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ABSTRACT

External shocks, internal shots: the geography of civil conflicts*

This paper uses detailed information on the latitude and longitude of conflict events in Sub-Saharan African countries to study the impact of external income shocks on the likelihood of violence. We consider a number of external demand shocks faced by the countries or the regions within countries - temporary shocks such as changes in the world demand for agricultural commodities, and longer-lasting events such as financial crises in the partner countries - and combine these with information reflecting the natural level of trade openness of the location. We find that (i) the incidence, intensity and onset of conflicts are generally negatively and significantly correlated with income variations at the local level; (ii) this relationship is significantly weaker for the most remote locations, i.e those located away from the main seaports, (iii) at the country-level, these shocks have an insignificant impact on the overall probability of conflict outbreak, but do affect the probability that conflicts start in the most opened regions. Altogether, our results therefore suggest that external income shocks are important determinants of the intensity and geography of conflicts, and provide support in favor of the opportunity cost theories of war.

JEL Classification: D74, F15, O13 and Q17
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1 Introduction

The role of income shocks as a determinant of civil conflict has been at the core of intense debates among economists and political scientists over the last decade. A particular attention has been given to the effect of commodity price variations, taken as a proxy for exogenous external income shocks (Besley and Persson, 2008, Bruckner and Ciccone, 2010, Fearon, 2005). At the country-level, the results are mixed at the very least.[1] Recently, Bazzi and Blattman (2013) have challenged most of the findings of the literature, arguing that a significant relationship between commodity prices and conflict incidence can only be detected using very specific samples, definitions of civil conflicts or estimators. On the other hand, the few results available at the micro-level points to a more robust causal relationship (Dube and Vargas, 2013). However, even when income shocks are found to significantly affect conflict probability, the identification of the precise transmission channel remains problematic.

This paper uses detailed information on the date and location of conflicts events in Sub-Saharan African (SSA) countries to study the effect of external income shocks on the likelihood of violence. We work with a full grid of SSA countries divided in sub-national units of 0.5×0.5 degrees latitude and longitude, i.e our unit of observation is the *cell-year*. We have two main objectives. The first is to use the different dimensions of our data to study the effect of external shocks both within and across countries, and to try to reconcile the results found by micro- and macro-level studies. The second is to discuss the plausibility of various channels through which external income shocks might affect conflict outbreak and intensity.

Our paper makes several contributions to the literature. First, existing papers have generally studied the impact of income shocks on conflict at the country-level, with the exception of Dube and Vargas (2013), who use geographically disaggregated data but for a single country (Colombia). We use fine-grained disaggregated data for the entire set of SSA countries, which significantly improves the external validity of the results. Second, the literature has almost exclusively used commodity price changes as a proxy for exogenous income variations. We propose a number of alternative ways to identify exogenous income shocks through international trade patterns. We improve the usual measures of commodity shocks by constructing region-specific measures of agricultural specialization. More precisely, we consider changes in the world demand for the agricultural commodities produced by the regions *within* the countries, removing the usual assumption that specialization is similar across cells. Moreover, we go further than the existing literature by also considering a longer-lasting external demand shock: the number of banking crises in the country's trading partners (weighted by the share of each partner in the country's total exports). Third, we combine these shocks with cell-specific information reflecting their "natural" level of trade openness, proxied by the distance to the nearest major seaport. Our study therefore differs from the existing literature in its level of analysis (both across and within countries) and scope (i.e. types of shocks). From an identification perspective, combining temporary and long-lasting external shocks with cell-specific information also ensures that we are capturing different aspects of exogenous changes in income. Moreover, our methodology allows us to study how external shocks affect the geography and intensity of conflict within countries.

[1] Among the most recent contributions, Besley and Persson, 2008 find a positive relationship between income shocks and civil war incidence, while Bruckner and Ciccone, 2010 find the opposite.

At the micro-level, we find that the incidence of conflicts is generally negatively and significantly correlated with income shocks within cells. Put differently, positive external income shocks reduce the probability to observe a conflict within a given cell. Second and importantly, the relationship between external income shocks and conflict is significantly weaker in naturally less open cells, i.e when one moves away from the seaports. This clearly suggests that we are identifying the effect of exogenous shocks related to international trade, which are less likely to affect the most remote regions. Importantly, this result holds for all our considered shocks, and is not sensitive to the use of several alternative measures of local agricultural specialization. Our findings also apply to conflict onset, ending and intensity, and remain remarkably robust to the use of various conflict data sources and samples, estimation techniques, as well as to the inclusion of additional country and cell-specific controls, among which are the cell's GDP and its distance to the capital city, to international borders, or to natural resource fields. Quantitatively, the estimated effect is important, and highly heterogenous: in the most open cells, a standard deviation increase in the world demand for the agricultural commodities produced by the cell increases conflict probability by 1 to 3 percentage points.[2] This effect is two to three times larger when we restrict the sample to cells in which at least one event occurs over the period. On the other hand, no significant effect can be detected in the most remote cells.

The fact that external demand variations affect the likelihood of conflict on average within cells, especially for the most open ones, implies that these shocks impact the intensity and geography of civil conflicts at the country-level. In that sense, income shocks act as threat multipliers, just like the sharp rise in food prices accelerated and intensified protests during the recent Arab Spring. The next step is to study the effect of our shocks conflict outbreak at the country-level. When doing so, we fail to find any significant effect, a result consistent with Bazzi and Blattman (2013). However, this is partly due to the fact that these trade-related shocks affect regions heterogeneously: moving back to the local level, we find that both types of shocks do significantly affect the probability that a country-level conflict starts in the most opened locations (the effect being slightly more robust in the case of our long-lasting shock, foreign financial crises). This illustrates the advantage of using geographically disaggregated data to study the determinants of violence, as country-level data ignores by definition local heterogeneity.

