		
					(0.004)	(0.005)			(0.004)	(0.006)		
CP Index x Ethnic Fraction.						0.0638***				0.0440***		
						(0.011)				(0.012)		
APP Index x Ethnic Polariz.							0.0063	-0.0375***			0.0012	-0.0317***
							(0.006)	(0.009)			(0.006)	(0.009)
Drought SPEI GS x Ethnic Polariz.							-0.0033	-0.0117***			-0.0028	-0.0095***
							(0.002)	(0.002)			(0.002)	(0.003)
CP Index x Ethnic Polariz.								0.0348***				0.0238***
								(0.005)				(0.006)
Observations	138,216	113,048	138,216	89,375	137,709	112,606	137,709	112,606	137,709	89,349	137,709	89,349
Unconditional_Probability_Riots %	2.817%	2.968%	2.817%	3.409%	2.826%	2.978%	2.826%	2.977%	2.826%	3.408%	2.826%	3.408%
Cell FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	NON	YES	NON	YES	NON	YES	NON	YES	NON	YES	NON	YES
Country x year FE	YES	NON	YES	NON	YES	NON	YES	NON	YES	NON	YES	NON
Country-specific time trend	NON	YES	NON	YES	NON	YES	NON	YES	NON	YES	NON	YES

Notes: The dependent variable is a binary variable that takes a value of one for conflicts following the definition of of ACLED riots database (Riots), The Agricultural price Index (APP Index), the SPEI growing season, and the Consumer Price Index (CP Index) coefficients displayed capture the sum of price impacts at t, t-1, and t-2. LPM estimations. Conley (2008) standard errors in parentheses, allowing for spatial correlation within a 110km radius and for five periods of correlation. p-values for the linear combination are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Control variables include the interactions between oil prices and oil dummy indicating the presence of an oil field in a given cell, and the interaction between the log of the price for the main mineral produced in a cell following the approximation of Berman et al. (2017) in both cases at t, t-1 and t-2. Years: 2001-2013.

Table B.20: Output Conflict: Agricultural Producer Prices, Drought SPEI Growing Season and Consumer Prices: Base Crops: M3 DATA.

ACLED CONFLICT	Violence	Violence	Violence	Violence	Violence	Violence	Violence	Violence	Violence	Violence	Violence	Violence
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
APP Index	0.0224***	0.0225***	0.0167***	0.0078	0.0112***	0.0181***	0.0120**	0.0198***	0.0104*	0.0020	0.0111**	0.0042
	(0.005)	(0.005)	(0.005)	(0.006)	(0.005)	(0.006)	(0.006)	(0.006)	(0.006)	(0.008)	(0.006)	(0.008)
Drought SPEI GS	-0.0001	0.0036***	-0.0023	0.0009	-0.0005	0.0034**	-0.0001	0.0037***	-0.0020	0.0011	-0.0017	0.0016
	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
CP Index		-0.0873***		-0.0638***		-0.0883***		-0.0891***		-0.0629***		-0.0637***
		(0.018)		(0.017)		(0.015)		(0.015)		(0.017)		(0.017)
APP Index x Excluded groups			-0.0027	0.0074					-0.0082	0.0058	-0.0066	0.0068
			(0.005)	(0.009)					(0.005)	(0.009)	(0.005)	(0.009)
Drought SPEI GS x Excluded groups			0.0060***	0.0080***					0.0063***	0.0081***	0.0064***	0.0080***
			(0.002)	(0.003)					(0.002)	(0.003)	(0.002)	(0.003)
CP Index x Excluded groups				0.0019						0.0002		0.0006
				(0.006)						(0.006)		(0.006)
APP Index x Monopoly groups			0.0825***	0.1540***					0.0790***	0.1566***	0.0792***	0.1571***
			(0.018)	(0.043)					(0.018)	(0.043)	(0.016)	(0.043)
Drought SPEI GS x Monopoly groups			-0.0040	0.0327					-0.0041	0.0332	-0.0040	0.0332
			(0.005)	(0.024)					(0.005)	(0.024)	(0.005)	(0.024)
CP Index x Monopoly groups				-0.1081***						-0.1147**		-0.1144***
				(0.036)						(0.036)		(0.036)
APP Index x Ethnic Fraction.					0.0388***	0.0176			0.0442***	0.0288		
					(0.012)	(0.017)			(0.012)	(0.018)		
Drought SPEI GS x Ethnic Fraction.					-0.0004	-0.0015			-0.0034	-0.0007		
					(0.004)	(0.004)			(0.004)	(0.005)		
CP Index x Ethnic Fraction.						0.0022*				0.0031		
						(0.012)				(0.012)		
APP Index x Ethnic Polariz.							0.0194***	0.0049			0.0208***	0.0094
.							(0.007)	(0.009)			(0.007)	(0.010)
Drought SPEI GS x Ethnic Polariz.							-0.0015	-0.0018			-0.0029	-0.0014
							(0.002)	(0.002)			(0.002)	(0.003)
CP Index x Ethnic Polariz.								0.0133**				0.0026
								(0.006)				(0.006)
Observations	127,584	106,197	138,216	89,375	137,709	112,606	137,709	112,606	137,709	89,349	137,709	89,349
Unconditional_Probability_Violence %	4.180%	3.805%	4.180%	4.262%	4.195%	3.820%	4.195%	3.820%	4.195%	4.262%	4.195%	4.263%
Cell FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	NON	YES	NON	YES	NON	YES	NON	YES	NON	YES	NON	YES
Country x year FE	YES	NON	YES	NON	YES	NON	YES	NON	YES	NON	YES	NON
Country-specific time trend	NON	YES	NON	YES	NON	YES	NON	YES	NON	YES	NON	YES

Notes: The dependent variable is a binary variable that takes a value of one for conflicts following the definition of of ACLED riots database (Violence), The Agricultural price Index (APP Index), the SPEI growing season, and the Consumer Price Index (CP Index) coefficients displayed capture the sum of price impacts at t, t-1, and t-2. LPM estimations. Conley (2008) standard errors in parentheses, allowing for spatial correlation within a 110km radius and for five periods of correlation. p-values for the linear combination are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Control variables include the interactions between oil prices and oil dummy indicating the presence of an oil field in a given cell, and the interaction between the log of the price for the main mineral produced in a cell following the approximation of Berman et al. (2017) in both cases at t, t-1 and t-2. Years: 2001-2013.

Table B.21: ACLED Factor Conflict: Agricultural Producer Prices, Drought SPEI Growing Season and Consumer Prices: Base Crops: BASE CROPS: BATTLES

ACLED BATTLES	Battles (1)	Battles (2)	Battles (3)	Battles (4)	Battles (5)	Battles (6)	Battles (7)	Battles (8)	Battles (9)	Battles (10)	Battles (11)	Battles (12)
APP Index	-0.0159***	-0.0137***	-0.0120***	-0.0102**	-0.0189***	-0.0164***	-0.0192***	-0.0166***	-0.0154***	-0.0168***	-0.0157***	-0.0174***
	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)	(0.004)	(0.005)	(0.004)	(0.006)	(0.004)	(0.006)
Drought SPEI GS	-0.0000	0.0015	-0.0018	0.0006	-0.0006	0.0019	-0.0005	0.0018	-0.0020	0.0005	-0.0019	0.0002
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
CP Index		0.0012		0.0192		-0.0003		-0.0005		0.0210		0.0211
		(0.012)		(0.014)		(0.012)		(0.014)		(0.014)		(0.014)
APP Index x Excluded groups			-0.0052	-0.0108					-0.0090	-0.0152	-0.0088	-0.0153
			(0.005)	(0.010)					(0.006)	(0.010)	(0.006)	(0.010)
Drought SPEI GS x Excluded groups			0.0040**	0.0006					0.0039**	0.0006	0.0040**	0.0006
			(0.002)	(0.002)					(0.002)	(0.002)	(0.002)	(0.002)
CP Index x Excluded groups				0.0168***						0.0165***		0.0167***
				(0.005)						(0.005)		(0.005)
APP Index x Monopoly groups			-0.1701***	-0.2202***					-0.1702***	-0.2190***	-0.1706***	-0.2193***
			(0.043)	(0.050)					(0.042)	(0.050)	(0.042)	(0.050)
Drought SPEI GS x Monopoly groups			0.0072	0.0749***					0.0073	0.0753***	0.0074	0.0753***
			(0.005)	(0.021)					(0.005)	(0.022)	(0.005)	(0.022)
CP Index x Monopoly groups				0.0726***						0.0703***		0.0705***
				(0.016)						(0.016)		(0.016)
APP Index x Ethnic Fraction.					0.0174	0.0156		0.0287**	0.0451**			
					(0.013)	(0.018)			(0.014)	(0.020)		
Drought SPEI GS x Ethnic Fraction.					0.0033	-0.0028			0.0010	0.0004		
					(0.004)	(0.004)			(0.004)	(0.005)		
CP Index x Ethnic Fraction.						0.0161*				-0.0033		
						(0.009)				(0.009)		
APP Index x Ethnic Polariz.							0.0108	0.0098			0.0165**	0.0264**
							(0.007)	(0.010)			(0.008)	(0.011)
Drought SPEI GS x Ethnic Polariz.							0.0016	-0.0010			0.0003	0.0011
							(0.002)	(0.002)			(0.002)	(0.002)
CP Index x Ethnic Polariz.								0.0091*				-0.0022
								(0.005)				(0.005)
Observations	170,112	139,136	170,112	110,000	169,488	138,592	169,488	138,592	169,488	109,968	169,488	109,968
Unconditional_Probability_Battles %	3.876%	3.351%	3.876%	3.812%	3.890%	3.364%	3.890%	3.364%	3.890%	3.813%	3.890%	3.813%
Cell FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	NON	YES	NON	YES	NON	YES	NON	YES	NON	YES	NON	YES
Country x year FE	YES	NON	YES	NON	YES	NON	YES	NON	YES	NON	YES	NON
Country-specific time trend	NON	YES	NON	YES	NON	YES	NON	YES	NON	YES	NON	YES

Notes: The dependent variable is a binary variable that takes a value of one for conflicts following the definition of ACLED battles database (BATTLES). The Agricultural price Index (APP Index), the SPEI growing season, and the Consumer Price Index (CP Index) coefficients displayed capture the sum of price impacts at t, t-1, and t-2. LPM estimations. Conley (2008) standard errors in parentheses, allowing or spatial correlation within a 110km radius and for five periods of correlation. p-values for the linear combination are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Control variables include the interactions between oil prices and oil dummy indicating the presence of an oil field in a given cell, and the interaction between the log of the price for the main mineral produced in a cell following the approximation of Berman et al. (2017) in both cases at t, t-1 and t-2.

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Table B.22: Conflict: Agricultural Producer Prices, Drought SPEI Growing Season and Consumer Prices: SPATIAL SPILLOVERS

Type of CONFLICT	UCDP_Incidence	UCDP_Incidence	UCDP_Incidence	ACLED_Riots	ACLED_Riots	ACLED_Riots	ACLED_Violence	ACLED_Violence	ACLED_Violence
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
small APP Index	-0.0181***	-0.0141***	-0.0139***	0.0272***	0.0342***	0.0340***	-0.0059	-0.0160**	-0.0157**
	(0.004)	(0.005)	(0.005)	(0.004)	(0.006)	(0.006)	(0.005)	(0.006)	(0.006)
Drought SPEI GS	0.0030***	0.0011	0.0009	0.0028***	0.0055***	0.0051***	0.0011	-0.0028	-0.0027
	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)	(0.002)
CP Index	0.0177	0.0344***	0.0252**	-0.0247***	-0.0099	-0.0094	0.0177	0.0318***	0.032***
	(0.011)	(0.013)	(0.013)	(0.010)	(0.011)	(0.011)	(0.012)	(0.013)	(0.013)
APP Index in neighbouring cells	0.0006	-0.0044	-0.0044	-0.0011	-0.0017	-0.0016	-0.0036	-0.0096	-0.0095
	(0.005)	(0.006)	(0.006)	(0.005)	(0.006)	(0.006)	(0.007)	(0.008)	(0.008)
Drought SPEI GS in neighbouring cells	0.0012	0.0008	0.0020	0.0011	0.0019	0.0018	0.0008	0.0040	0.0041
	(0.003)	(0.004)	(0.004)	(0.003)	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)
APP Index x Excluded groups		-0.0269***	-0.0264***		-0.0086	-0.0089		-0.0111	-0.0101
		(0.008)	(0.008)		(0.008)	(0.008)		(0.009)	(0.009)
Drought SPEI GS x Excluded groups		0.0076***	0.0075***		-0.0007	-0.0008		0.0068***	0.0067***
		(0.002)	(0.002)		(0.002)	(0.002)		(0.002)	(0.002)
CP Index x Excluded groups		-0.0030	-0.0029		0.0005	0.0010		0.0155***	0.0159***
		(0.004)	(0.004)		(0.004)	(0.004)		(0.005)	(0.005)
APP Index x Monopoly groups		-0.0885**	-0.0887**		-0.0511**	-0.0508**		-0.1542***	-0.1546***
		(0.038)	(0.038)		(0.021)	(0.021)		(0.044)	(0.044)
Drought SPEI GS x Monopoly groups		-0.0019	-0.0019		0.0028	0.0029		0.0421*	0.0420*
		(0.004)	(0.004)		(0.028)	(0.028)		(0.022)	(0.022)
CP Index x Monopoly groups		0.0245**	0.0245**		0.0370***	0.0370***		0.0798***	0.0805***
		(0.011)	(0.011)		(0.011)	(0.011)		(0.015)	(0.015)
APP Index x Ethnic Fraction.		0.0379**			-0.0087			0.0700***	
		(0.015)			(0.018)			(0.020)	
Drought SPEI GS x Ethnic Fraction.		-0.0039			-0.0153***			0.0041	
		(0.004)			(0.004)			(0.004)	
CP Index x Ethnic Fraction.		0.0108			0.0207**			-0.0035	
		(0.007)			(0.009)			(0.009)	
APP Index x Ethnic Polariz.			0.0195**			-0.0029			0.0362***
			(0.008)			(0.010)			(0.011)
Drought SPEI GS x Ethnic Polariz.			-0.0014			-0.0067***			0.0019
			(0.002)			(0.002)			(0.002)
CP Index x Ethnic Polariz.			0.0066			0.0093**			-0.0047
			(0.004)			(0.005)			(0.005)
Observations	139,136	109,968	109,968	139,136	109,968	109,968	139,136	109,968	109,968
Unconditional_Probability_Conflict	2.168%	2.434%	2.434%	2.696%	3.100%	3.100%	3.949%	4.236%	4.236%
Cell FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Country-specific time trend	YES	YES	YES	YES	YES	YES	YES	YES	YES

Notes: The dependent variable is a binary variable that takes a value of one for conflicts following the definition of UCDP-GED datase (UCDP_INCIDENCE) and ACLED riots (RIOTS), and violence against civilians (VIOLENCE) database. The Agricultural price Index (APP Index), the drought SPEI growing season, and the Consumer Price Index (CP Index) coefficients displayed capture the sum of price impacts at t, t-1, and t-2. LPM estimations. Conley (2008) standard errors in parentheses, allowing for spatial correlation within a 220km radius and for five periods of correlation. p-values are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Control variables include the interactions between oil prices and oil dummy indicating the presence of an oil field in a given cell, and the interaction between the log of the price for the main mineral produced in a cell following the approximation of Berman et al. (2017) in both cases at t, t-1 and t-2. Neighboring indexes are the average contiguity AAP Index and the drought SPEI Growing season in degree 1 and degree 2 neighboring cells.

Table B.23: Conflict: Agricultural Producer Prices, Drought SPEI Growing Season and Consumer Prices: Spatial and Serial Correlations. STANDARD ERRORS ANALYSIS

Type of CONFLICT	UCDP_Incidence	UCDP_Incidence	UCDP_Incidence	ACLED_Riots	ACLED_Riots	ACLED_Riots	ACLED_Violence	ACLED_Violence	ACLED_Violence
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
APP Index	**-0.0181**	**-0.0140**	**-0.0138**	**0.0272**	**0.0343**	**0.0338**	**-0.0059**	**-0.0158**	**-0.0154**
Standard error 55km, Time: 2 years	(0.003)	(0.004)	(0.004)	(0.003)	(0.005)	(0.005)	(0.004)	(0.006)	(0.006)
Standard error 55km, Time: Infinite	(0.003)	(0.004)	(0.004)	(0.003)	(0.005)	(0.005)	(0.004)	(0.006)	(0.006)
Standard error 1000km, Time: 2 years	(0.005)	(0.007)	(0.007)	(0.006)	(0.007)	(0.008)	(0.007)	(0.009)	(0.009)
Standard error 1000km, Time: Infinite	(0.005)	(0.007)	(0.007)	(0.006)	(0.008)	(0.008)	(0.007)	(0.009)	(0.009)
Drought SPEI GS	**0.0030**	**0.0011**	**0.0008**	**0.0028**	**0.0055**	**0.0050**	**0.0011**	**-0.0029**	**-0.0029**
Standard error 55km, Time: 2 years	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.001	(0.002)	(0.002)
Standard error 55km, Time: Infinite	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)
Standard error 1000km, Time: 2 years	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)	(0.003)	(0.002)
Standard error 1000km, Time: Infinite	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)	(0.003)	(0.003)
CP Index	**0.0250**	**0.0348**	**0.0344**	**-0.0247**	**-0.0099**	**-0.0135**	**0.0176**	**0.0316**	**-0.0322**
Standard error 55km, Time: 2 years	(0.009)	(0.011)	(0.011)	(0.009)	(0.009)	(0.010)	(0.010)	(0.012))	(0.012)
Standard error 55km, Time: Infinite	(0.009)	(0.011)	(0.011)	(0.009)	(0.009)	(0.010)	(0.010)	(0.012)	(0.012)
Standard error 1000km, Time: 2 years	(0.021)	(0.023)	(0.023)	(0.019)	(0.019)	(0.019)	(0.023)	(0.025)	(0.025)
Standard error 1000km, Time: Infinite	(0.021)	(0.023)	(0.023)	(0.019)	(0.019)	(0.019)	(0.023)	(0.025)	(0.025)
Observations	139,136	109,968	109,968	139,136	109,968	109,968	139,136	109,968	109,9681
Cell FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Country-specific time trend	YES	YES	YES	YES	YES	YES	YES	YES	YES

Notes: LPM estimations. Conley (2008) standard errors in parentheses, allowing for spatial and serial correlation. The table is the same as Table 3, Table 4, and Table 5 (columns (2), (10) and (12)) of main text, except that we allow different radius and time periods of spatial and serial correlation. The Agricultural price Index (APP Index), the drought SPEI growing season, and the Consumer Price Index (CP Index) coefficients displayed capture the sum of price impacts at t, t-1, and t-2. Control variables include the interactions between oil prices and oil dummy indicating the presence of an oil field in a given cell, and the interaction between the log of the price for the main mineral produced in a cell following the approximation of Berman et al. (2017) in both cases at t, t-1 and t-2.

Table B.24: Conflict: Agricultural Producer Prices, Drought SPEI Growing Season and Consumer Prices: Spatial and Serial Correlations. STANDARD ERRORS ANALYSIS. *Continuation*

Type of CONFLICT	UCDP_Incidence (1)	UCDP_Incidence (2)	UCDP_Incidence (3)	ACLED_Riots (4)	ACLED_Riots (5)	ACLED_Riots (6)	ACLED_Violence (7)	ACLED_Violence (8)	ACLED_Violence (9)
APP Index x Excluded groups		**-0.0269**	**-0.0265**		**-0.0086**	**-0.0095**		**-0.0111**	**-0.0101**
Standard error 55km, Time: 2 years		(0.007)	(0.007)		(0.007)	(0.007)		(0.008)	(0.008)
Standard error 55km, Time: Infinite		(0.007)	(0.007)		(0.007)	(0.007)		(0.008)	(0.008)
Standard error 1000km, Time: 2 years		(0.011)	(0.011)		(0.010)	(0.010)		(0.013)	(0.013)
Standard error 1000km, Time: Infinite		(0.011)	(0.011)		(0.010)	(0.010)		(0.013)	(0.013)
Drought SPEI GS x Excluded groups		**0.0076**	**0.0076**		**-0.0007**	**-0.0008**		**0.0068**	**0.0067**
Standard error 55km, Time: 2 years		(0.002)	(0.002)		(0.002)	(0.002)		(0.002)	(0.002)
Standard error 55km, Time: Infinite		(0.002)	(0.002)		(0.002)	(0.002)		(0.002)	(0.002)
Standard error 1000km, Time: 2 years		(0.003)	(0.003)		(0.002)	(0.002)		(0.003)	(0.003)
Standard error 1000km, Time: Infinite		(0.003)	(0.003)		(0.002)	(0.002)		(0.003)	(0.003)
CP Index x Excluded groups		**-0.0030**	**-0.0029**		**0.0006**	**0.0010**		**0.0154**	**0.0158**
Standard error 55km, Time: 2 years		(0.003)	(0.003)		(0.003)	(0.003)		(0.004)	(0.004)
Standard error 55km, Time: Infinite		(0.003)	(0.003)		(0.003)	(0.003)		(0.004)	(0.004)
Standard error 1000km, Time: 2 years		(0.006)	(0.006)		(0.005)	(0.005)		(0.008)	(0.007)
Standard error 1000km, Time: Infinite		(0.006)	(0.006)		(0.005)	(0.005)		(0.007)	(0.007)
APP Index x Monopoly groups		**-0.0885**	**-0.0887**		**-0.0512**	**-0.0509**		**-0.1549**	**-0.1553**
Standard error 55km, Time: 2 years		(0.032)	(0.032)		(0.021)	(0.021)		(0.041)	(0.041)
Standard error 55km, Time: Infinite		(0.034)	(0.034)		(0.021)	(0.021)		(0.042)	(0.042)
Standard error 1000km, Time: 2 years		(0.032)	(0.032)		(0.023)	(0.023)		(0.037)	(0.037)
Standard error 1000km, Time: Infinite		(0.033)	(0.033)		(0.023)	(0.023)		(0.038)	(0.038)
Drought SPEI GS x Monopoly groups		**-0.0019**	**-0.0019**		**0.0028**	**0.0030**		**0.0423**	**0.0422**
Standard error 55km, Time: 2 years		(0.003)	(0.003)		(0.028)	(0.028)		(0.022)	(0.022)
Standard error 55km, Time: Infinite		(0.003)	(0.003)		(0.028)	(0.028)		(0.021)	(0.021)
Standard error 1000km, Time: 2 years		(0.005)	(0.005)		(0.038)	(0.038)		(0.031)	(0.031)
Standard error 1000km, Time: Infinite		(0.005)	(0.005)		(0.037)	(0.037)		(0.031)	(0.031)
CP Index x Monopoly groups		**0.0245**	**0.0245**		**0.0371**	**0.0372**		**0.0798**	**0.0805**
Standard error 55km, Time: 2 years		(0.009)	(0.009)		(0.010)	(0.010)		(0.014)	(0.014)
Standard error 55km, Time: Infinite		(0.009)	(0.009)		(0.010)	(0.010)		(0.014)	(0.014)
Standard error 1000km, Time: 2 years		(0.015)	(0.015)		(0.016)	(0.016)		(0.025)	(0.025)
Standard error 1000km, Time: Infinite		(0.015)	(0.015)		(0.017)	(0.017)		(0.025)	(0.025)
APP Index x Ethnic Fraction.		**0.0379**			**-0.0087**			**0.0699**	
Standard error 55km, Time: 2 years		(0.014)			(0.017)			(0.019)	
Standard error 55km, Time: Infinite		(0.014)			(0.017)			(0.019)	
Standard error 1000km, Time: 2 years		(0.018)			(0.019)			(0.022)	
Standard error 1000km, Time: Infinite		(0.018)			(0.019)			(0.025)	
Drought SPEI GS x Ethnic Fraction.		**-0.0039**			**-0.0153**			**0.0041**	
Standard error 55km, Time: 2 years		(0.004)			(0.004)			(0.004)	
Standard error 55km, Time: Infinite		(0.004)			(0.004)			(0.004)	
Standard error 1000km, Time: 2 years		(0.004)			(0.004)			(0.005)	
Standard error 1000km, Time: Infinite		(0.004)			(0.004)			(0.005)	
CP Index x Ethnic Fraction.		**0.0108**			**0.0207**			**-0.0035**	
Standard error 55km, Time: 2 years		(0.006)			(0.008)			(0.009)	
Standard error 55km, Time: Infinite		(0.006)			(0.008)			(0.009)	
Standard error 1000km, Time: 2 years		(0.009)			(0.010)			(0.012)	
Standard error 1000km, Time: Infinite		(0.009)			(0.010)			(0.012)	
APP Index x Ethnic Polariz.			**0.0195**			**-0.0031**			**0.03621**
Standard error 55km, Time: 2 years			(0.008)			(0.009)			(0.011)
Standard error 55km, Time: Infinite			(0.008)			(0.009)			(0.011)
Standard error 1000km, Time: 2 years			(0.010)			(0.010)			(0.012)
Standard error 1000km, Time: Infinite			(0.010)			(0.010)			(0.012)
Drought SPEI GS x Ethnic Polariz.			**-0.0014**			**-0.0068**			**0.0020**
Standard error 55km, Time: 2 years			(0.002)			(0.002)			(0.002)
Standard error 55km, Time: Infinite			(0.002)			(0.002)			(0.002)
Standard error 1000km, Time: 2 years			(0.002)			(0.002)			(0.003)
Standard error 1000km, Time: Infinite			(0.002)			(0.002)			(0.003)
CP Index x Ethnic Polariz.			**0.0066**			**0.0093**			**-0.0046**
Standard error 55km, Time: 2 years			(0.004)			(0.004)			(0.005)
Standard error 55km, Time: Infinite			(0.004)			(0.004)			(0.005)
Standard error 1000km, Time: 2 years			(0.004)			(0.005)			(0.006)
Standard error 1000km, Time: Infinite			(0.005)			(0.005)			(0.006)
Observations	139,136	109,968	109,968	139,136	109,968	109,968	139,136	109,968	109,968
Cell FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Country-specific time trend	YES	YES	YES	YES	YES	YES	YES	YES	YES

Notes: LPM estimations. Conley (2008) standard errors in parentheses, allowing for spatial and serial correlation. The table is the same as Table 3, Table 4, and Table 5 (columns (2), (10) and (12)) of main text, except that we allow different radius and time periods of spatial and serial correlation. The Agricultural price Index (APP Index), the drought SPEI growing season, and the Consumer Price Index (CP Index) coefficients displayed capture the sum of price impacts at t, t-1, and t-2. Control variables include the interactions between oil prices and oil dummy indicating the presence of an oil field in a given cell, and the interaction between the log of the price for the main mineral produced in a cell following the approximation of Berman et al. (2017) in both cases at t, t-1 and t-2.

Table B.25: Conflict: Agricultural Producer Prices, Drought SPEI Growing Season and Consumer Prices: Spatial and Serial Correlations ONE DEGREE AGGREGATION

Type of CONFLICT	UCDP_Incidence	UCDP_Incidence	UCDP_Incidence	ACLED_Riots	ACLED_Riots	ACLED_Riots	ACLED_Violence	ACLED_Violence	ACLED_Violence
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
APP Index	-0.0330***	-0.0224**	-0.0257**	0.0338***	0.0670***	0.0665***	-0.0199*	-0.0214	-0.0273*
	(0.009)	(0.011)	(0.011)	(0.010)	(0.012)	(0.013)	(0.011)	(0.014)	(0.014)
Drought SPEI GS	0.0114***	0.0061	0.0056	0.0171***	0.0186***	0.0176***	0.0080***	0.0066	0.0062
	(0.003)	(0.004)	(0.004)	(0.003)	(0.004)	(0.004)	(0.003)	(0.004)	(0.004)
CP Index	0.0314	0.0283	0.0260	-0.0623	-0.0739***	-0.0622***	-0.0208	-0.0286	-0.0260
	(0.026)	(0.027)	(0.027)	(0.027)	(0.026)	(0.027)	(0.030)	(0.031)	(0.031)
APP Index x Excluded groups		-0.0112***	-0.0114**		-0.0098*	-0.0101*		-0.0065	-0.0069
		(0.005)	(0.005)		(0.005)	(0.005)		(0.006)	(0.006)
Drought SPEI GS x Excluded groups		0.0035***	0.0035**		-0.0010	-0.0012		0.0018	0.0018
		(0.002)	(0.001)		(0.001)	(0.001)		(0.001)	(0.001)
CP Index x Excluded groups		-0.0018	-0.0022		0.0033	0.0038		0.0072**	0.0075**
		(0.003)	(0.003)		(0.003)	(0.003)		(0.003)	(0.003)
APP Index x Monopoly groups		-0.1923***	-0.1926***		-0.2250***	-0.2246***		-0.2804***	-0.2837**
		(0.047)	(0.047)		(0.045)	(0.045)		(0.053)	(0.053)
Drought SPEI GS x Monopoly groups		0.0109	0.0108		-0.1052**	-0.1044*		0.0430	0.0424
		(0.011)	(0.010)		(0.052)	(0.052)		(0.042)	(0.042)
CP Index x Monopoly groups		0.0544***	0.0525***		0.1755***	0.1750***		0.2056***	0.2071***
		(0.017)	(0.017)		(0.024)	(0.024)		(0.030)	(0.030)
APP Index x Ethnic Fraction.		0.0475			-0.0522			0.0854**	
		(0.030)			(0.040)			(0.040)	
Drought SPEI GS x Ethnic Fraction.		0.0074			-0.0406***			-0.0762	
		(0.011)			(0.010)			(0.011)	
CP Index x Ethnic Fraction.		-0.0019			0.0795***			-0.0370	
		(0.019)			(0.022)			(0.023)	
APP Index x Ethnic Polariz.			0.0365**			-0.0275			0.0662***
			(0.018)			(0.022)			(0.024)
Drought SPEI GS x Ethnic Polariz.			0.0055			-0.0232***			-0.0031
			(0.006)			(0.006)			(0.006)
CP Index x Ethnic Polariz.			0.0062			0.0450***			-0.0273**
			(0.011)			(0.013)			(0.013)
Observations	35,216	35,216	35,216	35,216	35,216	35,216	35,216	35,216	35,216
Unconditional_Probability_Conflict	5.608%	5.608%	5.608%	8.067%	8.067%	8.067%	9.873%	9.873%	9.873%
Cell FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Country-specific time trend	YES	YES	YES	YES	YES	YES	YES	YES	YES

Notes: The dependent variable is a binary variable that takes a value of one for conflicts following the definition of UCDP-GED datase (UCDP_INCIDENCE) and ACLED riots (RIOTS), and violence against civilians (VIOLENCE) database. The Agricultural price Index (APP Index), the SPEI growing season, and the Consumer Price Index (CP Index) coefficients displayed capture the sum of price impacts at t, t-1, and t-2. LPM estimations. Conley (2008) standard errors in parentheses, allowing for spatial correlation within a 220km radius and for five periods of correlation. p-values for linear combination are reported in parentheses *** p<0.01, ** p<0.05, * p<0.1. Control variables include the interactions between oil prices and oil dummy indicating the presence of an oil field in a given cell, and the interaction between the log of the price for the main mineral produced in a cell following the approximation of Berman et al. (2017) in both cases at t, t-1 and t-2. Each cell is 110km x 110km at the equator.

Table B.26: Conflict: Agricultural Producer Prices, Drought SPEI Growing Season and Consumer Prices: Spatial and Serial Correlations TWO DEGREE AGGREGATION

Type of CONFLICT	UCDP_Incidence	UCDP_Incidence	UCDP_Incidence	ACLED_Riots	ACLED_Riots	ACLED_Riots	ACLED_Violence	ACLED_Violence	ACLED_Violence
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
APP Index	-0.0234	0.0141	0.0210	-0.0170	0.0634	0.0503	-0.0491*	0.0002	0.0031
	(0.021)	(0.034)	(0.035)	(0.024)	(0.040)	(0.041)	(0.026)	(0.045)	(0.047)
Drought SPEI GS	0.0294***	-0.0190	-0.0222	-0.0127	0.0063	0.0022	-0.0001	0.0072	0.0012
	(0.009)	(0.015)	(0.016)	(0.009)	(0.015)	(0.015)	(0.009)	(0.017)	(0.0173)
CP Index	-0.0702	-0.1273*	-0.1373*	-0.0081	-0.0523	-0.0679	-0.1714**	-0.2123**	-0.2037**
	(0.070)	(0.075)	(0.075)	(0.069)	(0.076)	(0.078)	(0.080)	(0.088)	(0.089)
APP Index x Excluded groups		-0.0042	-0.0042		-0.0069**	-0.0001		0.0003	0.0002
		(0.003)	(0.003)		(0.003)	(0.003)		(0.004)	(0.004)
Drought SPEI GS x Excluded groups		0.0044***	0.0046***		0.0008	0.0014		0.0008	0.0008
		(0.002)	(0.002)		(0.002)	(0.002)		(0.002)	(0.002)
CP Index x Excluded groups		0.0009	0.0010		-0.0025	-0.0001		0.0028	0.0029
		(0.002)	(0.002)		(0.002)	(0.002)		(0.002)	(0.002)
APP Index x Monopoly groups		-0.0859	-0.0781		-0.0895	-0.0784		-0.0572	-0.0568
		(0.073)	(0.073)		(0.093)	(0.093)		(0.105)	(0.104)
Drought SPEI GS x Monopoly groups		0.0076	00071		-0.2782**	-0.1691*		-0.1164	-0.1178
		(0.056)	(0.051)		(0.108)	(0.108)		(0.122)	(0.122)
CP Index x Monopoly groups		0.1426***	0.0721		0.1467**	0.1395*		0.2900***	0.2930***
		(0.052)	(0.053)		(0.075)	(0.075)		(0.082)	(0.082)
APP Index x Ethnic Fraction.		-0.0383			-0.0927			-0.1416	
		(0.073)			(0.086)			(0.095)	
Drought SPEI GS x Ethnic Fraction.		0.1101***			-0.0532			-0.0360	
		(0.038)			(0.036)			(0.039)	
CP Index x Ethnic Fraction.		0.0665			0.1065*			0.0377	
		(0.053)			(0.063)			(0.068)	
APP Index x Ethnic Polariz.			-0.0367			-0.0354			-0.0947
			(0.047)			(0.057)			(0.064)
Drought SPEI GS x Ethnic Polariz.			0.0685***			-0.0258			-0.0089
			(0.023)			(0.019)			(0.022)
CP Index x Ethnic Polariz.			0.0622*			0.0934**			0.0015
			(0.034)			(0.038)			(0.043)
Observations	8,912	8,176	8,176	8,912	8,176	8,176	8,912	8,176	8,176
Unconditional_Probability_Conflict	12.803%	13.650%	13.650%	21.061%	22.272%	22.272%	22.576%	24.009%	24.009%
Cell FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Country-specific time trend	YES	YES	YES	YES	YES	YES	YES	YES	YES

Notes: The dependent variable is a binary variable that takes a value of one for conflicts following the definition of UCDP-GED datase (UCDP_INCIDENCE) and ACLED riots (RIOTS), and violence against civilians (VIOLENCE) database. The Agricultural price Index (APP Index), the SPEI growing season, and the Consumer Price Index (CP Index) coefficients displayed capture the sum of price impacts at t, t-1, and t-2. LPM estimations. Conley (2008) standard errors in parentheses, allowing for spatial correlation within a 220km radius and for five periods of correlation. p-values for linear combination are reported in parentheses *** p<0.01, ** p<0.05, * p<0.1. Control variables include the interactions between oil prices and oil dummy indicating the presence of an oil field in a given cell, and the interaction between the log of the price for the main mineral produced in a cell following the approximation of Berman et al. (2017) in both cases at t, t-1 and t-2. Each cell is 220km x 220km at the equator.

Table B.27: Conflict: Agricultural Producer Prices, Drought SPEI Growing Season and Consumer Prices: Spatial and Serial Correlations:PRICE LAGS

Type of CONFLICT	UCDP_Incidence	UCDP_Incidence	UCDP_Incidence	ACLED_Riots	ACLED_Riots	ACLED_Riots	ACLED_Violence	ACLED_Violence	ACLED_Violence
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
APP Index	-0.0228***	-0.0373***	-0.0375***	0.0481***	0.0581***	0.0582***	0.0123*	-0.0043	-0.0034
	(0.005)	(0.006)	(0.006)	(0.005)	(0.008)	(0.008)	(0.007)	(0.009)	(0.009)
Drought SPEI GS	0.0048**	0.0001	-0.0001	0.0030**	0.0005	0.0002	0.0003	-0.0116***	-0.0112***
	(0.001)	(0.003)	(0.003)	(0.001)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)
CP Index	0.1285**	0.1426***	0.1422***	-0.0459***	-0.0335*	-0.0328*	0.1207***	0.1277***	0.1283***
	(0.019)	(0.022)	(0.022)	(0.015)	(0.018)	(0.018)	(0.021)	(0.024)	(0.024)
APP Index x Excluded groups		0.0000	0.0004		-0.0045	-0.0043		0.0028	0.0044
		(0.011)	(0.010)		(0.011)	(0.011)		(0.014)	(0.014)
Drought SPEI GS x Excluded groups		0.0167***	0.0167***		0.0040	0.0038		0.0175***	0.0174***
		(0.003)	(0.003)		(0.003)	(0.003)		(0.003)	(0.003)
CP Index x Excluded groups		-0.0077	-0.0077		-0.0099*	-0.0114**		0.0103	0.0107***
		(0.005)	(0.006)		(0.005)	(0.005)		(0.007)	(0.007)
APP Index x Monopoly groups		-0.0901**	-0.0905**		-0.0964***	-0.0960***		-0.1927***	-0.1934***
		(0.042)	(0.042)		(0.027)	(0.027)		(0.051)	(0.051)
Drought SPEI GS x Monopoly groups		0.0200***	0.0200***		-0.0063	-0.0062		-0.0232	-0.0234
		(0.006)	(0.006)		(0.044)	(0.044)		(0.036)	(0.036)
CP Index x Monopoly groups		0.0536***	0.0538***		0.1100***	0.1102***		0.1143***	0.1151**
		(0.011)	(0.011)		(0.022)	(0.022)		(0.022)	(0.022)
APP Index x Ethnic Fraction.		0.0786***			-0.0128			0.0903***	
		(0.020)			(0.026)			(0.029)	
Drought SPEI GS x Ethnic Fraction.		-0.0148**			-0.0087			0.0074	
		(0.006)			(0.006)			(0.006)	
CP Index x Ethnic Fraction.		-0.0128			0.0258*			-0.0054	
		(0.010)			(0.013)			(0.013)	
APP Index x Ethnic Polariz.			0.0431***			-0.0077			0.0447***
			(0.011)			(0.014)			(0.016)
Drought SPEI GS x Ethnic Polariz.			-0.0073**			-0.0039			0.0030
			(0.003)			(0.003)			(0.003)
CP Index x Ethnic Polariz.			-0.0059			0.0112			-0.0063
			(0.005)			(0.007))			(0.007)
Observations	139,136	109,968	109,968	139,136	109,968	109,968	139,136	109,968	109,968
Unconditional_Probability_Conflict	2.168%	2.434%	2.434%	2.696%	3.100%	3.100%	3.743%	4.236%	4.236%
Cell FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Country-specific time trend	YES	YES	YES	YES	YES	YES	YES	YES	YES

Notes: The dependent variable is a binary variable that takes a value of one for conflicts following the definition of UCDP-GED datase (UCDP_Incidence) and ACLED riots (Riots), and violence against civilians (Violence) database. The Agricultural price Index (APP Index), the drought SPEI growing season, and the Consumer Price Index (CP Index) coefficients displayed capture the sum of price impacts at t, t-1, t-2, t-3, t-4, and t-5. LPM estimations. Conley (2008) standard errors in parentheses, allowing for spatial correlation within a 110km radius and for five periods of correlation. p-values for the linear combination are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Control variables include the interactions between oil prices and oil dummy indicating the presence of an oil field in a given cell, and the interaction between the log of the price for the main mineral produced in a cell following the approximation of Berman et al. (2017), in both cases at t, t-1, t-2, t-3, t-4, and t-5.