Our findings yield at least two important conclusions. The first pertains to the predictions of workhorse models of conflict, which are a priori ambiguous. On the one hand, a larger income might decrease the risk of conflict, either by reducing the individuals' opportunity cost of insurrection or by increasing the capacity of the state to prevent rebelion (e.g. Fearon and Laitin, 2003); on the other hand, positive income shocks might raise the likelihood of conflict by increasing the value of resources to fight over (the "state-as-prize" mechanism). The fact that positive income shocks decrease conflict probability within cell clearly points to the first group of predictions. Between the opportunity cost and the state capacity mechanisms, we favor the opportunity cost interpretation, for several reasons. First, the state capacity mechanism should to be more prevalent in cells close to the political center of the country, i.e. the capital city (Buhaug, 2010); but the interaction term between distance to capital city and our shocks is not

[2]The unconditional probability of a conflict occurring in a given cell is between 2 and 4% depending on the sample.

significant in our estimations. Second, our shocks indeed have a significant effect on local level GDP per capita. Third, our shock do not increase military spending, and do not have a larger effect in countries in which revenue mobilization is more efficient, contrary to what we would expect if the state capacity mechanism were driving our findings.

The second implication of our results is that that external income shocks are probably more important to understand the geography and intensity of ongoing conflicts than the outbreak of wars at the country-level. Our findings suggest that if the opportunity cost story is relevant, it is mainly through the escalation and spatial evolution of ongoing conflicts, rather than through the outbreak of new ones. More generally, our results contribute to the literature on the impact of international trade on civil conflicts (Barbieri and Reuveny, 2005, Jha, 2008, Martin *et al.*, 2008). In particular, we show that trade openness might influence importantly the geography of conflicts within countries.

Our paper is related to the literature documenting the effect of income shocks at the micro-level. The limitations of cross-country studies, as well as the availability of more geographically detailed data, has recently pushed researchers to move toward a more disaggregated approach. Buhaug *et al.* (2011) find that within countries, conflicts are more likely to erupt in the poorest regions. Buhaug (2010) argues that civil wars originate further away from the capital in more powerful political regimes.[3] Following Miguel *et al.* (2004), Hidalgo *et al.* (2010) use data on Brazilian municipalities and find that favorable economic shocks, instrumented by rainfall[4], affect negatively the number of land invasions within municipalities. This is also the case for Bohlken and Sergenti (2010) in the case of Hindu-Muslim riots in India. These results provide support to the view according to which decreases in income incites individual to enroll in rebellions by lowering the opportunity cost of such activities. While this idea has received important anecdotal support[5], only few research papers have dealt with the determinants of participation in civil war. Humphrey and Weinstein (2008) find that monetary incentives played a significant role in explaining individuals' enrolment to the Revolutionary United Front in Sierra Leone in the early nineties. Enlistment has also been shown to be correlated with negative individual income variations or local economic downturns in Rwanda (Friedman, 2010), Nigeria (Guichaoua, 2010), or Burundi (Nillesen and Verwimp, 2009). Similarly, negative shocks to agricultural production and crops prices has been found to be positively correlated with conflict by Dube and Vargas (2013), in the case of coffee prices in Colombia[6], and Jia (2011), who finds that droughts increased the probability of (sweet-potatoes producing) peasants revolts in China using historical data over the 1470-1990 period. By focusing on a specific country, this strand of research is able

[3] These two papers use UCDP/PRIO data on the location of the first reported violent event of conflicts for a number of countries. They do not consider income shocks or the geography of conflicts afterwards.

[4] A controversy on the robustness of this instrumentation exists since the seminal paper of Miguel *et al.* (2004) – see Couttenier and Soubeyran (2014) for a literature review.

[5] NGOs have reported that the wages or payments paid or promised by armed groups were a primary motive for enrollment (Human Right Watch, 2003b, Human Right Watch, 2003a, Human Right Watch, 2003c, Dube and Vargas, 2013). The important drop in coffee prices in the late nineties has been proposed as one of the reasons explaining the occurrence of civil wars in Burundi, Rwanda and Uganda, three countries which heavily depend upon coffee revenues (Bruckner and Ciccone, 2010 – a similar link can be made between the 40% drop in coffee price in the late eighties and the civil wars in Uganda and Rwanda in the early nineties).

[6] Dube and Vargas (2013) find evidence in favor of both the opportunity costs and state as prize theories. More precisely, they show that positive commodity price shocks decrease the likelihood of conflicts in the case of coffee (a labor-intensive commodity) but raise the probability of conflict for oil (a capital intensive commodity).

to identify very precisely the effect of income shocks on conflicts through individuals' behavior. The generalization of these results is however made difficult by the external validity concerns inherent to any country-specific study. Our paper complements their findings and constitutes a first attempts to make a link between macro, cross-country studies and micro, country-specific ones, through the consideration of both within and between countries variations.

In the next section, we describes the data and our methodology to identify income shocks. Section III presents the empirical methodology. Section IV and V present our main results on the effect of external income shocks on conflict within and across countries. We discuss the interpretation and relation of our results with the existing literature in section VI. The last section concludes.

2 Data

Our main objective is to study how income shocks affect the probability of conflict both within and across countries. We therefore need data on (i) the location on conflict events within countries; (ii) external shocks potentially affecting conflict through income; (iii) location-specific characteristics influencing the way in which each location might respond to these external income shocks. Note that the online appendix contains further details on the data used throughout the paper.

2.1 Conflict data

Data description. We make use of three different datasets containing the geo-location of conflict events in Sub-Saharan Africa: two versions of the Armed Conflict Location and Event dataset[7] (ACLED), and the recently released UCDP-Georeferenced Event dataset (UCDP-GED). These datasets cover different countries and time periods. The first ACLED dataset[8] – ACLED I hereafter – contains only 12 African countries – all of which have known large civil war episodes over the period of study –, but covers a long time period (1960-2005). The second ACLED dataset[9] – ACLED II hereafter – covers all African countries, plus a small number of non African countries, but the data only starts in 1997. Finally, the UCDP-GED dataset[10] covers African countries and the period 1989-2010. General characteristics and the complete lists of countries covered by each dataset appear in Tables 9 to 12 in the appendix. The online appendix contains more information and discussion of the specificities of each data source.