Table B.28: Conflict: Agricultural Producer Prices, Drought SPEI Growing Season and Consumer Prices: Spatial and Serial Correlations: CONDITIONAL LOGIT

Type of CONFLICT	UCDP_Incidence	UCDP_Incidence	UCDP_Incidence	ACLED_Riots	ACLED_Riots	ACLED_Riots	ACLED_Violence	ACLED_Violence	ACLED_Violence
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
APP Index	-0.8742***	-0.5113*	-0.4393*	0.2589*	0.4887	0.4830	-0.3167**	-0.4772*	-0.4681
	(0.258)	(0.285)	(0.268)	(0.156)	(0.355)	(0.369)	(0.130)	(0.281)	(0.284)
Drought SPEI GS	0.1911	-0.0110	-0.0377	-0.0032	0.2156	0.2095	-0.1897*	-0.3319*	-0.3164
	(0.136)	(0.188)	(0.188)	(0.116)	(0.141)	(0.147)	(0.107)	(0.198)	(0.197)
CP Index	-0.8821	-0.1914	-0.2700	-0.8207	-0.2601	-0.2728	-1.0874*	-0.3904	-0.3826
	(1.641)	(1.786)	(1.763)	(0.774)	(1.821)	(1.776)	(0.648)	(1.865)	(1.863)
APP Index x Excluded groups		-0.4808	-0.4512		-0.4782	-0.4745		-0.1857	-0.1629
		(0.413)	(0.425)		(0.315)	(0.181)		(0.466)	(0.468)
Drought SPEI GS x Excluded groups		0.5482	0.5259		-0.0695	-0.0862		0.2400	0.2514
		(0.408)	(0.407)		(0.378)	(0.365)		(0.307)	(0.311)
CP Index x Excluded groups		-0.2146	-0.2246		0.2914	0.2756		0.0018	0.0020
		(0.434)	(0.428)		(0.328)	(0.323)		(0.387)	(0.385)
APP Index x Monopoly groups		-2.809**	-2.7472**		-2.3641	-2.3318		-1.6226	-1.6008
		(1.299)	(1.316)		(1.649)	(1.627)		(1.560)	(1.594)
Drought SPEI GS x Monopoly groups		-1.5771	-1.7767		0.3102*	0.3277*		0.6109***	0.6108***
		(2.267)	(2.366)		(0.167)	(0.171)		(0.229)	(0.224)
CP Index x Monopoly groups		3.7850***	3.9449***		1.9608**	1.9419**		2.6357***	2.6611***
		(0.723)	(0.794)		(0.786)	(0.774)		(0.516)	(0.524)
APP Index x Ethnic Fraction.		0.2238			0.0543			1.2352*	
		(1.313)			(0.599)			(0.653)	
Drought SPEI GS x Ethnic Fraction.		0.0387			-1.7459**			0.6749	
		(0.800)			(0.825)			(0.673)	
CP Index x Ethnic Fraction.		0.9036			-0.0604			-0.1663	
		(0.919)			(0.679)			(0.566)	
APP Index x Ethnic Polariz.			-0.1229			0.05397			0.6331*
			(0.678)			(0.384)			(0.337)
Drought SPEI GS x Ethnic Polariz.			0.1584			-0.9390*			0.2908
			(0.452)			(0.486)			(0.361)
CP Index x Ethnic Polariz.			0.6720			0.3899			-0.1154
			(0.532)			(0.419)			(0.294)
Observations	17,874	15,516	15,516	20,145	17,730	17,730	29,248	25,056	25,056
Unconditional_Probability_Conflict	2.168%	2.434%	2.434%	2.696%	3.100%	3.100%	3.949%	4.236%	4.236%
Cell FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Country-specific time trend	YES	YES	YES	YES	YES	YES	YES	YES	YES

Notes: The dependent variable is a binary variable that takes a value of one for conflicts following the definition of UCDP-GED datase (UCDP_INCIDENCE) and ACLED riots (RIOTS), and violence against civilians (VIOLENCE) database. The Agricultural price Index (APP Index), the drought SPEI growing season, and the Consumer Price Index (CP Index) coefficients displayed capture the sum of price impacts at t, t-1, and t-2. Conditional Logit estimations with fixed effects. Standard errors clustered at the country level. p-values for the linear combination are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Control variables include he interactions between oil prices and oil dummy indicating the presence of an oil field in a given cell, and the interaction between the log of the price for the main mineral produced in a cell following the approximation of Berman et al. (2017), in both cases at t, t-1 and t-2.

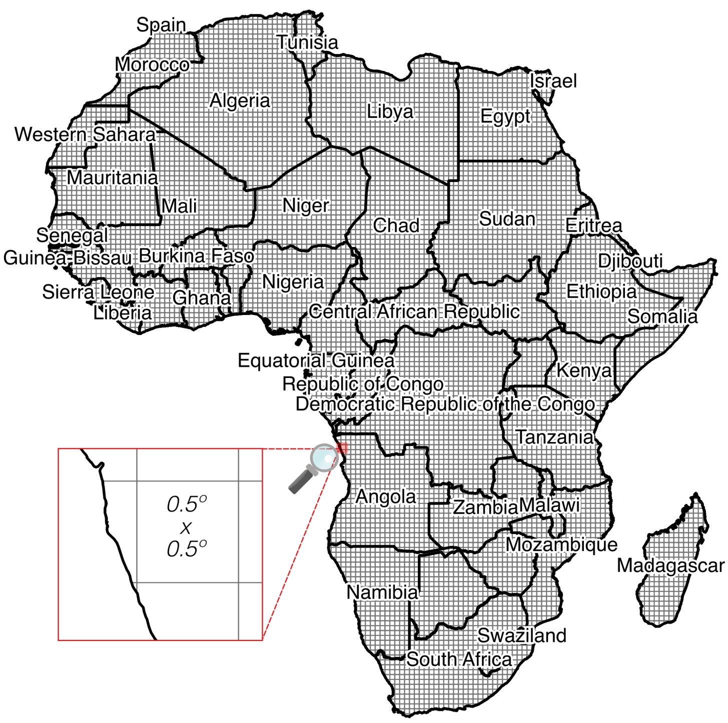
Table B.29: Conflict: Agricultural Producer Prices, Drought SPEI Growing Season and Consumer Prices: Spatial and Serial Correlations: CLIMATE VARIABLES

Type of CONFLICT	UCDP_Incidence	UCDP_Incidence	UCDP_Incidence	ACLED_Riots	ACLED_Riots	ACLED_Riots	ACLED_Violence	ACLED_Violence	ACLED_Violence
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
APP Index	-0.0173***	-0.0143***	-0.0142***	0.0270***	0.0353***	0.0349***	-0.0060	-0.0149**	-0.0145***
	(0.004)	(0.005)	(0.005)	(0.004)	(0.006)	(0.006)	(0.005)	(0.007)	(0.007)
Drought SPEI GS	0.0042***	0.0023	0.0021	0.0031***	0.0080***	0.0075***	0.0026***	0.0010	0.0010
	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)
CP Index	0.0228**	0.0317**	0.0314**	-0.0207**	-0.0047	-0.0043	0.0174	0.0318**	0.0323**
	(0.011)	(0.013)	(0.013)	(0.010)	(0.011)	(0.011)	(0.012)	(0.014)	(0.014)
Drought SPEI	0.0485***	0.0708***	0.0707***	-0.0478***	-0.0460***	-0.0463***	-0.0057	0.0172	0.0171
	(0.011)	(0.014)	(0.014)	(0.010)	(0.012)	(0.012)	(0.013)	(0.016)	(0.016)
APP Index x Excluded groups		-0.0296***	-0.0292***		-0.0131*	-0.0133**		-0.0134	-0.0124
		(0.008)	(0.008)		(0.008)	(0.007)		(0.009)	(0.009)
Drought SPEI GS x Excluded groups		0.0082***	0.0081***		-0.0033*	-0.0033**		0.0034*	0.0033
		(0.002)	(0.002)		(0.002)	(0.002)		(0.002)	(0.002)
CP Index x Excluded groups		-0.0021	-0.0020		0.0022	0.0026		0.0174***	0.0179***
		(0.004)	(0.004)		(0.004)	(0.004)		(0.005)	(0.005)
APP Index x Monopoly groups		-0.0883**	-0.0885**		-0.0480**	-0.0477**		-0.1537***	-0.1541***
		(0.037)	(0.038)		(0.021)	(0.021)		(0.044)	(0.044)
Drought SPEI GS x Monopoly groups		-0.0042	-0.0042		-0.0081	-0.0080		0.0360	0.0360
		(0.005)	(0.004)		(0.030)	(0.030)		(0.023)	(0.023)
CP Index x Monopoly groups		0.0208*	0.0208*		0.0352***	0.0353***		0.0772***	0.0778***
		(0.011)	(0.011)		(0.011)	(0.011)		(0.015)	(0.015)
APP Index x Ethnic Fraction.		0.0459***			-0.0030			0.0696***	
		(0.015)			(0.018)			(0.020)	
Drought SPEI GS x Ethnic Fraction.		-0.0073*.			-0.0195**			-0.0013	
		(0.004)			(0.009)			(0.004)	
CP Index x Ethnic Fraction.		0.0122			0.0195**			-0.0029	
		(0.008)			(0.009)			(0.009)	
APP Index x Ethnic Polariz.			0.0243***			-0.0001			0.0357***
			(0.008)			(0.010)			(0.011)
Drought SPEI GS x Ethnic Polariz.			-0.0034*			-0.0083***			-0.0006
			(0.002)			(0.002)			(0.002)
CP Index x Ethnic Polariz.			0.0071*			0.0090*			-0.0043
			(0.004)			(0.005)			(0.005)
Observations	134,208	107,264	107,264	134,208	107,264	107,264	134,208	107,264	107,264
Unconditional_Probability_Conflict	2.186%	2.424%	2.424%	2.731%	2.977%	2.977%	3.794%	4.192%	4.192%
Cell FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Country-specific time trend	YES	YES	YES	YES	YES	YES	YES	YES	YES

Notes: The dependent variable is a binary variable that takes a value of one for conflicts following the definition of UCDP-GED datase (UCDP_INCIDENCE) and ACLED riots (RIOTS), and violence against civilians (VIOLENCE) database. The Agricultural price Index (APP Index), the SPEI growing season, the Consumer Price Index (CP Index) and the drought SPEI coefficients displayed capture the sum of price impacts at t, t-1, and t-2. LPM estimations. Conley (2008) standard errors in parentheses, allowing for spatial correlation within a 220km radius and for five periods of correlation. p-values for linear combination are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Control variables include the interactions between oil prices and oil dummy indicating the presence of an oil field in a given cell, and the interaction between the log of the price for the main mineral produced in a cell following the approximation of Berman et al. (2017) in both cases at t, t-1 and t-2. We also control for other weather variables as Temperature, the cell-year mean temperature in degrees celsius, and Rainfall, the yearly total amount of precipitation (in millimeter) in the cell.

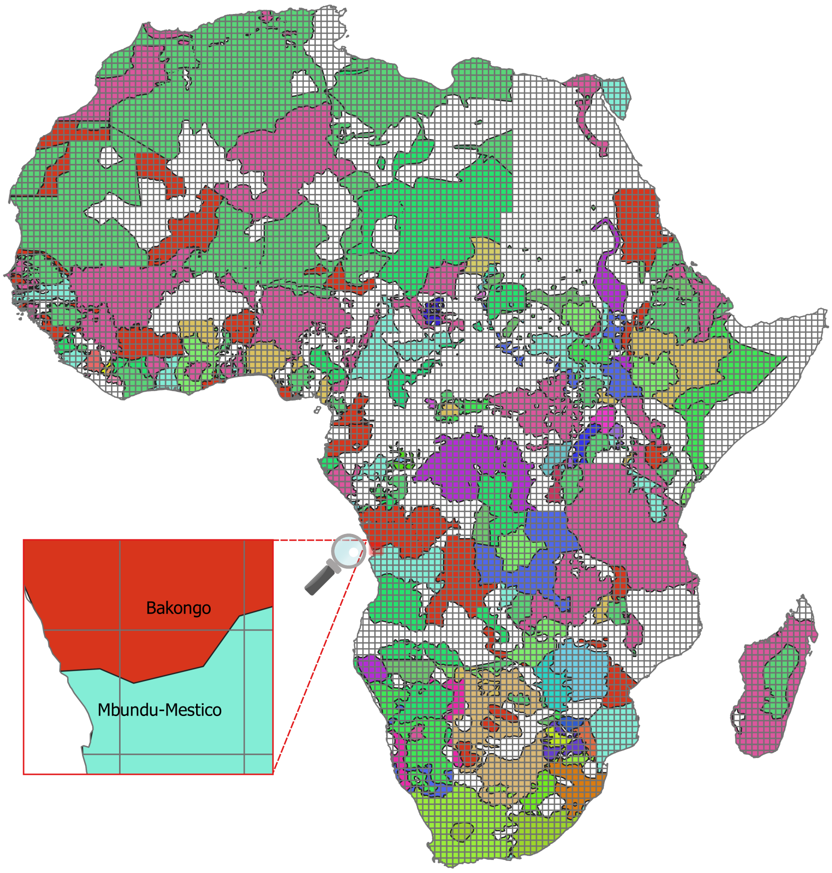
B.4 Additional Figures

Figure B.1: Cells Africa



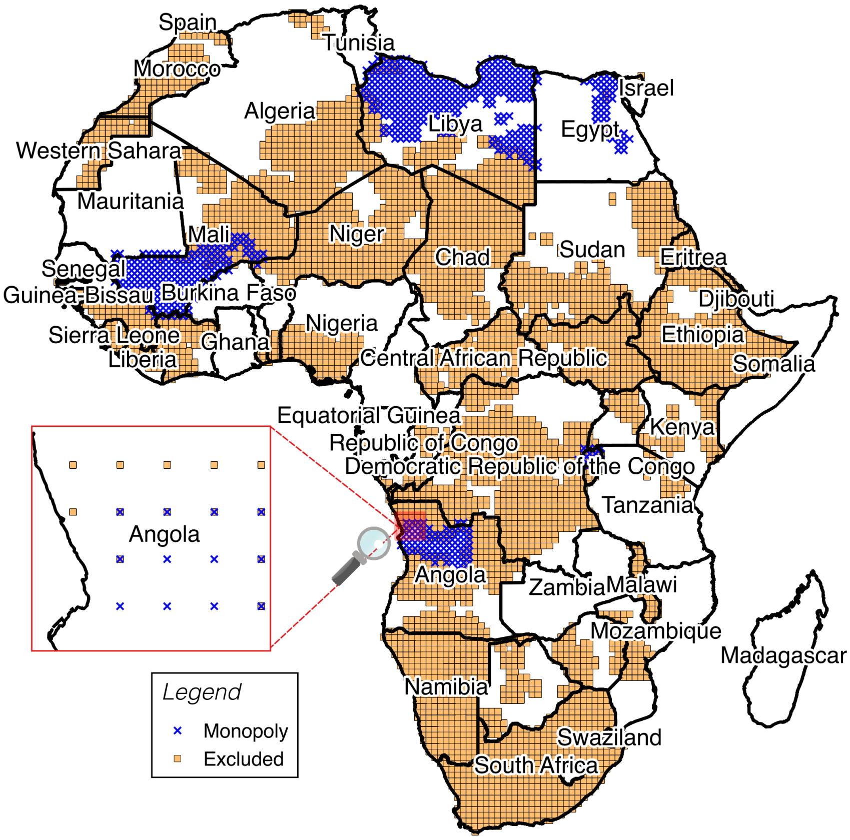
Source: PRIO-GRID grid structure matched with the African countries by the Global Administrative Unit Layers.

Figure B.2: Ethnic groups from Geo-referencing Ethnic Power Relation. Year 1997



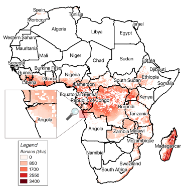
Source: Each color represents a settlement group of politically relevant ethnic groups in independent states with more than 500,000 inhabitants from 1946-2009. Own work based on the group list in the Ethnic Power Relations dataset version 2014. The database is filtered by the year 1997.

Figure B.3: Excluded and monopoly groups. Year 1997

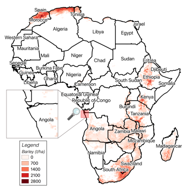


Source: Own work based on data from Ethnic Power Relations (EPR) Dataset Core 2014. Year 1997.

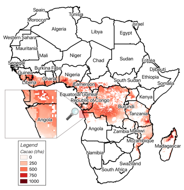
Figure B.4: Crops potential production



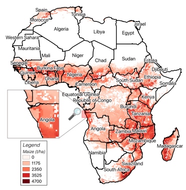
(a) Banana



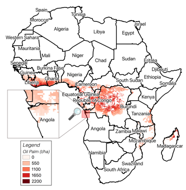
(b) Barley



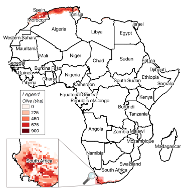
(c) Cacao



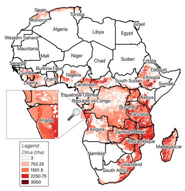
(d) Maize



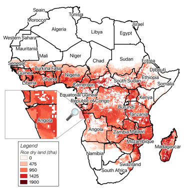
(e) Oil_Palm



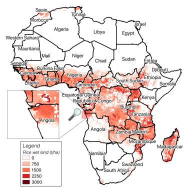
(f) Olive



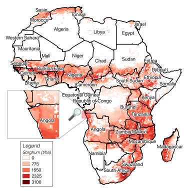
(g) Oranges



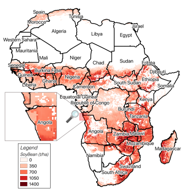
(h) Rice_Dry_Land



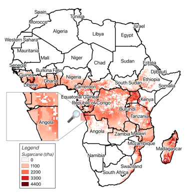
(i) Rice_Wet_Land



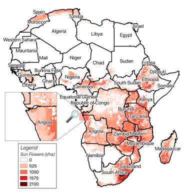
(j) Sorghum



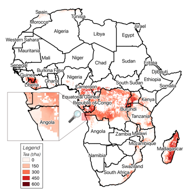
(k) Soybean



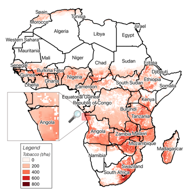
(l) Sugarcane



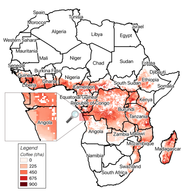
(m) Sunflower



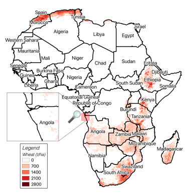
(n) Tea



(o) Tobacco



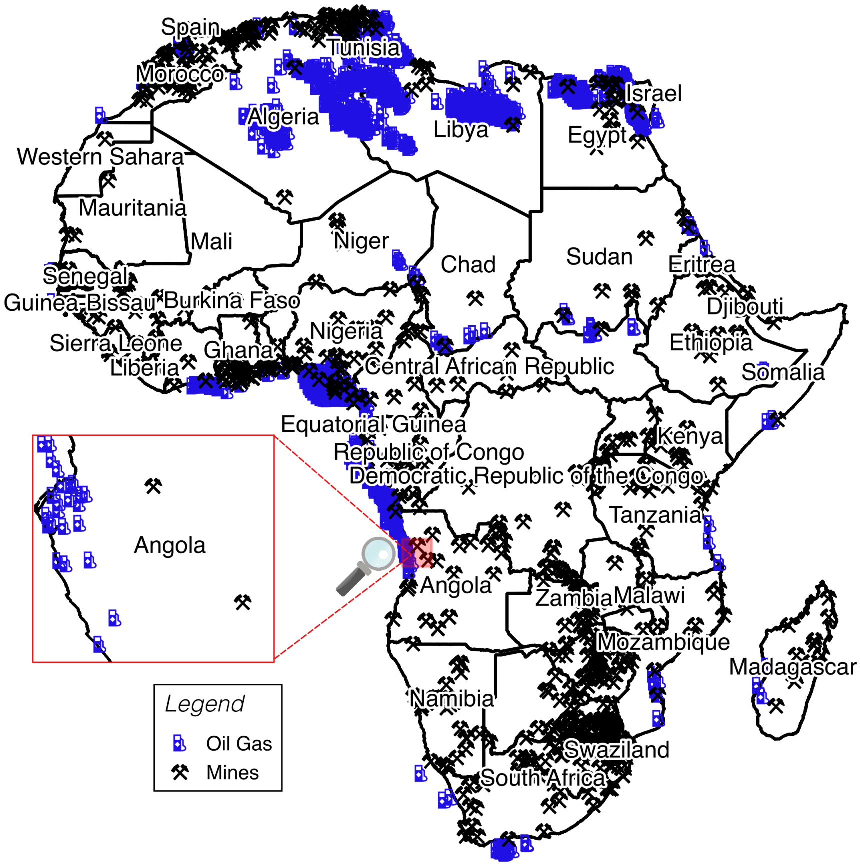
(p) Coffee



(q) Wheat

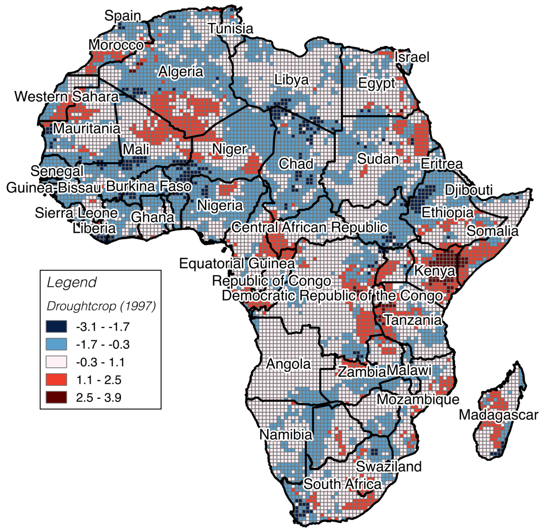
Source: Own work based on data from FAO's Global Agro-Ecological Zones (GAEZ) data.

Figure B.5: Natural Resources

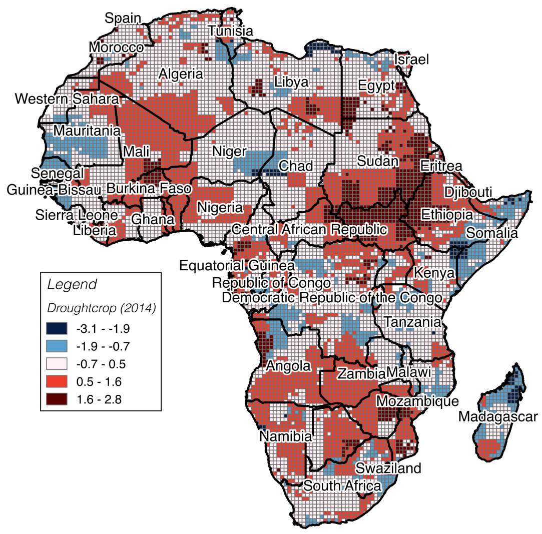


Sources: Own work based on data from Petroleum Dataset v. 1.2 and U.S. Geological Survey (USGS) dataset.

Figure B.6: Droughts SPEI growing season



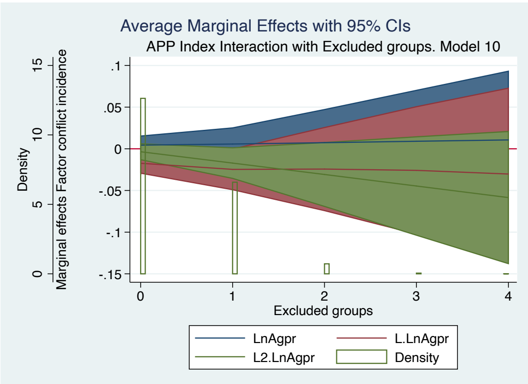
(a) Drought SPEI growing season 1997



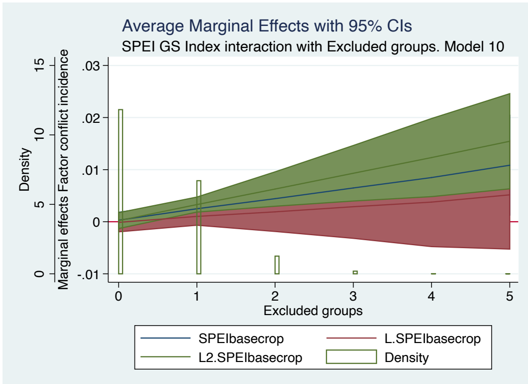
(b) Drought SPEI growing season 2014

Source: Own work based on SPEI Global Drought Monitor data.

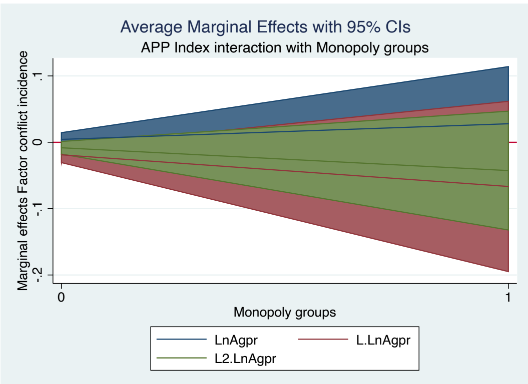
Figure B.7: Factor conflict - Significant interaction variables in full model with ethnic fractionalization



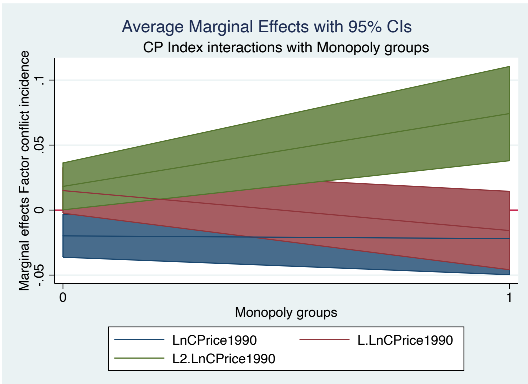
(a) APP index interaction excluded groups



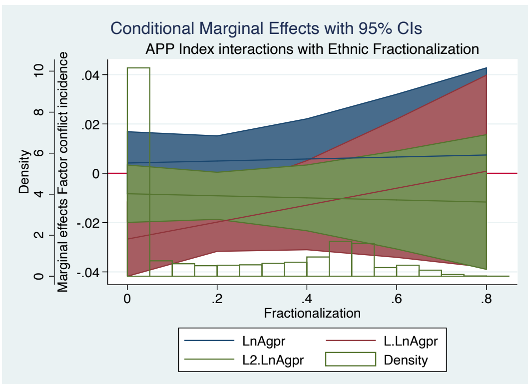
(b) Drought SPEI GS index interaction excluded groups



(c) APP index interaction monopoly groups

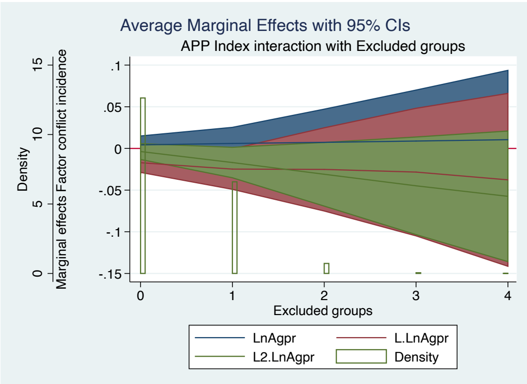


(d) CP index interaction monopoly groups

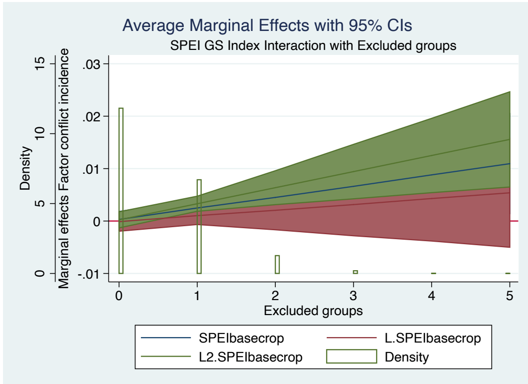


(e) APP index interaction Ethnic fractionalization

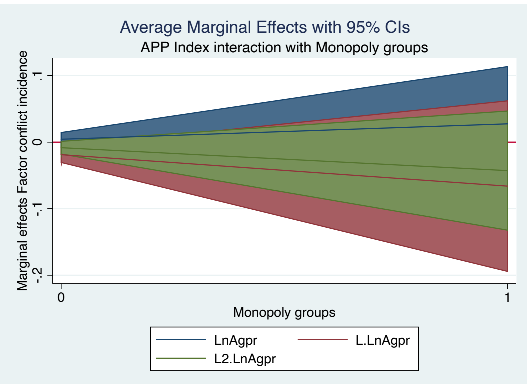
Figure B.8: Factor conflict - Significant interaction variables in full model with ethnic polarization



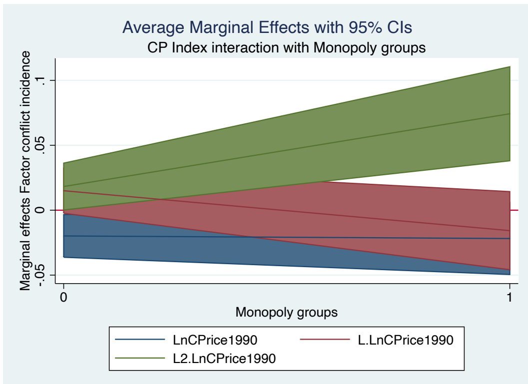
(a) APP index interaction excluded groups



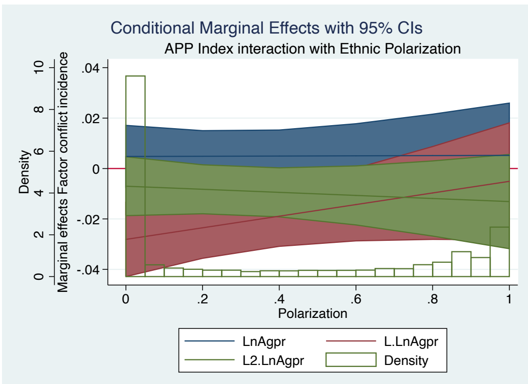
(b) Drought SPEI GS index interaction excluded groups



(c) APP index interaction monopoly groups

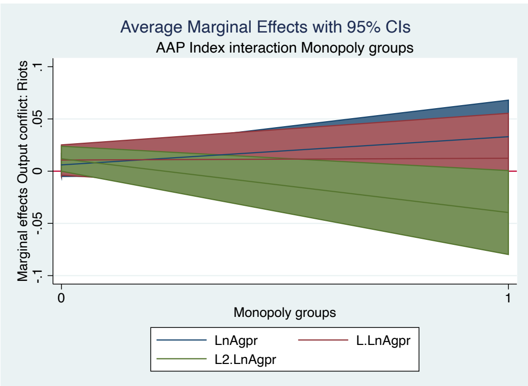


(d) CP index interaction monopoly groups

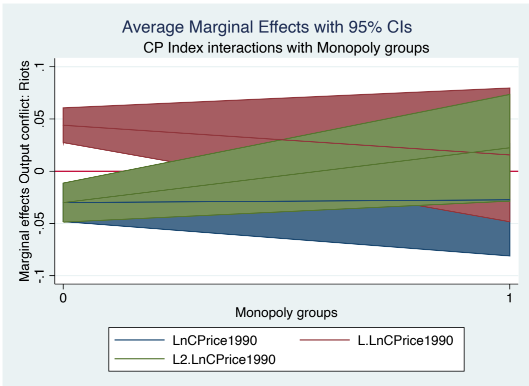


(e) APP index interaction Ethnic Polarization

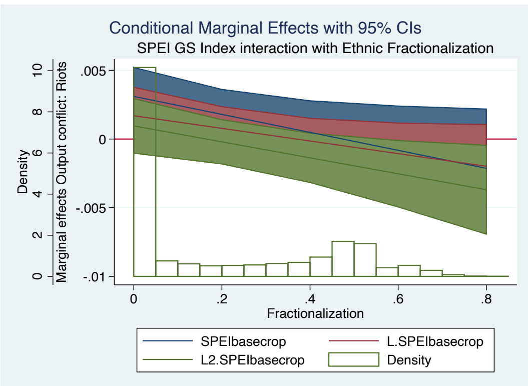
Figure B.9: Riots - Significant interaction variables in full model with ethnic fractionalization



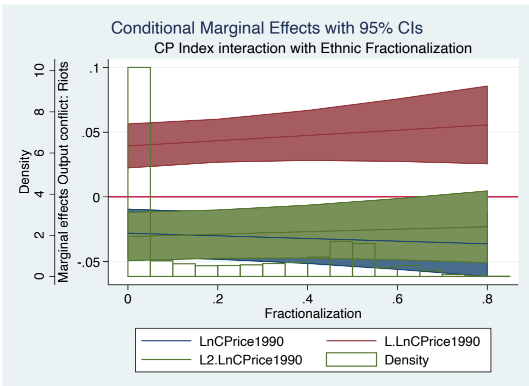
(a) APP index interaction monopoly groups



(b) CP index interaction monopoly groups

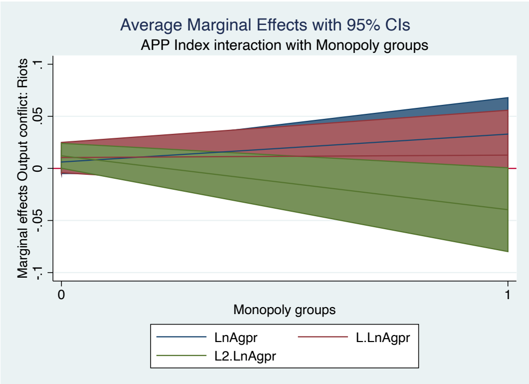


(c) Drought SPEI GS index interaction Ethnic fractionalization

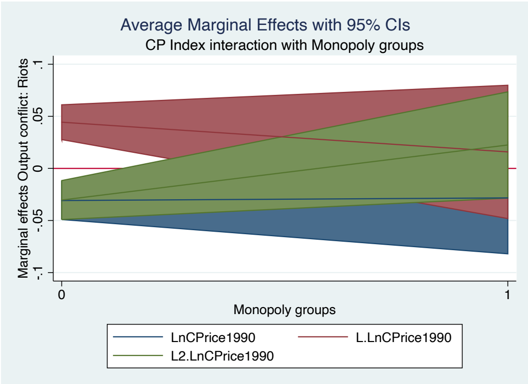


(d) CP index interaction Ethnic fractionalization

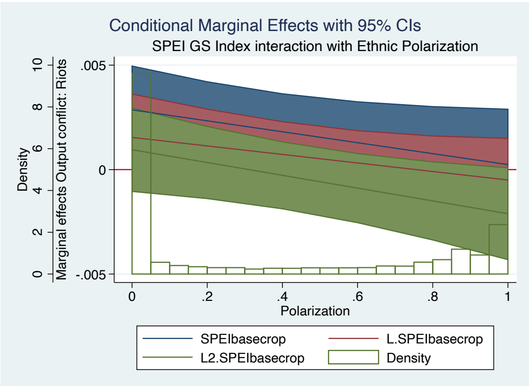
Figure B.10: Riots - Significant interaction variables in full model with ethnic polarization



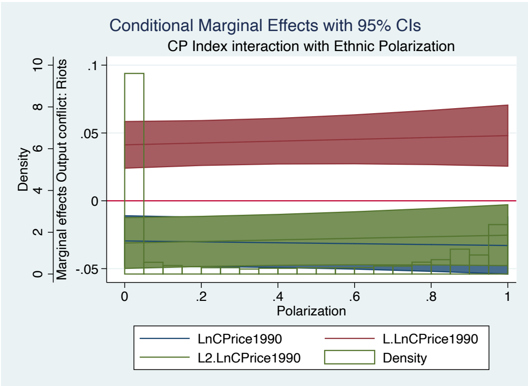
(a) APP index interaction monopoly groups



(b) CP index interaction monopoly groups

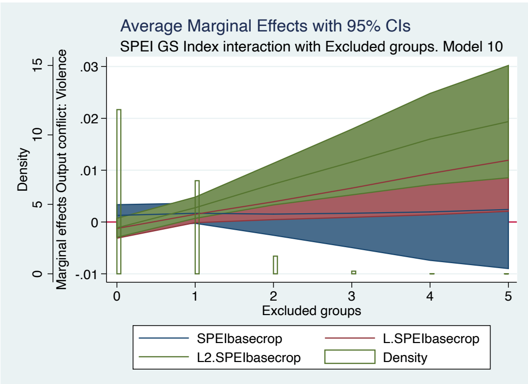


(c) Drought SPEI GS index interaction Ethnic polarization

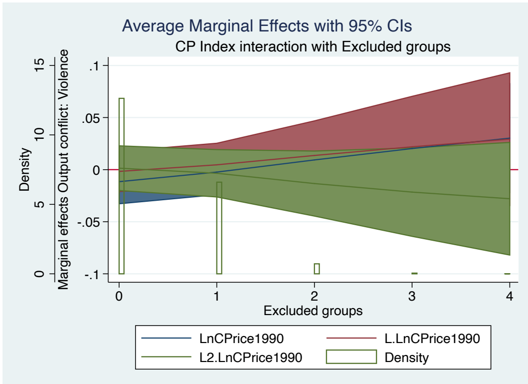


(d) CP index interaction Ethnic polarization

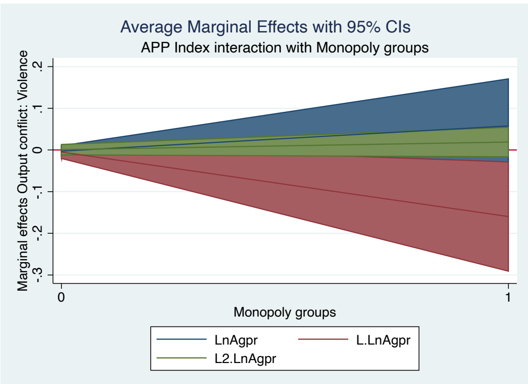
Figure B.11: Violence against civilians - Significant interaction variables in full model with ethnic fractionalization



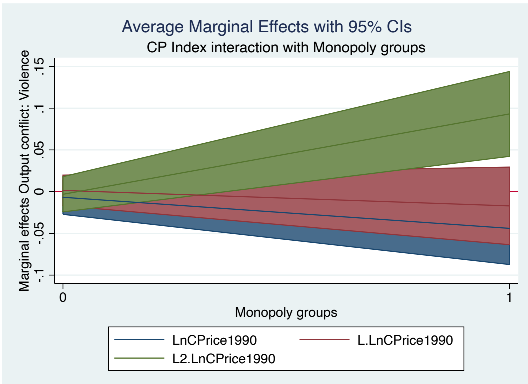
(a) Drought SPEI GS index interaction excluded groups



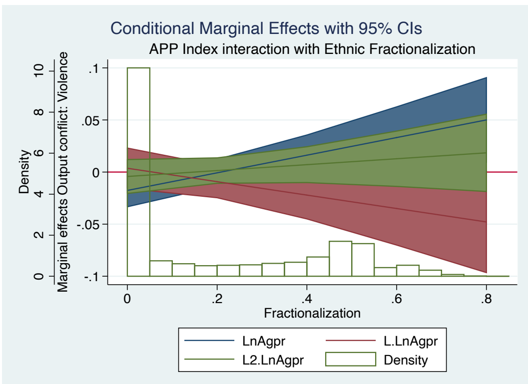
(b) CP index interaction excluded groups



(c) APP index interaction monopoly groups

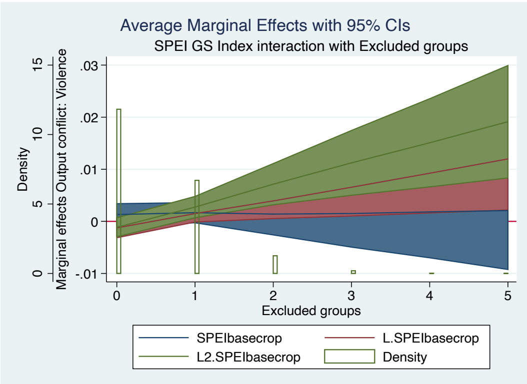


(d) CP index interaction monopoly groups

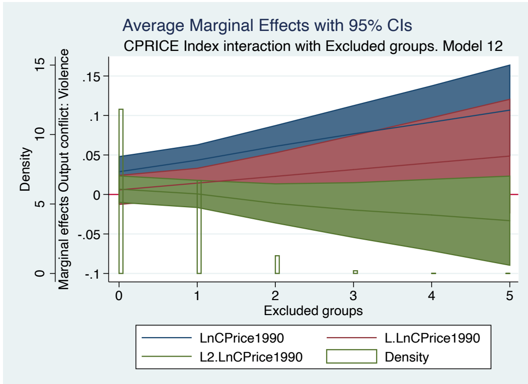


(e) APP index interaction Ethnic fractionalization

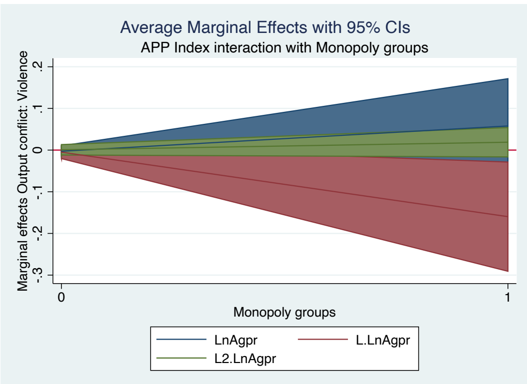
Figure B.12: Violence against civilians - Significant interaction variables in full model with ethnic polarization