In all datasets, the unit of observation is the event. We have information about the date (precise day most of the time), longitude and latitude of conflicts events within each country. These events are obtained from various sources, including press accounts from regional and local news, humanitarian agencies or research publications. The three datasets mainly differ in the rules they apply for the inclusion of events. ACLED I and UCDP-GED consider only events pertaining to conflicts reaching at least 25 battle-related deaths per year, which makes them

[7]See Michalopoulos and Papaioannous (2011), Harari and La Ferrara (2013) and Besley and Reynal-Queyrol (2013) for recent contributions using ACLED data.

[8]http://www.prio.no/CSCW/Datasets/Armed-Conflict/Armed-Conflict-Location-and-Event-Data/

[9]Raleigh *et al.* (2010). Available at http://www.acleddata.com/

[10]See Sundberg *et al.* (2010) and Melander and Sundberg (2011) for more details. Available at http://www.ucdp.uu.se/ged/.

comparable with the country-level data commonly used in the literature.[11] Note that UCDP-GED includes all events related to a given conflict – defined by a dyad of actors – even if during a specific year, this conflict did not cause more than 25 deaths. All the events related to a given conflict are included as soon as this conflict caused 25 deaths or more in any given year of the sample period. ACLED II, on the other hand, records all political violence including violence against civilians, rioting and protesting within and outside a civil conflict, without specifying a battle-related deaths threshold.[12] The broader definition of conflict makes the comparison with the country-level literature more difficult. Despite these different rules of inclusion, we show that our results are remarkably similar across samples.

The latitude and longitude associated with each event define a geographical "location". The three datasets contain information on the precision of the geo-referencing of the events. In all datasets, the geo-precision is at least the municipality level in at least 80% of the cases (more than 95% in ACLEDs datasets), and is even finer (village) for more than 65% of the observations (more than 80% in ACLEDs). The geo-precision is generally at the level of the province for the rest of the events. We drop the observations in the UCDP-GED dataset where the event cannot be localized at a finer level than the country (less than 2% of the observations).

For each data source, we aggregate the data by year[13] and 0.5×0.5 degree cell.[14] Our unit of observation is therefore a *cell-year* in the rest of the paper, i.e. we study how income shocks affect the probability that a conflict event occurs in given cell during a given year. Using this level of aggregation ensures that our definition of a location is not endogenous to conflict events.[15] It also mitigates concerns of potential measurement error in the geo-location of the events. Our level of geographical aggregation is the same as the one used in PRIO-GRID[16], which allows us to merge our conflict data with information contained in PRIO-GRID, including distances to capital city, national borders, and socio-economic information.

The structure of the dataset is therefore a full grid of Africa divided in sub-national units of 0.5×0.5 degrees latitude and longitude (which means around 50×50 kilometers at the equator). For each conflict dataset, we construct a dummy variable which equals one if at least one conflict happened in the cell during the year, which we interpret as cell-specific *conflict incidence*. This is our main dependent variable in the rest of the paper, although we also systematically consider for robustness cell-specific conflict onset, ending and intensity (see subsection 8.3 in the appendix).

While the geo-coding of the events is cross-checked in all three datasets, they are not immune from potential biases. We cannot rule out the possibility that each and every of these datasets is biased toward certain types of countries, regions or events. However, as they have been

[11]UCDP/PRIO defines an armed conflict (civil conflict) as "a contested incompatibility that concerns government or territory or both where the use of armed force between two parties results in at least 25 battle-related deaths" (Gleditsch et al., 2002: 618-619).

[12]In the case of ACLED II, we concentrated on violent events to be consistent with the other datasets.

[13]In most cases, we have information on the temporal precision of the event: for most events, the precise day it took place is known, but in a few case only the week, the month or even the year is know. ACLEDs do not consider events for which the precision is lower than a month, but UCDP-GED include some events for which we only know the year. Given that we aggregate the information over time, at the yearly frequency, this has however no impact on our results.

[14]Previous versions of the paper used the definition of a location provided by the ACLED dataset. The results were very similar. See Berman and Couttenier (2012) for more details.

[15]See Harari and La Ferrara (2013), Michalopoulos (2012) or Besley and Reynal-Queyrol (2013) for papers using a similar methodology.

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

constructed by different institutions, and according to different rules of inclusion, these biases are likely to be differ across sources. As a matter of fact, the correlation between our conflict variables and location-specific variables (such as distances to ports, capital city, border or natural resources or population and GDP) differs across datasets (Table A.5 in online appendix), even when considering only the set of overlapping countries and years. Obtaining so similar results across samples is therefore reassuring. Our empirical methodology, in particular through the inclusion or cell and country-year fixed-effects, makes also unlikely the possibility that our results arise because of systematic biases in the reporting of events.

Table 1: Basic statistics on each sample

Sample	UCDP-GED	ACLED I	ACLED II
# countries	48	12	44
Period	1989-2006	1980-2005	1997-2006
# grid cells	8378	2700	8367
Total # events	16364	4139	15561

Descriptive statistics. We concentrate on Sub-Saharan African countries as this is the zone covered by the three datasets. Our final sample contains between 12 and 48 countries depending on the conflict data we use (Table 1). We however show robustness checks using the ACLED I data available for other regions, including some MENA, Asian and European countries. Finally, we concentrate on the 1980-2006 period due to data availability for the computation of income shocks and to the fact that the post-2007 period was characterized by a global financial crisis which had unprecedented and still not fully understood effects on international trade and commodity prices. The list of countries and descriptive statistics about the conflict data are provided in Tables 9 to 12 in the appendix, and maps A.1 to A.6 in the online appendix show the geographical distribution of events.