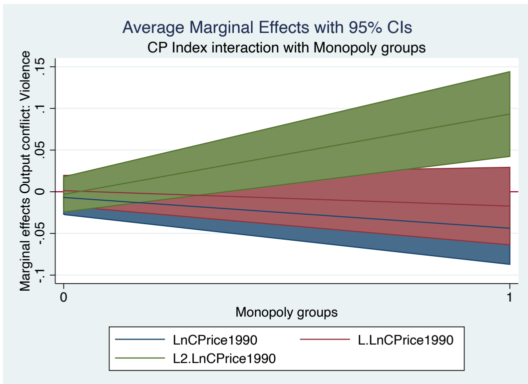
(a) Drought SPEI GS index interaction excluded groups



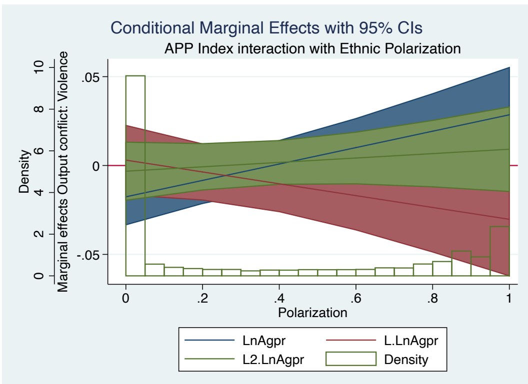
(b) CP index interaction excluded groups



(c) APP index interaction monopoly groups



(d) CP index interaction monopoly groups



(e) APP index interaction Ethnic polarization

Appendix C

Appendix Chapter 3

C.1 Descriptive Statistics

Table C.1: Nigerian GHS-PANEL (2010-2018) Main variables

Variable	Obs	Mean	Std. Dev.
Agricultural characteristics			
Real_Agricultural_Output	6948	121853.8	1424141
Land_area	6881	3.776	39.699
Labor_days	6936	403.274	683.606
Total_area_plot	6934	4.054	144.296
Endowment_Labor	6946	3.709	2.12
Harvest_Cassava	6112	461.996	6036.478
Harvest_Maize	6112	320.691	1224.193
Land_Harvested_Cassava	6112	0.278	11.275
Land_Harvested_Maize	6112	0.492	10.841
Fertility	6904	0.474	0.499
Pesticide	6932	0.232	0.422
Herbicide	6932	0.268	0.443
Improved_Seeds	6877	0.980	0.140
Yield_Maize	2107	9268.011	122933.2
Yield_Cassava	1502	7027.574	25916.07
Yield	6649	11390.3	167277.5
Household characteristics			
Age_head_household	6946	51.232	14.997
literacy	6592	0.595	0.491
Migration	6363	0.689	1.369
household_size	6948	7.683	3.995
Weather and terrain conditions characteristics			
Temperature_mean	6948	26.314	0.955
Rainfall_mean	6948	1264.633	409.651
Slope	6948	3.224	3.266
Elevation	6948	298.059	213.416
PotentialWetness	6948	14.19	3.152
Nutrient_Availability	6948	1.824	0.815
Nutrient_Retention	6948	1.574	0.602
Rooting	6948	1.415	0.719
Oxygen_to roots	6948	1.197	0.501
Exces salt	6948	1.024	0.273
Toxicity	6948	1.008	0.217
Workability	6948	1.482	0.747

Notes: Real Agricultural Output measured in 2010 Naira. Land is measured in hectares. Temperature is measured in degrees Celsius. Sample restricted to farming households. Own work using data from the Nigeria GHS-Panel.

Table C.2: Nigerian GHS-PANEL (2010-2018). Additional variables

Variable	Obs	Mean	Std. Dev.
Sex	117888	1.506	.5
Age	110167	23.908	21.478
Industry	33245	3.898	4.086
AnyWork	61117	0.555	0.497
Work (agriculture)	61117	0.286	0.452
Dummy for migration	121690	0.365	0.481
Prime age male	121690	0.158	0.364
Literacy	98601	0.633	0.482
Secondary	75105	0.185	0.389
Total_hours	31887	40.551	21.897
Real_Employment_Income	10216	56175.91	591485.5
Illness_	61384	0.097	0.296
Number_days_Ill	40121	0.710	3.196
Rural	223356	0.712	0.453
Urban	222996	0.287	0.452

Notes: Full Sample. Own work using data from the Nigeria GHS-Panel.

Table C.3: Summary Functions for Oil-Spill Pollution

Variable	Obs	Mean	Std. Dev.
Cumulative_Oilspill	6948	0.388	3.139
FCumulative_Oilspill	6948	0.388	3.137
Oil Spill	6948	0.238	1.987
TCumulative_Oilspill	6948	2.276	17.985
Dummy_Oil5Km	6948	0.063	0.243
Cum_Volumen_OilSpill	6854	37.803	360.02
Volumen_OilSpill	6854	37.793	359.989
FCum_Volumen_OilSpill	6697	10.035	99.128
TCum_Volumen_OilSpill	6854	216.577	2068.179

Summarize Oil pollution variables for locations within 5 km. Own work using data from NOSDRA.

C.2 Additional Tables

Table C.4: Data Collection Dates for Surveys and Oil-Spill Incidents

		Post-Planting		Post-Harvest		Oil-spill_Incident	
Wave	Survey	Start	End	Start	End	Start	End
1	2010-2011	31/8/10	15/10/10	1/2/11	1/4/11	1/1/06	31/3/11
2	2012-2013	1/9/12	1/11/12	1/2/13	1/4/13	1/1/06	31/3/13
3	2015-2016	1/9/15	1/11/15	1/2/16	1/4/16	1/1/06	31/3/16
4	2018-2019	1/7/18	1/9/18	1/1/19	28/2/19	1/1/06	31/12/18

Notes: The table shows the data collection dates from the Nigeria GHS-surveys, and the dates used on the main variable of proxy for Oil Spill Pollution, from The Oil Spill Monitor. Note that the agriculture data on the post-harvest period of wave 4 ends in December 2018.

Table C.5: First Stage Regression. Column 3 of Table 2

VARIABLES	LnLand (1)	LnLabor_days (2)
Ln(Total Own land)	0.3784***	0.1824***
	(0.020)	(0.016)
Ln(Number of adult equivalents)	0.1311***	0.4386***
	(0.036)	(0.034)
Observations	9689	10190
F-test excluded instruments	63.18***	159.21****
R-squared	0.640	0.470

Notes: Robust standard errors are in parentheses. Standard errors are clustered at LGA level. All regressions include a dummy for being within 5 kilometers of an oil spill and the interaction between that dummy and the trend. Farmer controls are included. See Table 2 for more details. Significance is denoted as follows: *** p<0.01. ** p<0.05. * p<0.1

Table C.6: Imperfect Instruments with Multiple Endogenous Variables

λ_{land}	λ_{Labor}	$\hat{\delta}$	$\hat{\alpha}$	
0	0	-0.03	0.50	0.33
0	0.1	-0.02	0.35	0.53
0	0.2	0.00	-1.39	2.86
0	0.3	-0.03	1.14	-0.53
0	0.4	-0.03	0.88	-0.18
0	0.5	-0.03	0.81	-0.08
0	0.6	-0.03	0.77	-0.04
0	0.7	-0.03	0.75	-0.01
0	0.8	-0.03	0.74	0.01
0	0.9	-0.03	0.73	0.02
0	1	-0.03	0.72	0.03
0.1	0	-0.03	0.82	0.20
0.1	0.1	-0.03	0.59	0.40
0.1	0.2	-0.10	6.27	-4.76
0.1	0.3	-0.04	1.39	-0.33
0.1	0.4	-0.03	1.22	-0.16
0.1	0.5	-0.03	1.15	-0.11
0.1	0.6	-0.03	1.12	-0.08
0.1	0.7	-0.03	1.10	-0.06
0.1	0.8	-0.03	1.09	-0.05
0.1	0.9	-0.03	1.08	-0.04
0.1	1	-0.03	1.07	-0.04
0.2	0	0.07	-7.00	3.48
0.2	0.1	-0.01	-1.02	1.25
0.2	0.2	-0.03	0.98	0.51
0.2	0.3	-0.04	1.97	0.13
0.2	0.4	-0.05	2.57	-0.09
0.2	0.5	-0.06	2.97	-0.24
0.2	0.6	-0.06	3.26	-0.35
0.2	0.7	-0.06	3.47	-0.43
0.2	0.8	-0.07	3.64	-0.49
0.2	0.9	-0.07	3.77	-0.54
0.2	1	-0.07	3.88	-0.58
0.3	0	-0.02	-0.32	0.68
0.3	0.1	-0.02	-0.07	0.75
0.3	0.2	-0.03	0.53	0.95
0.3	0.3	-0.08	4.67	2.27
0.3	0.4	0.03	-3.80	-0.44
0.3	0.5	0.01	-2.04	0.12
0.3	0.6	0.00	-1.61	0.26
0.3	0.7	0.00	-1.41	0.33
0.3	0.8	0.00	-1.30	0.36
0.3	0.9	0.00	-1.23	0.39
0.3	1	0.00	-1.18	0.40

Table C.6: Continued

λ_{land}	λ_{Labor}	$\hat{\delta}$	$\hat{\alpha}$	
0.4	0	-0.02	-0.07	0.57
0.4	0.1	-0.02	0.04	0.70
0.4	0.2	-0.03	0.37	1.11
0.4	0.3	0.04	-4.55	-5.04
0.4	0.4	-0.01	-0.74	-0.27
0.4	0.5	-0.01	-0.51	0.01
0.4	0.6	-0.01	-0.43	0.12
0.4	0.7	-0.01	-0.39	0.17
0.4	0.8	-0.02	-0.36	0.20
0.4	0.9	-0.02	-0.34	0.22
0.4	1	-0.02	-0.33	0.24
0.5	0	-0.02	0.02	0.53
0.5	0.1	-0.02	0.08	0.67
0.5	0.2	-0.02	0.28	1.20
0.5	0.3	0.00	-1.08	-2.28
0.5	0.4	-0.02	-0.28	-0.25
0.5	0.5	-0.02	-0.19	-0.01
0.5	0.6	-0.02	-0.15	0.08
0.5	0.7	-0.02	-0.13	0.13
0.5	0.8	-0.02	-0.12	0.16
0.5	0.9	-0.02	-0.11	0.18
0.5	1	-0.02	-0.11	0.19
0.6	0	-0.02	0.07	0.51
0.6	0.1	-0.02	0.10	0.66
0.6	0.2	-0.02	0.23	1.25
0.6	0.3	-0.01	-0.43	-1.78
0.6	0.4	-0.02	-0.10	-0.24
0.6	0.5	-0.02	-0.05	-0.02
0.6	0.6	-0.02	-0.03	0.07
0.6	0.7	-0.02	-0.02	0.11
0.6	0.8	-0.02	-0.01	0.14
0.6	0.9	-0.02	-0.01	0.16
0.6	1	-0.02	-0.01	0.17
0.7	0	-0.02	0.10	0.50
0.7	0.1	-0.02	0.11	0.65
0.7	0.2	-0.02	0.19	1.28
0.7	0.3	-0.02	-0.16	-1.56
0.7	0.4	-0.02	0.00	-0.23
0.7	0.5	-0.02	0.03	-0.03
0.7	0.6	-0.02	0.04	0.06
0.7	0.7	-0.02	0.04	0.10
0.7	0.8	-0.02	0.05	0.13
0.7	0.9	-0.02	0.05	0.15
0.7	1	-0.02	0.05	0.16

Table C.6: Continued

λ_{land}	λ_{Labor}	$\hat{\delta}$	$\hat{\alpha}$	
0.8	0	-0.02	0.11	0.49
0.8	0.1	-0.02	0.12	0.65
0.8	0.2	-0.02	0.17	1.31
0.8	0.3	-0.02	-0.02	-1.44
0.8	0.4	-0.02	0.07	-0.23
0.8	0.5	-0.02	0.08	-0.03
0.8	0.6	-0.02	0.08	0.05
0.8	0.7	-0.02	0.09	0.10
0.8	0.8	-0.02	0.09	0.12
0.8	0.9	-0.02	0.09	0.14
0.8	1	-0.02	0.09	0.16
0.9	0	-0.02	0.13	0.49
0.9	0.1	-0.02	0.13	0.65
0.9	0.2	-0.02	0.15	1.33
0.9	0.3	-0.02	0.08	-1.37
0.9	0.4	-0.02	0.11	-0.22
0.9	0.5	-0.02	0.11	-0.03
0.9	0.6	-0.02	0.12	0.05
0.9	0.7	-0.02	0.12	0.09
0.9	0.8	-0.02	0.12	0.12
0.9	0.9	-0.02	0.12	0.14
0.9	1	-0.02	0.12	0.15
1	0	-0.02	0.14	0.48
1	0.1	-0.02	0.14	0.64
1	0.2	-0.02	0.13	1.34
1	0.3	-0.02	0.14	-1.32
1	0.4	-0.02	0.14	-0.22
1	0.5	-0.02	0.14	-0.03
1	0.6	-0.02	0.14	0.04
1	0.7	-0.02	0.14	0.09
1	0.8	-0.02	0.14	0.11
1	0.9	-0.02	0.14	0.13
1	1	-0.02	0.14	0.15

Notes: The tables show the estimates used to construct Figure 3

Table C.7: Additional checks: Spatial disaggregation

VARIABLES	Ln Agricultural Output					
	(1)	(2)	(3)	(4)	(5)	(6)
Spills_5	-0.0328*	-0.0335	-0.0383	-0.0390*	-0.0395*	-0.0373*
	(0.018)	(0.021)	(0.025)	(0.021)	(0.021)	(0.022)
Spills_7	-0.0822	-0.0864	-0.1267	-0.1040	-0.0799	-0.0584
	(0.107)	(0.130)	(0.126)	(0.130)	(0.138)	(0.134)
Spills_10	-0.0066	-0.0085	-0.0096	-0.0124	-0.0116	-0.0107
	(0.014)	(0.017)	(0.020)	(0.017)	(0.017)	(0.018)
Spills_20	0.0096	0.0062	0.0038	0.0039	0.0039	0.0028
	(0.014)	(0.014)	(0.013)	(0.014)	(0.014)	(0.014)
Spills_30	0.0067	0.0119	0.0291	0.0089	0.0087	0.0139
	(0.076)	(0.061)	(0.070)	(0.063)	(0.064)	(0.063)
Spills_40	-0.0027	-0.0018	-0.0011	-0.0014	-0.0014	-0.0014
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Spills_50	0.0109**	0.0116**	0.0126**	0.0120**	0.0119**	0.0120**
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
LnLand		0.2577***	0.5403***	0.2474***	0.2467***	0.2471***
		(0.023)	(0.171)	(0.023)	(0.023)	(0.023)
LnLabor_days		0.2010***	0.2940*	0.1915***	0.1918***	0.1883***
		(0.024)	(0.153)	(0.024)	(0.024)	(0.023)
Estimation	OLS	OLS	2SLS	OLS	OLS	OLS
Observations	6369	6115	6114	6059	6059	6059
R-squared	0.610	0.640	0.619	0.643	0.643	0.644
Farmer controls	YES	YES	YES	YES	YES	YES
Other inputs	NON	NON	NON	YES	YES	YES
Heterogeneous trend	NON	NON	NON	NON	YES	YES
Climate & environmental variables	NON	NON	NON	NON	NON	YES
Waves dummies	YES	YES	YES	YES	YES	YES
LGA fixed effects	YES	YES	YES	YES	YES	YES

Notes: Robust standard errors are in parentheses. Standard errors clustered at the LGAs levels. Spill_5 to Spill_30 are the total number of Oil spills in with an exponential decay over time, at distance of 5 km to 30 km from nearby locality e. Farmers controls: age of head of household and literacy, an indicator of whether the household owns its farm plot, Heterogenous trend: distances to federal road, main towns, main markets, states capitals, and border post on the main road. Climate and environmental variables: mean temperature and rainfall, rooting, slope, nutrient retention, excel salt, oxygen to roots, toxicity, and workability. Significance is denoted as follows: *** p<0.01. ** p<0.05. * p<0.1 Columns 3 is estimated using 2SLS. The excluded instruments are the log of the area of land managed, and the log of the number of adults equivalents in the household.

Table C.8: Additional checks: Main Results in enumeration areas up to 7.5km from oil spills

VARIABLES	LnAg._Output	LnAg._Output	LnAg._Output	LnYield	LnYield_Cassava	LnYield_Maize
	(1)	(2)	(3)	(4)	(5)	(6)
Cumulative_OilSpill	-0.0307	-0.0248*	-0.0241**	-0.0157***	-0.0210**	-0.0047
	(0.027)	(0.015)	(0.010)	(0.006)	(0.009)	(0.011)
LnLand		0.2577***	0.5373***			
		(0.023)	(0.171)			
LnLabor_days		0.1992***	0.2967*			
		(0.024)	(0.153)			
Estimation	OLS	OLS	2SLS	OLS	OLS	OLS
Observations	6342	5998	5935	9056	1101	2493
R-squared	0.612	0.632	0.604	0.312	0.293	0.290
Waves dummies	YES	YES	YES	YES	YES	YES
LGAs fixed effects	YES	YES	YES	YES	YES	YES

Notes: Robust standard errors are in parentheses. Standard errors are clustered at LGA level. All regressions include a dummy for being within 7.5 kilometers of an oil spill. Farmer controls: columns 2 to 4 and column 6 include age of head of household, literacy, and an indicator of whether the household owns its farm plot. Significance is denoted as follows: *** p<0.01. ** p<0.05. * p<0.1 Column 3 is estimated using 2SLS. The excluded instruments are the log of the area of land managed and the log of the number of equivalent adults in the household.

Table C.9: Additional checks: Additional distance robustness in enumeration areas near oil spills

Variable	Ln Agricultural Output									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Cumulative_OilSpill_10km	0.0046	0.0023								
	(0.011)	(0.014)								
Cumulative_OilSpill_20km			0.0055	0.0028						
			(0.011)	(0.011)						
Cumulative_OilSpill_30km					-0.0114**	-0.0119***				
					(0.005)	(0.004)				
Cumulative_OilSpill_40km							-0.0014	-0.0008		
							(0.002)	(0.002)		
Cumulative_OilSpill_50km									0.0012	0.0024
									(0.003)	(0.003)
Lntmp_area	0.2572***	0.5222***	0.2569***	0.5280***	0.2574***	0.5052***	0.2565***	0.5174***	0.2575***	0.5162***
	(0.024)	(0.175)	(0.024)	(0.173)	(0.024)	(0.176)	(0.024)	(0.176)	(0.024)	(0.176)
LnLabor_days	0.2007***	0.3225**	0.2011***	0.3206**	0.2006***	0.3160*	0.2010***	0.3261**	0.2006***	0.3240**
	(0.025)	(0.162)	(0.025)	(0.161)	(0.025)	(0.162)	(0.025)	(0.162)	(0.025)	(0.163)
Estimation	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS
Observations	6130	6114	6130	6114	6130	6114	6130	6114	6130	6114
R-squared	0.640	0.016	0.640	0.014	0.641	0.025	0.640	0.017	0.640	0.017
Waves dummies	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
LGA fixed effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Notes: Robust standard errors are in parentheses. Standard errors are clustered at LGA levels. All regressions include a dummy for being within 10, 20, 30, 40 or 50 kilometers, depending on the distance considered to construct the Cumulative OilSpill variable. Farmer controls: columns 1 to 10 include age of head of household, literacy, and an indicator of whether a household owns its farm plot. Significance is denoted as follows: *** p<0.01. ** p<0.05. * p<0.1.

Table C.10: Additional checks: 2SLS Estimation

VARIABLES	Ln Agricultural Output			
	(1)	(2)	(3)	(4)
Cumulative_OilSpill	-0.0276***	-0.0284***	-0.0257***	-0.0264***
	(0.007)	(0.007)	(0.007)	(0.007)
LnLand	0.5356***	0.5494***	0.5780***	0.5933***
	(0.177)	(0.179)	(0.184)	(0.191)
LnLabor_days	0.2717*	0.2636*	0.2690*	0.2332
	(0.155)	(0.156)	(0.162)	(0.165)
Fertilizers	0.2129***	0.2173***		0.2254***
	(0.073)	(0.072)		(0.072)
Pesticides	0.1313*	0.1290*		0.1189
	(0.073)	(0.073)		(0.074)
Herbicides	0.0135	0.0202		0.0172
	(0.097)	(0.099)		(0.100)
Improved_Seeds	-0.0290	-0.0172		-0.0050
	(0.271)	(0.272)		(0.272)
Rooting			0.4527**	0.4519**
			(0.217)	(0.213)
Oxygen to roots			-0.0791	-0.0429
			(0.191)	(0.194)
Toxicity			0.1821	-0.0054
			(0.578)	(0.564)
Excessalt			-0.1781	-0.0875
			(0.505)	(0.484)
Workability			-0.4099**	-0.4070**
			(0.205)	(0.206)
Nutrient_Retention			0.3319	0.3698
			(0.243)	(0.242)
Nutrient_Availability			-0.2897	-0.2917
			(0.222)	(0.220)
Mean temperature			0.0003	0.0032
			(0.013)	(0.013)
Mean rainfall			0.0006	0.0007
			(0.001)	(0.001)
Slope			0.0204	0.0195
			(0.018)	(0.017)
Estimation	2SLS	2SLS	2SLS	2SLS
Observations	6058	6058	6114	6058
R-squared	0.622	0.620	0.615	0.617
Waves dummies	YES	YES	YES	YES
LGA fixed effects	YES	YES	YES	YES

Notes: Robust standard errors are in parentheses. Standard errors are clustered at the LGAs levels. All regressions include a dummy for being within 5 kilometers of an oil spill. Farmer controls: columns 1 to 5 include age of head of household, literacy, and an indicator of whether a household owns its farm plot. Columns 3 to 5 include indicators from time trends with distances to federal roads, main towns, main markets, states capitals, and border posts on the main road. The excluded instruments are the log of the area of land managed and the log of the number of equivalent adults in the household. Significance is denoted as follows*** p<0.01. ** p<0.05. * p<0.1.

Table C.11: Additional checks: Alternative measurements of oil pollution

VARIABLES	LnAg._Output (1)	LnAg._Output (2)	LnYield (3)	LnAg._Output (4)	LnAg._Output (5)	LnYield (6)	LnAg._Output (7)	LnAg._Output (8)	LnYield (9)
OilSpill	-0.0388***	-0.0440***	-0.0377						
	(0.010)	(0.013)	(0.038)						
FCumulative_OilSpill				-0.0234***	-0.0274***	-0.0285*			
				(0.005)	(0.007)	(0.017)			
TCumulative_OilSpill							-0.0017**	-0.0022**	-0.0039***
							(0.001)	(0.001)	(0.001)
LnLand	0.2572***	0.5390***		0.2572***	0.5384***		0.2572***	0.5361***	
	(0.023)	(0.172)		(0.023)	(0.171)		(0.023)	(0.171)	
LnLabor_days	0.2000***	0.2951*		0.2001***	0.2954*		0.2001***	0.2979*	
	(0.024)	(0.153)		(0.024)	(0.153)		(0.024)	(0.153)	
Estimation	OLS	2SLS	OLS	OLS	2SLS	OLS	OLS	2SLS	OLS
Observations	6115	6114	8887	6115	6114	8887	6115	6114	8887
R-squared	0.639	0.618	0.316	0.639	0.618	0.316	0.639	0.618	0.316
Waves dummies	YES	YES	YES	YES	YES	YES	YES	YES	YES
LGA fixed effects	YES	YES	YES	YES	YES	YES	YES	YES	YES

Notes: Robust standard errors are in parentheses. Standard errors are clustered at LGA levels. All regressions include a dummy for being within 5 kilometers of an oil spill. Total_OilSpill measures the number of oil spills near a location in the year of each wave. FCumulative_OilSpill measures cumulative oil spills persistent for five years only. TCumulative_OilSpil is the total number of oil spills at a location within 5km up to the last day of the harvest survey for each wave. Farmer controls: columns 1, 2, 4, and 5, and columns 7 and 8 include age of head of household, literacy, and an indicator of whether a household owns its farm plot. Significance is denoted as follows: *** $p<0.01$. ** $p<0.05$. * $p<0.1$ The excluded instruments are the log of the area of land managed and the log of the number of adults equivalents in the household.

Table C.12: Additional checks: Alternative measurements of oil pollution. Estimated number of barrels lost in spills.

VARIABLES	LnAg._Output (1)	LnAg._Output (2)	LnYield (3)	LnAg._Output (4)	LnAg._Output (5)	LnYield (6)	LnAg._Output (7)	LnAg._Output (8)	LnYield (9)	LnAg._Output (10)	LnAg._Output (11)	LnYield (12)
Cum_Volumen_OilSpill (barrels)	-0.0004**	-0.0004**	-0.0000									
	(0.000)	(0.000)	(0.000)									
Volumen_OilSpill (barrels)				-0.0004	-0.0005	-0.0002						
				(0.000)	(0.000)	(0.000)						
FCum_Volumen_OilSpill (barrels)							-0.0004**	-0.0004**	-0.0000			
							(0.000)	(0.000)	(0.000)			
TCum_Volumen_OilSpil (barrels)										-0.0001	-0.0001*	-0.0001*
										(0.000)	(0.000)	(0.000)
LnLand	0.2560***	0.5364***	-0.6918***	0.2524***	0.4868***	-0.6959***	0.2560***	0.5364***		0.2562***	0.5340***	-0.6917***
	(0.024)	(0.177)	(0.019)	(0.024)	(0.187)	(0.019)	(0.024)	(0.177)		(0.024)	(0.177)	(0.019)
LnLabor_days	0.2020***	0.3012*	0.2319***	0.1973***	0.3083*	0.2340***	0.2020***	0.3012*		0.2018***	0.3035*	0.2319***
	(0.024)	(0.157)	(0.017)	(0.024)	(0.166)	(0.018)	(0.024)	(0.157)		(0.024)	(0.157)	(0.017)
Estimation	OLS	2SLS	OLS	OLS	2SLS	OLS	OLS	2SLS	OLS	OLS	2SLS	OLS
Observations	6035	6034	8709	5893	5892	8481	6035	6034	8768	6035	6034	8709
R-squared	0.634	0.613	0.530	0.636	0.620	0.532	0.634	0.613	0.323	0.634	0.613	0.530
Waves dummies	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
LGA fixed effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Notes: Robust standard errors are in parentheses. Standard errors are clustered at LGA levels. All regressions include a dummy for being within 5 kilometers of an oil spill. Cum_Volumen_OilSpill (barrels) is the total estimated number of barrels spilt near locations up to the last day of the harvest survey for each wave degraded over time. Volumen_OilSpill (barrels) measures the estimated number of barrels lost in spills near a location in the year of each wave. FCum_Volumen_OilSpill (barrels) measures cumulative oil spills persisting for five years only. TCum_Volumen_OilSpil (barrels) is the total estimated number of barrels spilt near locations up to the last day of the harvest survey for each wave. Farmers control: columns 1and 2. 4 and 5. and columns 7 and 8 include age of head of household, literacy, and an indicator of whether a household owns its farm plot. Significance is denoted as follows *** p<0.01. ** p<0.05. * p<0.1 The excluded instruments are the log of the area of land managed and the log of the number of equivalent adults in the household.

Table C.13: Additional checks: Additional checks: Additional robustness in enumeration areas within 7.5km of oil spills

VARIABLES	LnAg._Output (1)	LnAg._Output (2)	LnAg._Output (3)	LnAg._Output (4)	LnAg._Output (5)
Cumulative_OilSpill	-0.0317	-0.0256*	-0.0280*	-0.0232*	-0.0259*
	(0.027)	(0.015)	(0.015)	(0.014)	(0.015)
LnLand		0.2471***	0.2464***	0.2571***	0.2468***
		(0.023)	(0.023)	(0.024)	(0.023)
LnLabor_days		0.1895***	0.1900***	0.1969***	0.1865***
		(0.024)	(0.024)	(0.023)	(0.023)
Fertilizers	0.3235***	0.2591***	0.2614***		0.2707***
	(0.076)	(0.073)	(0.072)		(0.072)
Pesticides	0.3397***	0.2192***	0.2151***		0.2098***
	(0.066)	(0.064)	(0.065)		(0.064)
Herbicides	0.1921**	0.0876	0.0997		0.1025
	(0.095)	(0.095)	(0.095)		(0.095)
Improved_Seeds	0.2539	0.1518	0.1608		0.1487
	(0.338)	(0.263)	(0.262)		(0.261)
Rooting				0.4520*	0.4450*
				(0.253)	(0.239)
Oxygen to roots				-0.0503	-0.0214
				(0.186)	(0.188)
Toxicity				0.6026	0.3784
				(0.492)	(0.495)
Exces salt				-0.5721	-0.4171
				(0.399)	(0.405)
Workability				-0.4471*	-0.4441*
				(0.237)	(0.229)
Nutrient_Retention				0.2577	0.2847
				(0.243)	(0.238)
Nutrient_Availability				-0.2598	-0.2581
				(0.214)	(0.210)
Mean temperature				0.0134	0.0170
				(0.014)	(0.014)
Mean rainfall				-0.0001	0.0001
				(0.000)	(0.000)
Slope				0.0126	0.0106
				(0.017)	(0.016)
Estimation	OLS	OLS	OLS	OLS	OLS
Observations	6275	5943	5943	5998	5943
R-squared	0.618	0.636	0.636	0.634	0.638
Waves dummies	YES	YES	YES	YES	YES
LGA fixed effects	YES	YES	YES	YES	YES

Notes: Robust standard errors are in parentheses. Standard errors are clustered at LGA level. All regressions include a dummy for being within 7.5 kilometers of an oil spill. Farmer controls: Columns 1 to 5 include age of head of household, literacy, and an indicator of whether a household owns its farm plot. Columns 3 to 5 include indicators from time trends with distances to federal roads, main towns, main markets, states capitals, and border posts on the main road. Significance is denoted as follows: *** p<0.01. ** p<0.05. * p<0.1.

Table C.14: Additional checks: Specific Zones and Areas

DEPENDENT VARIABLE	LnAg._Output							
	Non NCentral	Non NEast	Non NWest	Non SEast	Non SSouth	Non SWest	Niger Delta	ND/Out ND
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Cumulative_OilSpill	-0.0250***	-0.0260***	-0.0259***	-0.0198***	0.0342	-0.0217***	-0.0346***	
	(0.006)	(0.006)	(0.005)	(0.005)	(0.140)	(0.006)	(0.007)	
(A) Cumulative_OilSpill*NigerDelta								-0.8711***
								(0.269)
(B) Cumulative_OilSpill*Outside NigerDelta								-0.5180***
								(0.270)
Test (A)-(B)								
p-value								0.144
LnLand	0.2749***	0.2680***	0.2698***	0.2583***	0.2385***	0.2295***	0.2706***	0.2228***
	(0.026)	(0.026)	(0.024)	(0.028)	(0.024)	(0.025)	(0.042)	(0.028)
LnLabor_days	0.1805***	0.1997***	0.1981***	0.2197***	0.2093***	0.1925***	0.2037***	0.1641***
	(0.026)	(0.026)	(0.025)	(0.028)	(0.025)	(0.025)	(0.043)	(0.027)
Estimation	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS
Observations	4883	4954	4897	4917	5431	5487	1402	4149
R-squared	0.647	0.629	0.636	0.652	0.641	0.627	0.607	0.465
Waves dummies	YES	YES	YES	YES	YES	YES	YES	NON
Year fixed effects	NON	NON	NON	NON	NON	NON	NON	YES
LGA fixed effects	YES	YES	YES	YES	YES	YES	YES	YES
EA X trend	NON	NON	NON	NON	NON	NON	NON	YES

Notes: Robust standard errors are in parentheses. Standard errors are clustered at LGA level. All regressions include a dummy for being within 5 kilometers of an oil spill. Farmer controls: Columns 1 to 8 include age of head of household, literacy, and an indicator of whether a household owns its farm plot. Columns 1 to 6 exclude one specific area. Column 8 restricts the analysis to the Niger Delta and column 9 restricts the analysis from Wave 1 to Wave 3 with panel data compare the Niger Delta and non-Niger Delta areas. Significance is denoted as follows: *** p<0.01. ** p<0.05. * p<0.1.

Table C.15: Additional checks: Conflict versus Non Conflict Areas

VARIABLES	LnAg._Output (1) CONFLICT AREA	LnAg._Output (2) NON CONFLICT AREA	LnAg._Output (3)
Cumulative_OilSpill	-0.0086*	-1.2303*	
	(0.005)	(0.630)	
(A) Cumulative_OilSpill*Conflict Area			-0.8038***
			(0.274)
(B) Cumulative_OilSpill*Non-Conflict Area			-1.1970***
			(0.221)
Test (A)-(B)			
p-value			0.017
LnLand	0.3323***	0.1686***	0.2478***
	(0.032)	(0.055)	(0.028)
LnLabor_days	0.1703***	0.1741***	0.1602***
	(0.038)	(0.044)	(0.032)
Observations	2917	1014	3310
R-squared	0.656	0.489	0.451
Waves dummies	YES	YES	NON
Year fixed effects	NON	NON	YES
LGA fixed effects	YES	YES	YES
EA X trend	NON	NON	YES

Notes: Robust standard errors are in parentheses. Standard errors are clustered at LGA level. All regressions include a dummy for being within 5 kilometers of an oil spill. Farmer controls: Columns 1 to 3 include age of head of household, literacy, and an indicator of whether a household owns its farm plot. Significance is denoted as follows: *** p<0.01. ** p<0.05. * p<0.1.

Table C.16: Oil Spill Pollution during the year and Self-reported Illness

Variable	Ill in previous four weeks			Ln (Number of days off work)		
	(1)	(2)	(3)	(4)	(5)	(6)
OilSpill	0.0004	-0.0021	0.0010**	-0.0012	0.0594	-0.0045
	(0.001)	(0.001)	(0.000)	(0.003)	(0.049)	(0.003)
Sample	All	Urban	Rural	All	Urban	Rural
Observations	36675	9498	26196	23001	5916	16491
R-squared	0.070	0.056	0.080	0.225	0.178	0.252
Waves dummies	YES	YES	YES	YES	YES	YES
LGA fixed effects	YES	YES	YES	YES	YES	YES

Notes: Robust standard errors are in parentheses. Standard errors are clustered at LGA level. All regressions include a dummy for being within 5 kilometers of an oil spill and individual controls such as age, age^2, gender, an indicator of ecological zone, and rural area. “Ill in previous four weeks” is an indicator that takes a value of 1 if any individual reports being ill during the last four weeks. This does not include injures. “Ln (Number of days off work)” is the log of the number of days that an individual reports ceasing to engage in any usual activity. Significance is denoted as follows: *** p<0.01, ** p<0.05, * p<0.1

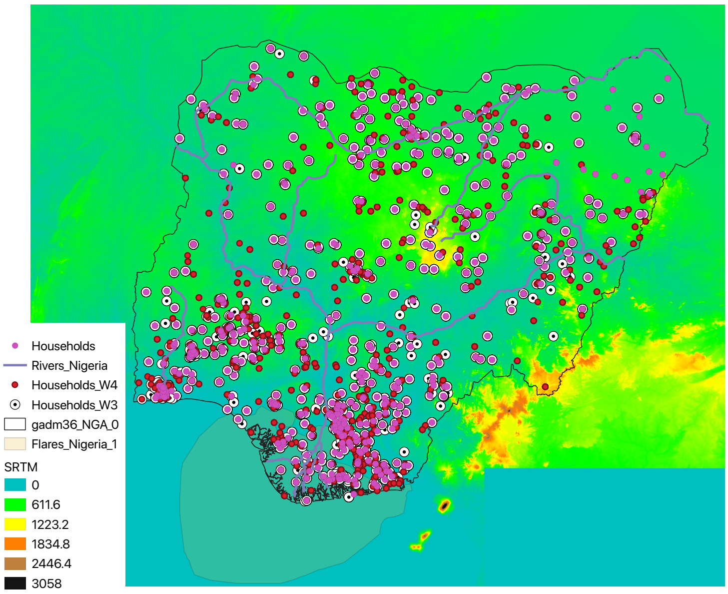
Table C.17: Oil Spill Pollution and Labor Outcomes for urban workers

Variable	Ln(Total hours worked)		Ln(Real Employment Income)	
	(1)	(2)	(3)	(4)
OilSpill	-0.0108***	-0.0084***	-0.2201***	-0.2275***
	(0.004)	(0.003)	(0.012)	(0.012)
Sample	All urban workers	Urban non-agric. workers	All urban workers	Urban non-agric. workers
Observations	4782	4369	2846	2788
R-squared	0.240	0.130	0.398	0.389
Waves dummies	YES	YES	YES	YES
LGA fixed effects	YES	YES	YES	YES

Notes: Robust standard errors are in parentheses. Standard errors are clustered at LGA levels. All regressions include a dummy for being within 5 kilometers of an oil spill, and an industrial dummy. Columns 1 and 2 include individual controls such as age, age^2, literacy status, and household size. Columns 3 and 4 add additional controls in the form of the log of the total number of hours worked. All regressions exclude oil industry workers. Significance is denoted as follows: *** p<0.01, ** p<0.05, * p<0.1

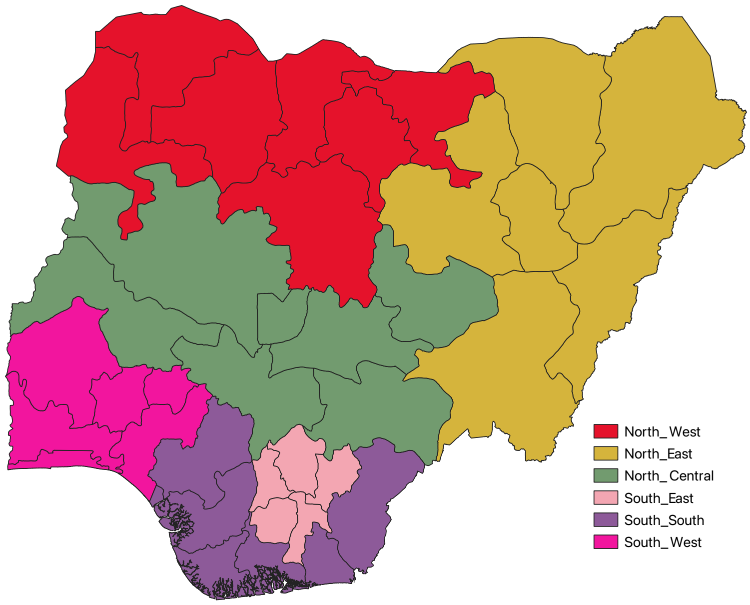
C.3 Figures

Figure C.1: Map of Nigeria showing wetlands, rivers, enumeration areas and gas flares



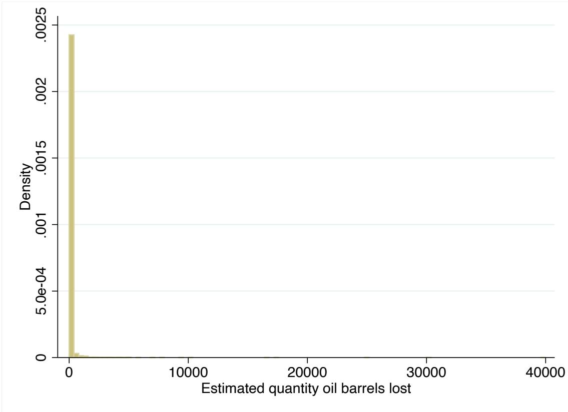
Notes: The figure shows a map of Nigeria with enumeration areas, rivers, and gas flares. Sources: Own work based on Nigerian GHS-PANEL data, gas flares shapefile from the Defense Meteorological Satellite Program (NOAA National Centers for Environmental Information), and wetlands data from Tropical and Subtropical Peatland Distribution (Center for International Forestry Research (CIFOR)).