Several elements are worth mentioning. First, the unconditional probability of observing at least one conflict in a given cell a given year is low in all three samples: between 2 and 4% depending on the dataset (Table 2). ACLED II dataset contains more events per country than the two others, which was expected as they use a broader definition of conflicts events. Conditioning on observing a conflict during the year, the average number of events by cell is between 3 and 4 depending on the dataset. In the vast majority of cells no event occurs over the entire period. Note that we run robustness checks using only the cells in which at least one event occur over the period – "high conflict risk" cells – and show that the quantitative effects of our shocks are much higher in this case.

Second, countries are highly heterogeneous in how they are affected by conflicts, both in terms of number of events and of their geographical coverage (Tables 9 to 12 in the appendix). Some countries do not display any event over the period (Botswana or Equatorial Guinea in the UCDP-GED dataset for instance), while countries like the Democratic Republic of Congo, Sierra

Leone or Uganda experience a large number of events in all three datasets. Some countries, like Sudan, experienced a large number of conflict events, but these cover only a small share of the total area of the country (given by the total number of grid cells). On the other hand, conflict events cover almost the entire area of some small countries like Burundi or Rwanda.

Table 2: Descriptive statistics

	Obs.	Mean	S.D.	1st Quartile	Median	3rd Quartile
Sample I: UCDP-GED						
Pr(conflict)	150804	0.03	0.17	0.00	0.00	0.00
# conflicts	144522	0.11	1.50	0.00	0.00	0.00
# conflicts (if > 0)	4384	3.73	7.76	1.00	1.00	3.00
Distance to closest port (km)	150804	768.96	436.91	402.37	742.71	1111.65
Distance to border (km)	146430	152.88	127.75	51.00	118.00	221.00
Distance to capital (km)	150804	615.69	394.32	305.00	520.00	882.00
Distance to natural resources (km)	150804	295.77	213.66	126.41	249.64	410.59
Rel. distance to closest port[1]	150804	0.59	0.24	0.41	0.62	0.78
Rel. distance to border[1]	146430	0.35	0.25	0.14	0.30	0.53
Rel. distance to capital city[1]	150804	0.47	0.24	0.27	0.46	0.66
Rel. distance to nat. res.[1]	150804	0.45	0.25	0.24	0.43	0.65
ln agr. com. shock	136026	9.98	0.97	9.55	10.09	10.56
Exp. to crises	148842	0.14	0.18	0.01	0.06	0.21
Sample II: ACLED I						
Pr(conflict)	70200	0.02	0.14	0.00	0.00	0.00
# conflicts	70200	0.06	0.75	0.00	0.00	0.00
# conflicts (if > 0)	1436	2.88	4.43	1.00	2.00	3.00
Distance to closest port (km)	70200	908.99	476.38	505.02	956.56	1296.77
Distance to border (km)	70200	179.37	149.06	56.00	137.00	275.00
Distance to capital (km)	70200	709.30	415.99	359.00	665.00	1002.00
Distance to natural resources (km)	70200	289.95	244.73	106.45	210.48	394.02
Rel. distance to closest port[1]	70200	0.58	0.24	0.40	0.62	0.76
Rel. distance to border[1]	70200	0.37	0.26	0.15	0.32	0.56
Rel. distance to capital city[1]	70200	0.50	0.23	0.32	0.51	0.69
Rel. distance to nat. res.[1]	70200	0.41	0.25	0.20	0.36	0.60
ln agr. com. shock	43435	9.84	0.98	9.45	9.97	10.34
Exp. to crises	70200	0.19	0.19	0.03	0.10	0.26
Sample III: ACLED II						
Pr(conflict)	83670	0.04	0.20	0.00	0.00	0.00
# conflicts	83670	0.19	2.36	0.00	0.00	0.00
# conflicts (if > 0)	3550	4.38	10.64	1.00	2.00	4.00
Distance to closest port (km)	83670	769.87	436.47	403.71	743.93	1112.38
Distance to border (km)	81350	152.39	127.28	51.00	118.00	221.00
Distance to capital (km)	83670	611.40	393.55	303.00	514.00	875.00
Distance to natural resources (km)	83670	295.07	212.69	126.19	249.10	410.12
Rel. distance to closest port[1]	83670	0.59	0.24	0.41	0.62	0.78
Rel. distance to border[1]	81350	0.35	0.25	0.14	0.30	0.53
Rel. distance to capital city[1]	83670	0.47	0.24	0.27	0.45	0.65
Rel. distance to nat. res.[1]	83670	0.45	0.25	0.24	0.43	0.65
ln agr. com. shock	75520	10.17	0.95	9.80	10.28	10.72
Exp. to crises	82630	0.07	0.12	0.00	0.02	0.06

Note: Source: ACLED, UCDP-GED, PRIO and authors' computations.[1] relative to maximum distance, computed by country.

2.2 Income shocks

Our identification strategy rests upon the use of both country-wide income shocks and cell-specific characteristics. Our first objective is to study the effects of external (i.e. foreign) shocks on the incidence, onset or intensity of conflict in a given cell within a given country. All these shocks are based on variations in the foreign demand for the goods produced by the country or region to which the cell belongs. We focus on two different types of foreign shocks. While they are all supposed to capture exogenous variations in foreign demand for the goods exported by the cell, they are different in their scope and nature. In particular, while the first type of shock (based on the world demand for agricultural commodities) can arguably be considered as temporary and limited in scope, the second (based on financial crises) is larger and longer-lasting. Considering different shocks allows to check the robustness of the results, but also to discuss the way in which income shocks affect the incidence of conflicts. Descriptive statistics on each of the income shocks variables are provided in Table 2, and the online appendix contains more details about the construction of these variables.