Figure C.2: Geopolitical Zones of Nigeria

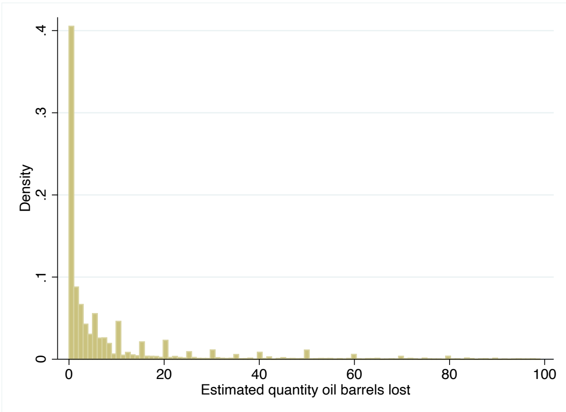


Sources: Own work based on data from the Nigerian Oil Spill Monitor (NOSDRA) and the Database of Global Administrative Areas (GADM) map for Nigeria.

Figure C.3: Density function of the estimated quantity of oil lost in spills (in barrels)



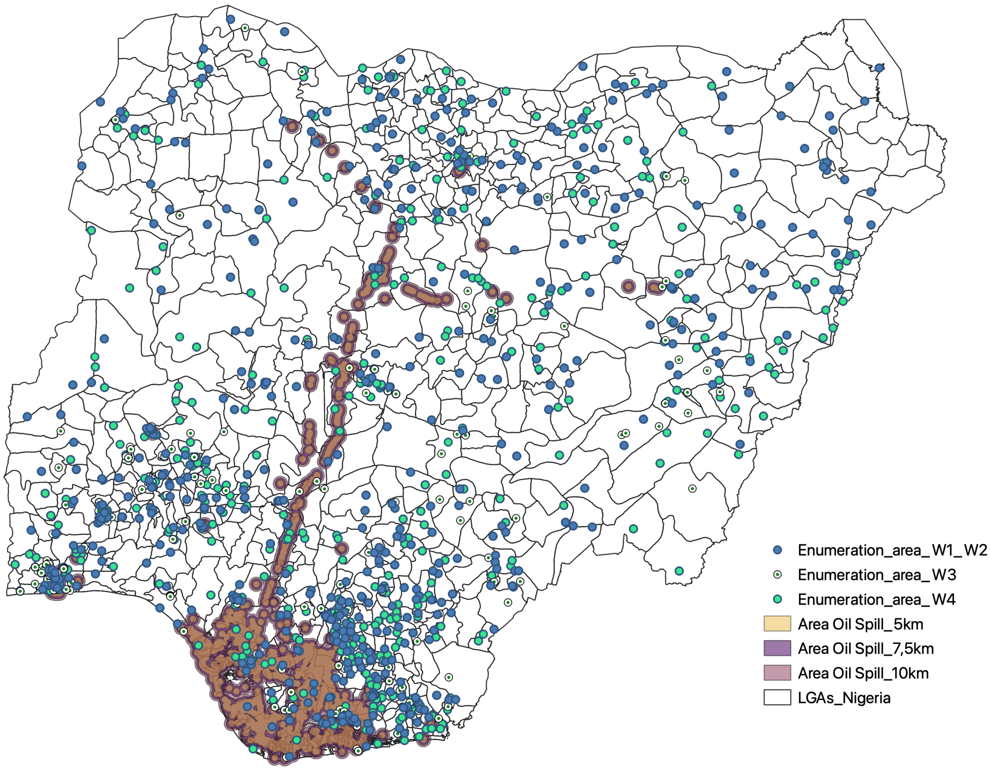
(a) Estimated quantity lost (in barrels)



(b) Estimated quantity of oil lost (in barrels) (less than 100 barrels)

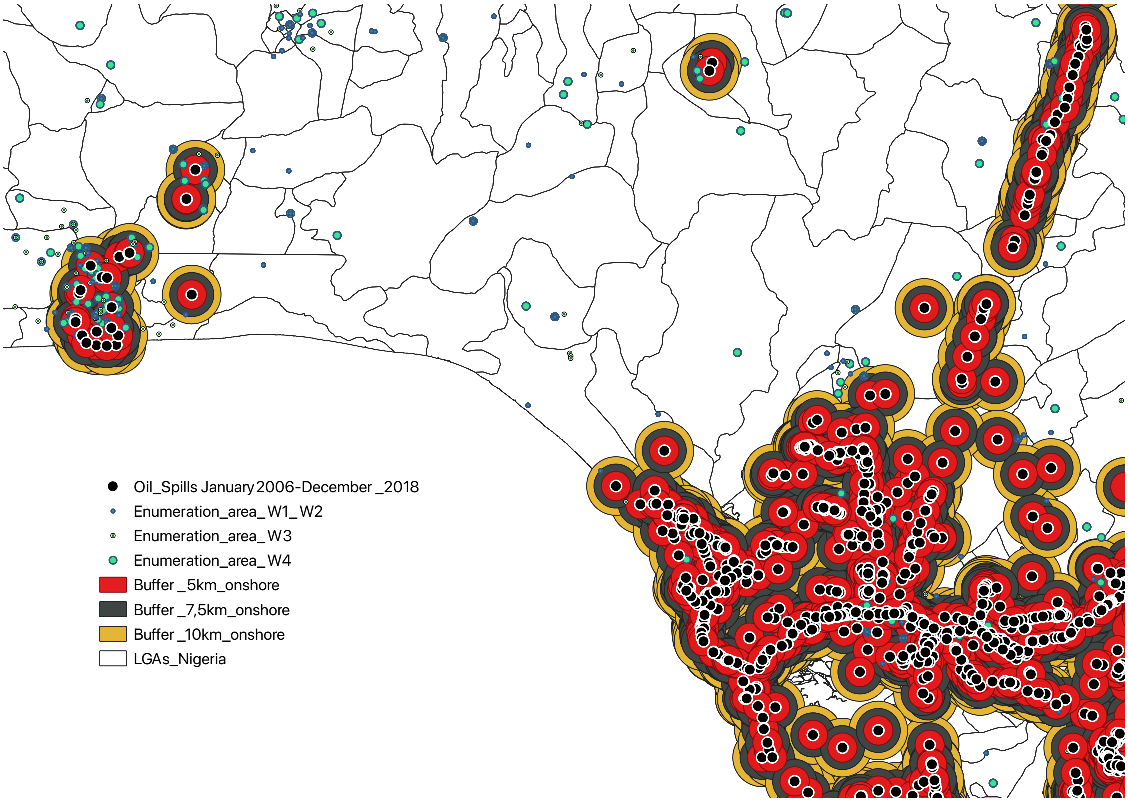
Notes: The figures show the density function for the variable "estimated quantity of oil lost in spills (in barrels)" from the table reported in the data from the Nigerian Oil Spill Monitor *NOSDRA*. Panel a) shows the density function for all the data reported, and Panel b) shows that for data reported with less than 100 barrels.

Figure C.4: Map of Areas 5km to 10km from Oil-Spills



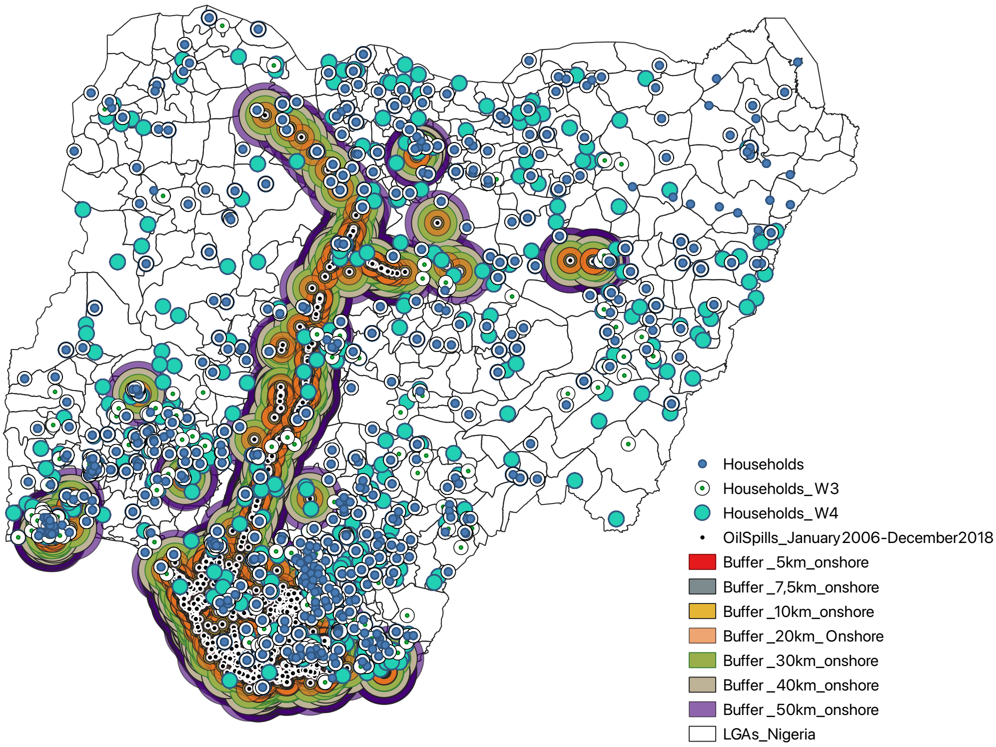
Sources: Own work based on Nigerian GHS-PANEL data and Nigerian Oil Spill Monitor *NOSDRA* data.

Figure C.5: Zoom of locations of onshore oil spills, enumeration areas, and buffer zones at 5km, 7.5km and 10km



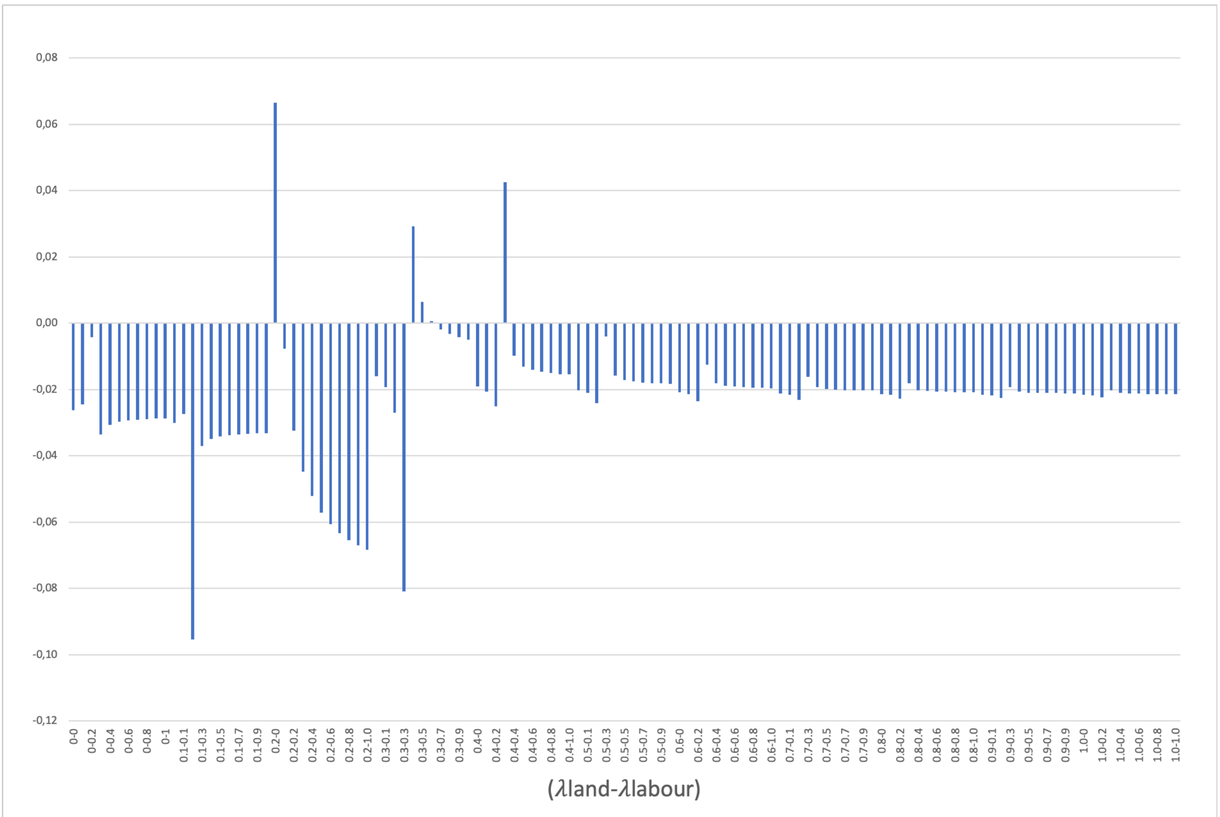
Sources: Own work based on Nigerian GHS-PANEL data and Nigerian Oil Spill Monitor *NOSDRA* data.

Figure C.6: Onshore oil spills, enumeration areas, and buffers from 5km to 50km



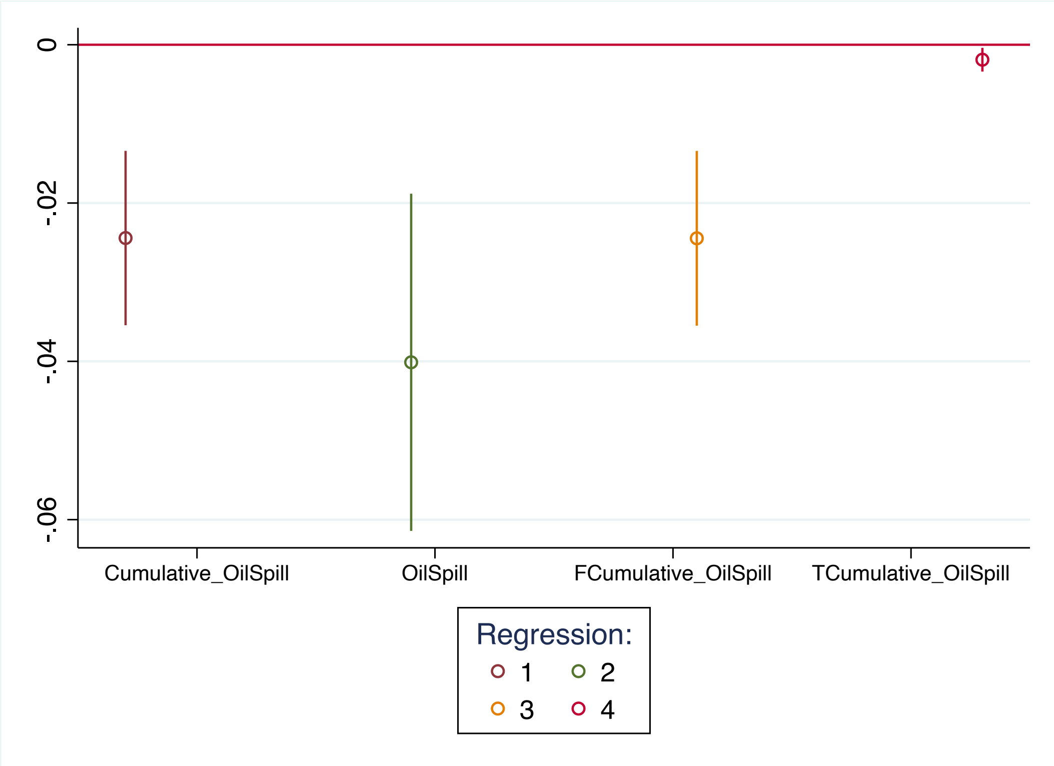
Sources: Own work based on Nigerian GHS-PANEL data and Nigerian Oil Spill Monitor *NOSDRA* data.

Figure C.7: Estimates of δ with IIV approach.



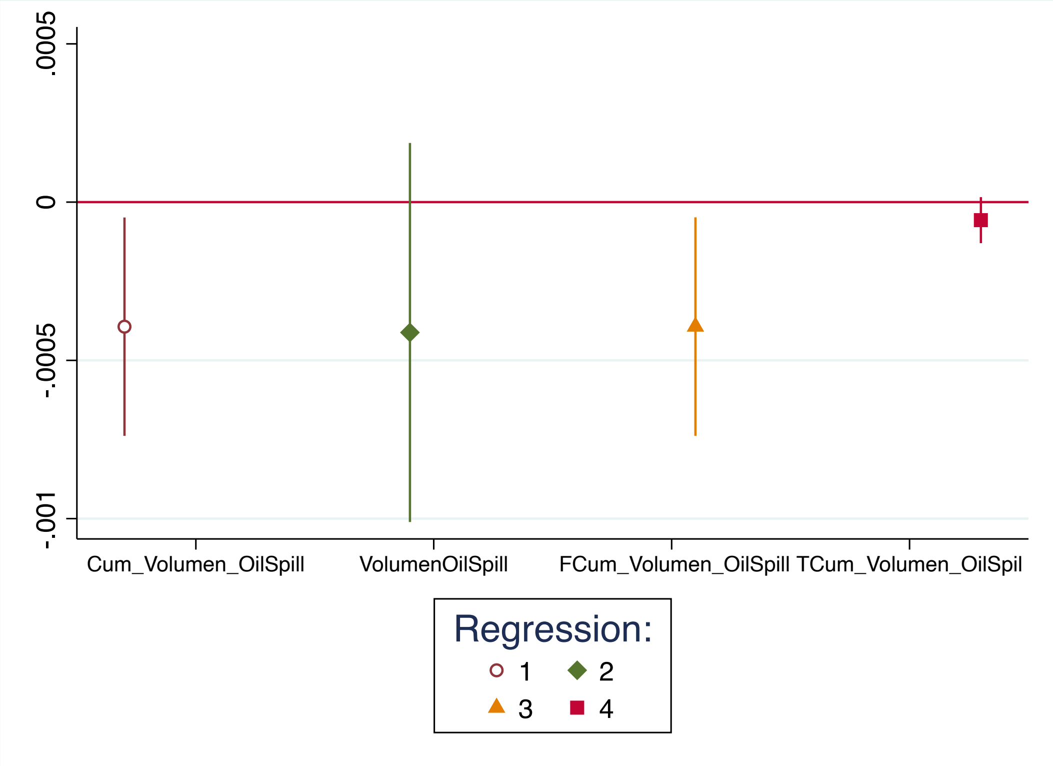
Notes: This figure shows the estimates of δ with the IIV approach.Vertical axis shows the value of δ for different values of $\lambda_{land\_harvested}$ and λ_{Labor}. Under the IIV methodology, I identify parameter bounds rather than points estimated. Each parameter measures the ratioof correlation of the instrumental variable and the regressor with the error term, which measures how well the instrument satisfies the exogeneity assumption. For instance, $\lambda_j = corr(Z_{j,\varepsilon})/corr(X_{j,\varepsilon})$ where $j = (land\_harvested, Labor)$, X is the input used, Z is the instrumental variable, and ε is the error term. The instrument is considered to be less correlated to the error term than the endogenous variable when $\varepsilon < 1$. I find that in 96% of all combinations of $\lambda_{land\_harvested}$ and λ_{Labor}, the effect on residual productivity is negative, and for all combinations where $\lambda_{land\_harvested} > 0.4$ and $\lambda_{Labor} > 0.2$, the corresponding estimate of the effect of oil-spill pollution on agricultural output is negative.

Figure C.8: Effects of oil spills pollution on agricultural output. Different oil-spill pollution measurements.