Temporary shock: agricultural commodities. As mentioned earlier, a number of papers have tried to identify the effect of commodity shocks on the likelihood of conflict across countries. Little work has been done within country (with the notable exception of Dube and Vargas, 2013, focusing on Colombia). In the following, c denotes a cell, p an agricultural commodity (product), i the country to which the cell belongs, and t the year. Our objective is to compute a time-varying cell-specific measure of external demand for the commodities produced by the cell of the form:

$$\mathrm{WD}_{ct} = \sum_{c} \alpha_{pc} \times M^{W}_{ipt} \text{ where } M^{W}_{ipt} = \sum_{j \neq i} M^{W}_{jpt} \tag{1}$$

where α_{pc} is the share[17] of agricultural commodity (product) p in cell c, and M^{W}_{ipt} is the world import value of commodity p in year t minus the imports of country i. Considering the world value of imports instead of world prices allows us to consider a wider range of commodities, including commodities which do not have a world price.[18] Data on M^{W}_{ipt} is provided by UN-Comtrade. To measure α_{pc}, we use three alternative sources.

Baseline shock: FAO Agro-maps. First, we use FAO Agro-maps information to obtain a region-specific measure of agricultural specialization. The FAO Agro-maps data contains information on the volume of production of different agricultural commodities at the sub-national level, for a number of years. Agro-maps uses the Second Administrative Level Boundaries (SALB) defined by the UN based on national administrative units. These administrative units appear in light grey on maps A.1 to A.6 in the online appendix. When a cell contains multiple regions, we sum the shock variable across regions and weight by the share of the cell's area occupied by each region. For each commodity, we obtain the value of production by multiplying the volume provided by the FAO by unit values computed from UN-Comtrade data. We consider here 70

[17] When multiple years of data are available, we use the average share but we perform a number of robustness checks with alternative shares – see discussion below.

[18] Earlier versions of our paper also checked that our results are robust to the use of commodity price variations using the data from Bazzi and Blattman (2013), and to the use the quantity component of M^{W}_{ipt} only.

commodities such as bananas, cocoa, coffee or tomatoes and we focus on the post-1989 period to be able to match the product classification with HS trade data from UN-COMTRADE.[19]

The FAO-agromaps data covers the period 1982-2011, but the data is generally available only for a small number of years within this time period for each country. In our baseline estimations, we use the average share of each commodity in the total agricultural production value of the region over the available period for the computation of α_{pc}. However, we show that the results are similar when using alternative shares, including shares computed over the 1982-1993 period (in which case we run the estimations on the post-1993 period) or binary shares which equal one if region r has produced the commodity c at least one year over the period. Finally, another potential issue is that country-wide conflicts might affect M^W_{ipt} if the country is a large exporter or importer of the commodity: we show that our results are robust to the exclusion of the commodities for which the country exports or imports represents more than 1% of world trade value.

Alternative measures of agricultural specialization: M3-crops and suitability. The FAO-Agromaps data contains actual production for a long time period and covers most Sub-Saharan African countries. However, it contains also many missing values, and is available at a higher level of aggregation than our level of observation, which might cause measurement error. The fact that is focuses on actual rather than potential production might also be a source of endogeneity. To check the robustness our results, we rely on two additional sources. These are based on GIS raster data and therefore contain more geographically disaggregated information, which allows us to compute two alternative versions of α_{pc} at the level of the cell. More details are provided in the online appendix.

First, we use the M3-CROPS data from Monfreda *et al.* (2008) which contains information on the harvested area in hectares for 137 different crops at a resolution of 5 arc minutes$\times$5 arc minutes for the year 2000 (also used in Harari and La Ferara, 2013). This dataset has a different approach than the FAO Agro-map data. It focuses on the land use and dos not provide information on the production. It has the advantage of being more fine-grained and to include more crops than FAO Agro-maps (Monfreda *et al.*, 2008). On the other hand, it is only available for the year 2000.

Second, we consider the suitability of a cell for cultivating 45 crops from the FAO's Global Agro-Ecological Zones (GAEZ).[20] This data is constructed from models that use location characteristics such as climate information (rainfall and temperature for instance) and soil characteristics. This information is combined with crops' characteristics (in terms of growing requirements) to generate a global GIS raster of the suitability of a grid cell for cultivating each crop. Suitability is then defined as the percentage of the maximum yield that can be attained in each grid cell. Following Nunn and Qian (2011) and Alesina *et al.* (2011), we define a cell as suitable for a crop if it can achieve at least 40% of the maximum yield. The main advantage of this data is that crop suitability is exogenous to conflicts, as it is not based on actual production.

[19]The data section of the online appendix contains the complete list of commodities, as well as the years for which the production data is available for each countries. It also discusses extensively potential sources of measurement error in the FAO-Agromaps data, and their consequences.

[20]http://gaez.fao.org/Main.html. See Nunn and Qian (2011) for an excellent discussion of the FAO-GAEZ data.

Note that we interpret an increase of WD_{ct} as a positive income shock for region, despite the fact that we do not know whether production is actually exported or sold domestically. Indeed, even if the product is not exported, our shock might have an effect – albeit lower – on income, as world demand might affect the domestic prices of the commodities produced by a given region. Moreover, as explained in more details in the next subsection, we interact our shocks with measures of trade openness computed at the level of the cell. For a given level of production, the most opened regions are more likely to be net exporters of the commodity. Finally, we compute a alternative version of WD_{ct} which concentrates on the commodities which are exported at some point by the countries over the sample period, and show that our results are unchanged.[21]

Changes in the demand for agricultural commodities are generally modest, and can be considered as temporary.[22] Our second type of external demand shocks is based on large foreign event – financial crises – which might affect domestic income more importantly, and more durably.

Long-lasting shock: Banking crises. Our next measure of income shock is the exposure of the country to financial crises in the rest of the world.[23] Financial crises destroy trade[24], and are arguably exogenous to trading partners' economic or political situation (especially if the trading partner is a small African economy). Importantly, they typically last several years (on average 4.3 years in our sample) and have persistent effects on the real economy (Cerra and Saxena, 2008) and on imports (Abiad *et al.*, 2011), especially when the origin country is in Sub-Saharan Africa (Berman and Martin, 2012).

For each country i, we compute the following time-varying indicator:

$$\text{Crisis exposure}_{it} = \sum_{j} \omega_{ij} \times C_{jt} \tag{2}$$

where j is the destination country and t is the year. ω_{ij} is the average share of destination j in country i's total exports over the period, and C_{jt} is a dummy which equals 1 if destination j experienced a banking crisis during year t. The trade data comes from the IMF Direction of Trade Statistics (DOTS), and the crisis data from Reinhart and Rogoff (2011).[25] The *Crisis exposure*$_{it}$ variable therefore represents the number of banking crises in the destinations served by country i, weighted by the average share of each destination in its total exports. It represents a global demand shock on all the goods exported by the country.[26]

[21] Still, some regions could in principle be net importers of the commodities they produce (this would however be difficult to reconcile with our results), which would complicate the interpretation of our variable. This would be the case for populous regions with little production capacities which are heavily biased toward certain commodities. We will control for cell's population in our estimations. Moreover, the use of GAEZ data ensures that we are not not capturing consumption patterns.

[22] Table A.29 in the online appendix confirms this assertion in our sample. We regress the log-change of our baseline agricultural commodity shock – based on Agro-Maps data – on its first, second and third lags, controlling for year dummies and 4-digit product fixed effects. We fail to find evidence of persistence.

[23] As a robustness, we also use the African Growth Opportunity Act (AGOA) as an alternative long-lasting shock. See online appendix, section 12 for more details.

[24] See also for instance Abiad *et al.* (2011) for a long-term perspective, and the literature on the recent trade collapse summarized in Baldwin (2009).

[25] Reinhart and Rogoff (2011) define a crisis as (1) "bank runs that lead to the closure, merging, or takeover by the public sector of one or more financial institutions; and (2) if there are no runs, the closure, merging, takeover, or large-scale government assistance of an important financial institution (or group of institutions), that marks the start of a string of similar outcomes for other financial institutions."

[26] Again, if a grid cell contains several countries, we use the sum of *Crisis exposure*$_{it}$ weighted by the share of each country in the cell's total area.

As this variable is based on trade shares, we interpret it as a real shock on demand for the country's produced goods, despite the fact that we are looking at a financial event. We consider indeed as unlikely the possibility that the shock affects conflict through the country's financial system: even though the geographical distribution of international financial linkages is closely related to trade in goods (see for instance Aviat and Coeurdacier, 2007), Sub-Saharan countries' financial systems are arguably too small and closed to generate such an effect.

Note that we have checked that financial crises in the partner countries indeed affect exports of the countries included in our sample. Columns (1) and (2) of Table 5 in the appendix show the results of the estimation of a gravity-like equation which regresses the log of bilateral trade between our exporting countries and the rest of the world countries on a dummy capturing the occurrence of a banking crisis in the importer country. We control for bilateral fixed effects, year dummies, as well as for both countries GDPs in column (2). Banking crises are associated with a 8 to 11% drop in bilateral imports. Our results are consistent with Abiad *et al.* (2011) and Berman and Martin (2012) among others. In column (3) we regress country-level exports on $\textit{Crisis exposure}_{it}$ (plus country and year dummies); although slightly more imprecisely estimated, its effect is large and negative as expected.[27]

2.3 Natural openness

All the shocks described above are based on variations in the foreign demand for the goods produced by the country or region to which the cell belongs, or by the cell itself. As these are income shocks based on international trade, we expect them to have a lower impact on the cells that are naturally less open, i.e. on the cells for which trade costs are higher. Income in these cells might be primarily driven by self-consumption and disconnected from the world market.

We therefore construct measures of natural trade openness which we then interact with our external income shocks. This has first an identification purpose: to ensure that we are identifying the effect of (exogenous) external foreign demand shocks, and not of some other (e.g. internal) shocks that may be correlated with them. Beyond that, it allows to study how external income shocks affect the *geography* of conflicts within each country and to show that these shocks have heterogenous effects within countries, which to our knowledge has not been done so far. This identification strategy also help us to reconcile the divergent results found by the cross-country and within-country literatures: the fact that only certain regions – the most opened ones – are affected has implications for the effect of these shocks on country-level conflict outbreaks.

For each cell, we compute the distance (in kilometers) between the centroid and the closest major seaport.[28] We retain the main ports of each country with a maximum draft of at least 10 meters. Note that the closest seaport is not necessarily located in the same country, as some countries are landlocked, or some cells closer to a foreign port.[29]

[27] Figure A.7 in the online appendix shows how the effect of crises on bilateral trade persists and gets magnified as the crisis in the importer country lasts. The specification is similar to Table 5, column (2), except that we replace the crisis variable by a set of dummies representing the number of years since the crisis started.

[28] The data on major seaports comes from http://www.e-ships.net/ports.php and Couttenier and Vicard (2012).

[29] The location of seaports can be seen in Figures A.1 to A.6 in the online appendix. We show that our main findings are robust to considering seaports with a maximum draft larger or equal to 12 meters, which is the threshold used internationally to consider a port as a "deep-water" one. These ports are defined as deep-water because they can accommodate loaded "Panamax" ships, which dimensions are determined by the ones allowed by the Panama Canal's lock chambers. We have checked that all our results are unchanged when using this

As we are using a cross-country dataset, a potential issue with using distance in levels is that it will be on average higher in larger countries. If conflict probability is different in these countries for other (unobserved) reasons, this might bias our results. As a robustness, we systematically verify that our results are unchanged when taking the ratio between this distance and the largest distance observed by country.

2.4 Other cell-specific data

Our remoteness variables might be correlated with other cell-specific characteristics, such as economic activity or closeness to natural resources. To ensure that we are indeed identifying the effect of trade openness, we include in our robustness checks measures of distance between the cell's centroid and the capital city, the closest international border, and natural resource fields. The first two come from PRIO-GRID. The last is computed using information on the latitudes and longitudes of diamond and oil fields from PRIO.[30] Finally, we control for economic activity and size by using data from PRIO-GRID – which itself relies on the G-Econ dataset developed by Nordhaus *et al.* (2006) – on the population and GDP of the region.[31] G-econ data contains information about these indicators every five years between 1990 to 2005 for most countries in the world, divided by 1 × 1 degree grid cells. We assign each 0.5×0.5 degree cell to the 1×1 degree cell to which it belongs. Descriptive statistics about these various measures are provided in Table 2.