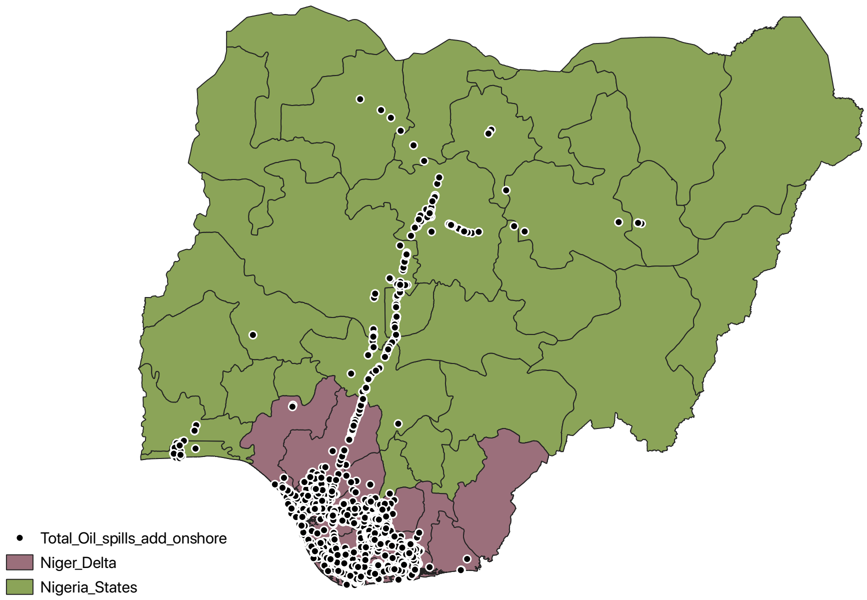
Notes: This figure shows the estimates of regressions for the effect of oil-spill pollution on agricultural output when alternative specifications are considered for the function $g(n)$. (CUMULATIVE_OILSPILLS) is the variable used in the main analysis. (OILSPILL) is the total number of oil-spill events per location during the year of each wave. (FCUMULATIVE_OILSPILL) takes the same approach as the main analysis but I only consider the number of spills up to five years before as a persistent effect for inclusion in the exponential decay. (TCUM_VOLUMEN_OILSPIL) is the total number of oil-spill events per location and wave, with no degradation effect. Circles represent point estimates, while lines indicate the 95 percent confidence interval.

Figure C.9: Effects of oil-spill pollution on agricultural output. Different measurements of oil pollution. Oil pollution is approximated by the estimated number of barrels of oil lost.



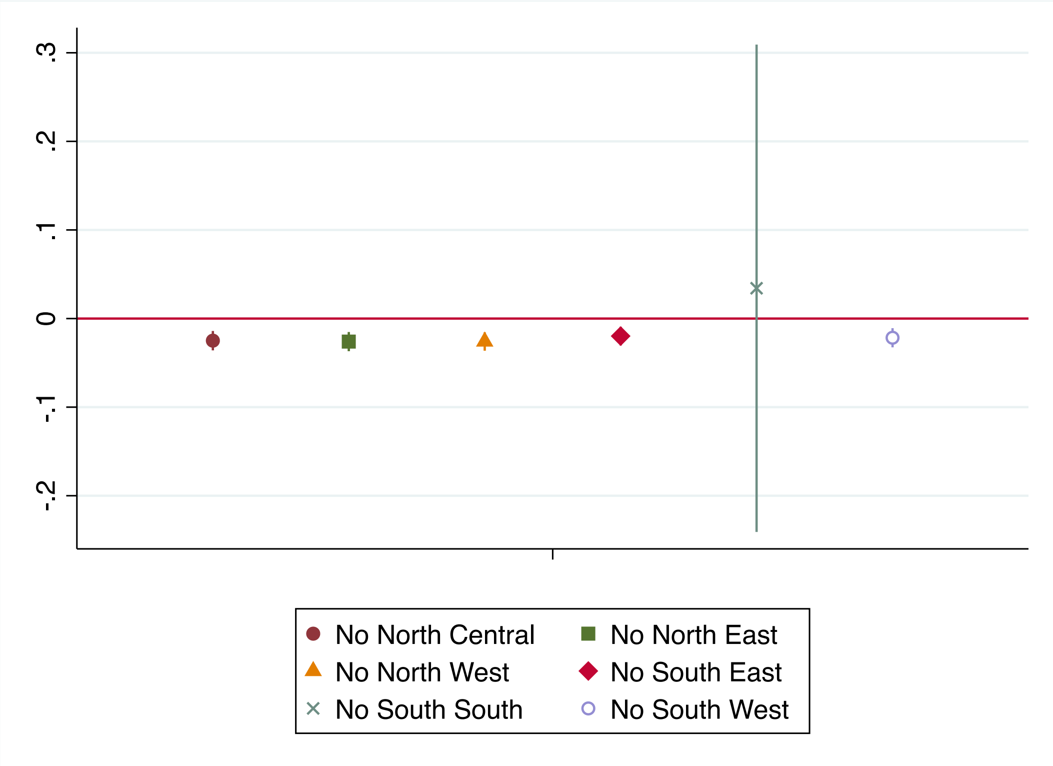
Notes: This figure shows the estimates of regressions for the effect of oil-spill pollution on agricultural output when alternative specifications are considered for the function $g(n)$. (Cum_Volumen_OilSpill barrels) is the variable used in the main robustness analysis. (Volumen_OilSpill barrels) measures the estimated number of barrels lost near a location in the year of each wave. (FCum_Volumen_OilSpill (barrels) is the total estimated number of barrels spilt near locations until the last day of the harvest survey for each wave, with no degradation effect. Geometric figures represent point estimates, while lines indicate the 95 percent confidence interval.

Figure C.10: States and the Niger Delta



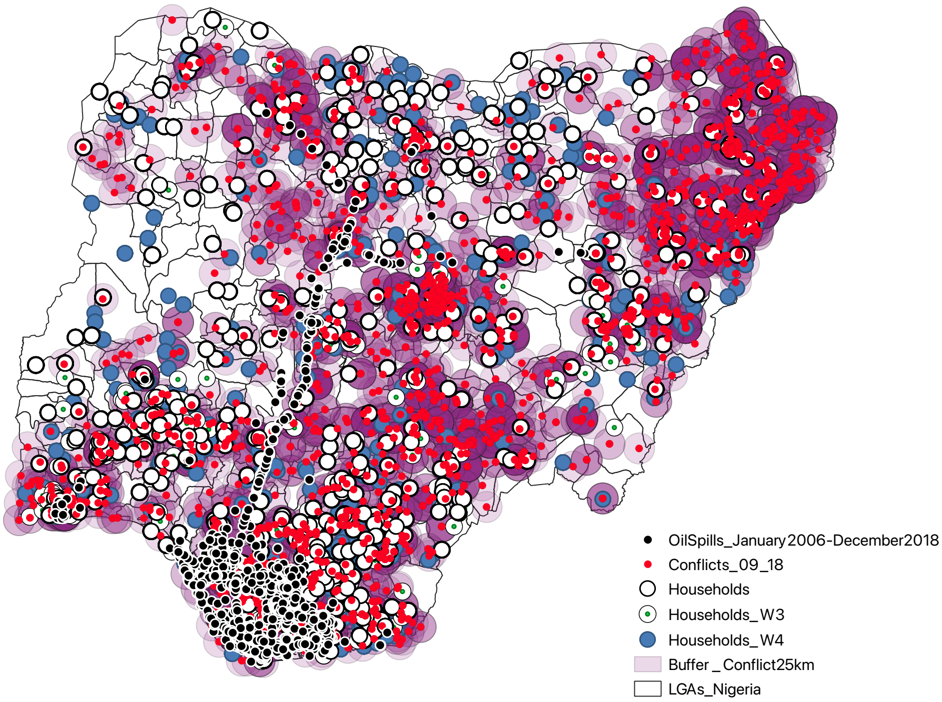
Sources: Own work based on data from the Nigerian Oil Spill Monitor *NOSDRA* and the Database of Global Administrative Areas (GADM) map for Nigeria.

Figure C.11: Main specification excluding geopolitical zones



Notes: This figure shows the estimates of regressions for the effect of oil-spill pollution on agricultural output when geographical zones are dropped one by one. Geometric figures represent point estimates, while lines indicate the 95 percent confidence interval.

Figure C.12: Conflicts and Buffer zones of 25 km around them. ACLED database



Notes: The figure shows buffer zones of 25 km around violent conflicts. Years: 2009-2018. Source: Own work based on the ACLED database.

Appendix D

Resumen y Conclusiones

D.1 Resumen

El objetivo de esta tesis es abordar las causas y las consecuencias de los conflictos en un mundo globalizado. Para ello se considera la importancia de los patrones espaciales y el uso de datos geolocalizados, a la hora de abordar los problemas de causalidad en modelos econométricos con datos en panel y con datos de corte transversal repetidos. En el segundo capítulo de esta tesis, analizamos el vínculo entre la globalización y la incidencia de los conflictos civiles para un conjunto de datos de panel de 159 países durante el período 1972-2009. Para ello, distinguimos varias dimensiones de la globalización identificadas en la literatura de economía política, como son la globalización económica, social y política. Abordamos la endogeneidad potencial de las variables de globalización con la introducción de efectos fijos por país en el análisis. Además, utilizamos un enfoque de variables instrumentales para estimar el efecto causal del grado de integración sobre el conflicto. En el tercer capítulo, utilizamos información geolocalizada para estudiar cómo los factores étnicos se interrelacionan con las variaciones de ingresos relacionadas con los alimentos, en los conflictos africanos, con el fin de explicar los procesos subyacentes del mismo. Para ello, proponemos el uso de una base de datos de panel, de una cuadrícula completa de países africanos divididos en unidades subnacionales de 0,5 por 0,5 grados de latitud y longitud (10.638 celdas), que cubre el período 1998-2013. Contribuimos a la literatura anterior analizando varias teorías sobre los efectos de los shocks de ingresos en los conflictos, utilizando datos geolocalizados que consideran la interacción entre estas variaciones de ingresos y la diversidad étnica. Finalmente, en el cuarto capítulo, examino el daño ambiental que podría derivarse de los conflictos, como son los derrames de petróleo en Nigeria, y su impacto en la producción agrícola. Utilizo un marco conceptual sobre la producción y consumo en los hogares, para comprender cómo la contaminación por derrames de petróleo, puede generar ajustes en el comportamiento óptimo de los hogares. A continuación, estimo una función de producción agrícola utilizando un modelo de corte transversal repetido, con microdatos georreferenciados para un conjunto de hogares agrícolas, y cuatro paneles de encuestas entre los años 2009 y 2018, ambos incluidos, de la base de datos Nigeria General Household Survey (GHS-Panel). Para calcular una variable proxy de la contaminación por derrames de petróleo, creo una función que utiliza datos geoespaciales con información sobre alrededor de 12.000 derrames de petróleo del Nigerian Oil Spill Monitor.

D.2 Conclusiones

En esta tesis se ha aplicado novedosas metodologías empíricas para analizar varias causas y consecuencias del conflicto. En este sentido, un aspecto clave de la misma, ha sido el considerar los patrones espaciales y utilizar datos geolocalizados para hallar la dirección correcta de causalidad. Este marco de análisis ayuda a comprender los procesos que subyacen a la globalización y su efecto en los conflictos para encontrar herramientas de política para enfrentar este desafío. Aunque las principales conclusiones de los estudios llevados a cabo de la misma se proporcionan al final de cada capítulo, en esta sección, reviso algunos resultados destacables de cada artículo y señalo futuras líneas de investigación.

El Capítulo 2 ha llevado a abordar adecuadamente la potencial endogeneidad de las variables de globalización, lo que es particularmente importante para establecer el vínculo causal entre globalización y conflicto civil. A diferencia de la literatura anterior que relaciona varias dimensiones de la globalización y el conflicto, he buscado junto con mi co-director Roberto Ezcurra, abordar la causalidad inherente entre los dos fenómenos. Con ese fin, hemos introducido efectos fijos de país para abordar las variables omitidas. Sin embargo, no ha sido sencillo encontrar variables instrumentales para cada dimensión de la globalización para resolver el problema de endogeneidad. De hecho, cuando hemos observado cómo los flujos comerciales y financieros, los intercambios culturales y las cuestiones políticas se extienden por el mundo, nos hemos dado cuenta de que estos fenómenos siguen un patrón espacial. Así, cada dimensión del índice KOF se relaciona con la del vecino, siguiendo las teorías de la geografía y la interdependencia espacial de los modelos teóricos de la denominada "Nueva geografía económica" (Krugman, 1998). En consecuencia, hemos creado variables instrumentales que asocian cada índice de globalización de un país con el índice de globalización del resto de países, aplicando una matriz espacial exógena basada en distancia geográfica entre ellos. Con estas variables (una para dimensión) abrimos un camino para resolver cualquier problema de endogeneidad relacionado con la globalización.

Una de las conclusiones clave de esta tesis es considerar que la asociación no significativa entre globalización y guerra civil no implica necesariamente que los procesos de globalización económica, social o política no conduzcan al conflicto. Mas bien, podría significar que no existe un vínculo directo debido a la complejidad de las interacciones entre los diferentes actores involucrados en el proceso. Esta conclusión lleva a preguntarse por el estudio de factores que indirectamente podrían conectar la globalización con el conflicto. Por lo tanto, consideramos dos implicaciones de mis resultados: Primero, la necesidad de aislar y cuantificar diferentes canales de transmisión que puedan vincular ambos fenómenos, y segundo, considerar que el análisis a nivel de país podría no ser la mejor opción para estudiar ciertas causas de conflicto. Es decir, los resultados muestran que no existe una asociación directa entre las dos variables a nivel de país. Pero, podríamos afirmar que el efecto podría ser local, y podría depender de factores como la desigualdad espacial, aspectos geográficos, étnicos, culturales e históricos, y la calidad de la gobernanza, entre otros.

Por estas razones, he decidido estudiar el papel de las variaciones en los precios externos de las materias primas agrícolas como proxy de variaciones en los ingresos y su efecto sobre el conflicto, dependiendo de las características étnicas desde una perspectiva a nivel micro. El uso novedoso de datos geolocalizados me ha dado la oportunidad de aplicar el nivel de celda para estudiar el conflicto, que debería haber asegurado que sea exógeno a los eventos de conflicto. Bajo este enfoque, he podido combinar varias bases de datos georreferenciadas, lo que ha dado una imagen más detallada de las características de cada ubicación.

Así, la principal contribución en el Capítulo 3, junto con Fidel Pérez Sebastián y Miguel Angel Campo-Bescós, ha sido considerar que la diversidad étnica actúa indirectamente sobre el conflicto. Nuestra propuesta surgió de la idea de que las causas del conflicto pueden no ser homogéneas y dependen de las características locales, cómo en este caso tanto diversidad política como la étnica podría indicarnos diferentes mecanismos por los cuáles se activan los conflictos.

Los resultados obtenidos en este capítulo nos conducen a varias conclusiones interesantes. Por ejemplo, después de una variación de ingresos que conduce a la violencia, siempre es preferible tomar en consideración qué tipo de conflicto ha surgido tras esa perturbación. Puntualizamos que es necesario distinguir entre el conflicto armado organizado y la violencia no organizada para establecer los mecanismos correctos detrás de estos actos de violencia. Además, la interacción con variables políticas étnicas lleva a sugerir que los gobiernos débiles poseen menos capacidad para beneficiarse de la capacidad de represión a la rebelión que ofrecen los shocks de ingresos positivos. Y definitivamente, el sentimiento de agravio en algunos grupos étnicos es más importante para convertirse en alborotadores temporales que en soldados.

Desde una perspectiva de política, los resultados contienen una lección clara. Hemos demostrado que las fluctuaciones de los precios agrícolas provocan conflictos a nivel local. Por lo tanto, podría ser necesario un mecanismo de estabilización de precios agrícolas, pero abordar la política adecuada también depende de la naturaleza de la diversidad étnica y el tipo de violencia.

En línea con estos hallazgos, el análisis de Esteban y Ray (2017) muestra que, particularmente en el África sub-sahariana, la desigualdad de ingresos está íntimamente ligada a la identidad étnica. Siguiendo esta aproximación, la etnicidad en nuestro caso actúa de forma indirecta, respondiendo a cómo tras un shock positivo, la distribución de las plusvalías y rentas económicas entre la población podría generar conflicto. Alesina (2016) señala que el aspecto más importante en el desarrollo económico es paliar las diferencias económicas entre grupos étnicos que conviven en un mismo país. Este último es más significativo que el porcentaje de diversidad étnica que convive en un lugar. En este capítulo, demostramos que esta conclusión también es extensible al conflicto a nivel local.

Finalmente, quiero destacar el caso de Nigeria. Nigeria es un ejemplo de fracaso en convertir sus ganancias extraordinarias del petróleo en desarrollo. La exploración de petróleo ha provocado un aumento de la contaminación por petróleo en Nigeria, regularmente en el área del Delta del Níger. La mayoría de los derrames de petróleo se dan por sabotajes motivados por cuestiones de autodeterminación, protesta por agravios por el peligroso impacto de la explotación petrolera y el robo.

Por estas razones, he decidido estudiar en Capítulo 4 el efecto de los derrames de petróleo en la productividad agrícola ya que son consecuencia de este tipo de conflictos. Estos conflictos han aumentado el nivel de pobreza de los agricultores alrededor de los oleoductos. El desplazamiento de los agricultores de las zonas rurales, debido a la continua degradación ambiental, ha llevado a un porcentaje significativo de los habitantes locales a permanecer en la pobreza y la miseria cíclicas. Para encontrar el efecto de los derrames de petróleo en la productividad agrícola, también he utilizado datos novedosos de ubicación geográfica tanto de los derrames de petróleo como de la ubicación de los agricultores dentro de un área de gobierno local (LGA) específica. He aplicado una metodología de diferencias en diferencias para identificar adecuadamente el efecto de los derrames de petróleo en la productividad agrícola. No obstante, he considerado todo tipo de derrames de petróleo ya que el efecto sobre la producción agrícola es indiferente a la causa del derrame del petróleo, aunque la mayoría de ellos son provocados por sabotajes.

Aunque las principales conclusiones se incluyen en el capítulo, es un hallazgo notable que el efecto de los derrames de petróleo sobre la productividad agrícola se localice en fincas a menos de 10 kilómetros de los puntos de los vertidos, así que sean persistentes en el tiempo. Además, he desarrollado una medida de polución medioambiental basada en el número total de derrames de petróleo que se ha producido a una distancia del vertido determinada teniendo en cuenta un patrón de degradación exponencial. Desde el punto de vista de las medidas políticas, este resultado sugiere la realización de un tipo de política adecuada a prevenir nuevos derrames, y enfatizar una limpieza efectiva de las tierras contaminadas, tanto sobre las parcelas directamente afectadas, como en las tierras circundantes. También es necesaria una fórmula de compensación en las localidades que hayan sido afectadas por los derrames de petróleo en cualquier momento. Dado que la mayoría de los oleoductos están cerca de los humedales y para encontrar un radio de acción adecuado alrededor de los derrames de petróleo, las investigaciones futuras podrían incorporar una estrategia empírica basada en la distancia más cercana entre los vertidos de petróleo y los hogares a través del cauce de los ríos.

De acuerdo con futuras líneas de investigación, la búsqueda de la identificación adecuada del papel de la desigualdad de ingresos en los conflictos podría ser una continuación lógica de esta tesis. Los próximos estudios podrían considerar el efecto de la desigualdad espacial sobre el conflicto. En particular, utilizando la nueva variable de desigualdad de ingresos, por ejemplo, el índice de Gini espacial per cápita calculado con la emisión de luz nocturna promedio del conjunto de datos DMSP-OLS Nighttime Lights Time Series, y los datos de población de la base de datos abierta Geospatial World pop. Esta aproximación podría ser una futura área de investigación en el vínculo entre desigualdad y conflicto utilizando datos geolocalizados. Además, otro punto relevante que ha sido pasado por alto por la mayoría de las investigaciones sobre conflictos civiles es que los conflictos están correlacionados en el espacio y el tiempo. Es probable que los conflictos internos y las guerras sean contagiosos, dado que los flujos de refugiados, las enfermedades, la anarquía y el comercio ilícito de drogas, caza furtiva, armas y minerales pueden generar efectos indirectos en las regiones vecinas de las zonas de conflicto. Estos hallazgos con respecto al papel del espacio sugieren que es necesario acomodar tal interdependencia en el proceso de modelado y que se requiere una explicación explícita de los efectos espaciales utilizando modelos econométricos espaciales.

Comprender las causas y consecuencias de los conflictos es un desafío de primer orden de importancia para los economistas de economía política, de desarrollo y del medio ambiente. Esta tesis contribuye a esta búsqueda al presentar dos ejemplos concretos de causas de conflicto y una determinada consecuencia ambiental derivada de la violencia con el fin de proporcionar las acciones políticas adecuadas.

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