3 Empirical methodology

3.1 Baseline specification: Micro Level

Our objective is to study the way in which foreign demand shocks affect the likelihood and intensity of conflict within countries. Let us denote by c a specific cell, i a country and t a year. In general, we estimate a specification of the form:

$$\text{Conflict}_{c,t} = \beta \text{shock}_{i,t} + \gamma \text{shock}_{i,t} \times \text{remoteness}_c + \eta_t + \mu_c + \varepsilon_{c,t} \tag{3}$$

where $\text{Conflict}_{c,t}$ is a variable that captures the incidence, onset or intensity of a conflict in a given cell, during a given year. The variable $\text{shock}_{i,t}$ denotes a shock affecting the external demand for the goods produced by country i or cell c: alternatively (i) the world demand for agricultural commodities produced by the region (equation (1) – in this case the variable is cell or region-specific, i.e. $\text{shock}_{c,t}$); (ii) the exposure to banking crises (equation (2)). Finally, remoteness_c represents our inverse measure of the "natural trade openness" of the cell. In our baseline estimations, this variable is the log of the distance between cell c and the nearest seaport.

In all estimations we control for time dummies η_t and cell-specific characteristics μ_c. The latter capture time-invariant characteristics that may affect the average likelihood of conflict in a given cell, e.g. the distance to the closest port, to the capital, to natural resources, or the region's roughness. Cell-fixed effect also capture potential systematic difference in terms of press

alternative size threshold for seaports.

[30] http://www.prio.no/CSCW/Datasets/Geographical-and-Resource/

[31] See also the online appendix for more details about the variables described in this section.

coverage across regions. In a second step, we show that our results are robust to the inclusion of additional interactions terms between $\text{shock}_{i,t}$ and other cell-specific characteristics.

The sign of β is theoretically ambiguous, as explained in more details in section 5. Assume that an increase of $\text{shock}_{i,t}$ represents an exogenous increase in country i's income (e.g. higher demand for the country's products). According to the state-as-prize theory, this larger income should increase the likelihood of conflict by increasing the value of the state, which can be captured through rebellion; β should be positive in this case. On the contrary, the opportunity cost theory predicts that this larger income should increase the opportunity cost of fighting, therefore reducing the risk of conflict; β should be negative. But a negative estimate of β can be also interpreted as evidence in favor of the state capacity channel: The increase in country i's income provides the state with the financial means to strengthen the control of opponents or buy off opposition. Section 5 presents a number of tests which incite us to favor the opportunity cost mechanism.

We expect β and γ to be of opposite signs: the most remote cells face larger trade costs, are more inward-oriented, and should be less relatively affected by foreign income shocks. These shocks should therefore influence the *geography* of conflicts.

By studying the effect of external shocks in relatively open regions, do we identify only specific types of conflicts? Put differently, are income shocks triggering only certain conflicts? It would be the case, for instance instance, if open regions were systematically located away from international borders: our methodology would be less likely to identify separatists events. This of course matters for the interpretation of our results and their external validity. The online appendix (section 5) contains a general discussion of this issue. We argue that the type of conflicts occurring in the cells that we identify as being open are not, on average, different from the conflicts observed in the sample in general. We also show that our results hold *within* specific conflicts, i.e. within a given dyad of actors.

3.2 Econometric issues

Conflict incidence. We assess the effect of external shocks the incidence of conflict. We first estimate a probabilistic model of the form:

$$\Pr(\text{Conflict}_{c,t} > 0) = \beta_1 \text{shock}_{i,t} + \gamma_1 \text{shock}_{i,t} \times \text{remoteness}_c + \eta_t + \mu_c + \varepsilon_{c,t} \tag{4}$$

where the dependent variable is conflict *incidence*, i.e. a dummy taking the value 1 if cell c experienced a conflict during year t. The cleaner way to estimate this specification is through a conditional logit estimator that accounts for all cell-specific time-invariant unobserved characteristics. This is our preferred estimator, but it has two drawbacks. First, it drops the all cells for which the outcome of interest does not vary over the entire period, i.e. all cells in which conflicts always or never occur. Second, it makes the size of the coefficients difficult to interpret. Therefore, we systematically report the results obtained with a linear estimator (LPM) with cell fixed effects.

Conflict onset, ending, and intensity. Our results are similar when we use as a dependent variable (i) conflict onset, i.e. conditioning on no conflict happening in cell c during year $t-1$;

(ii) conflict ending, i.e. conditioning on a conflict occurring in cell c during year $t-1$; (iii) conflict intensity, i.e. the number of events observed in cell c during year t. Section 8.3 in the appendix provides more discussion of these results. The full details of the estimations appear in Table A.9 to A.20 on the online appendix.

Country-level conflict outbreak. The above specification provides information on the effect of external income shocks on the likelihood of conflicts within a given cell in general, i.e. not conditioning on whether a conflict is already taking place elsewhere in the country. It might be the case, however, that income shocks have an effect on the way in which conflicts evolve within countries over time, without being necessarily at the source of the outbreak of the event. In order to better understand whether external income shocks influence the *outbreak* of a civil conflict we estimate a variant of equation (8) where we condition on conflict onset at the country level, i.e.:

$$\Pr(\text{Conflict}_{c,t} > 0|\text{Conflict}_{i,t-1} = 0) = \beta_1 \text{shock}_{i,t} + \gamma_1 \text{shock}_{i,t} \times \text{remoteness}_c + \eta_t + \mu_c + \varepsilon_{c,t} \quad (5)$$

where $\text{Conflict}_{i,t-1}$ equals 1 if at least one violent event is recorded in country i during year $t-1$. This specification allows us to study whether external income shocks affect the location of conflicts when a civil conflict starts, and, in general, whether these shocks are significant determinants of conflicts outbreak at the *country-level.*

Standard errors. In all estimations, we use robust standard errors, clustered the regional level, where a region is defined at the SALB-ADM1 level, which is the level of geographical aggregation of our baseline agricultural commodities shock. We also check that our results are robust to a non-parametric estimation of the standard errors allowing for both cross-sectional spatial correlation and cell-specific serial correlation (Conley, 1999; Hsiang *et al.*, 2011)[32], or, alternatively, to clustering at country-year level.[33]

3.3 Relation with the cross-country literature: Macro Level

As we are using cell fixed effects, our results should be interpreted as the effect of external shocks within a given cell, over time. By studying how the probability of conflict varies for each cell, we are implicitly studying the intensity of conflict at the country-level: an increase in the probability of conflict on average across cells implies a magnification of conflict intensity at the country-level. To ease the comparison between our results and those of the existing literature (e.g. Bazzi and Blattman (2013)), we perform a number of additional estimations at the country-level. More

[32]We have also tried to include spatial covariates in the estimations: the average agricultural commodity shock or the number of conflicts within a 100km radius around the cell, in the spirit of Harrari and La Ferrara (2013), to control for the spatial correlation and diffusion of shocks and violence. Our results are similar.

[33]When standard errors are clustered at some administrative level (region or country), we face the issue that a cell can contain several administrative units. In this case, we assign a main country or region to the cell, as defined as the country or region with the highest share of the cell's total area. Note that we consider administrative units which are based on the end of the period and fixed over time: we do not consider changes in international or regional borders as these are potentially endogenous to conflict. Note however that distance to capital and to international borders, which are taken from PRIO-GRID are time-varying, i.e. take into account changes in international borders, which occurred in Erithrea (1993), Ethiopia (1993), Namibia (1990) and South Africa (1990) during our period of study.

precisely, we study the effect of our various income shocks on conflict onset, incidence or intensity at the country-level, i.e. estimate a specification of the form:

$$\text{Conflict}_{i,t} = \beta \text{shock}_{i,t} + \eta_t + \mu_i + \varepsilon_{i,t} \tag{6}$$

where $\text{Conflict}_{i,t}$ denotes conflict incidence (a dummy which equals 1 if at least one violent event was recorded during year t in country i), onset (a dummy which equals 1 if at least one violent event was recorded during year t in country i, but no violent event was recorded in $t-1$)[34], ending (a dummy which equals 1 if no violent event was recorded in year t, but a least 1 was recorded in $t-1$), or intensity (number of cells with violent events, or total number of violent events observed in country i during year t). Finally, in all estimations we include time dummies η_t and control for country-specific unobservable characteristics through the inclusion of country fixed effects μ_i.

In the case of conflict incidence, a potential issue raised by the macro-level literature is that conflict being a persistent variable, one should estimate a dynamic model with the lagged conflict variable included on the right hand side. As discussed by Bazzi and Blattman (2013) this is however equivalent to modeling onset and ending separately (Beck and Katz, 2011), as we do here for both micro and macro level estimations. Note that this problem is less stringent on the micro-level estimations, as conflict is in this case much less persistent: at the cell-level, the vast majority of conflicts – around 75 to 80% – do no last more than 2 years.

4 Micro-level results

4.1 Temporary shocks: demand for agricultural commodities

Baseline results. We first consider agricultural commodity shocks. As mentioned earlier, we use an indicator of income shock based on the agricultural specialization of the region to which the cell belongs, i.e. the foreign demand for the region agricultural products as defined by equation (1). Our baseline estimations are based on FAO Agro-maps data. We consider the impact of changes in foreign demand on the probability of conflict within a given cell. We further interact this variable with the remoteness of the cell, proxied by the distance to the nearest seaport. Changes in foreign demand are expected to affect less the most remote locations, for which trade costs are higher – and therefore trade openness is naturally lower.

Our baseline results are shown in Table 3. Panel A contains estimations in which the effect is assumed to be the same across regions. Panel B includes the additional interaction term between our shock variable and distance to the closest seaport. Columns (1) and (2) use UCDP-GED conflict data, columns (3) and (4) ACLED I, and columns (5) and (6) ACLED II data. Finally, odd numbered columns contain FE-logit estimations, an even numbered ones shows LPM results. Most of the tables of the paper are organized in the same way.

An increase in world demand of the region's agricultural commodities generally decreases the probability of conflict incidence within cells. This result is robust across conflict datasets, except in column (4) (Panel A). However, not all cells are equally opened to trade and therefore equally likely to be affected by foreign demand. In Panel B, we indeed find that the effect is

[34] This variable is coded as "missing" for ongoing conflicts.

Table 3: Agricultural commodities demand and conflict

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.	Conflict incidence		Conflict incidence		Conflict incidence	
Estimator	FE logit	FE-LPM	FE logit	FE-LPM	FE logit	FE-LPM
PANEL A						
ln agr. shock	-2.534^a	-0.044^a	-1.749^a	-0.003	-1.563^b	-0.020^b
	(0.628)	(0.012)	(0.583)	(0.012)	(0.675)	(0.009)
PANEL B						
ln agr. shock	-5.054^a	-0.234^a	-5.860^a	-0.106^b	-5.500^a	-0.263^a
	(1.079)	(0.062)	(1.551)	(0.043)	(1.604)	(0.072)
ln agr. shock × remoteness[1]	0.495^a	0.031^a	0.758^a	0.017^a	0.676^a	0.039^a
	(0.153)	(0.009)	(0.225)	(0.006)	(0.243)	(0.011)
PANEL C						
ln agr. shock	-3.525^a	-0.100^a	-3.298^a	-0.040^a	-2.947^a	-0.072^a
	(0.567)	(0.024)	(0.872)	(0.014)	(0.880)	(0.025)
ln agr. shock × remoteness[2]	2.660^a	0.101^a	2.769^a	0.068^a	2.705^a	0.089^a
	(0.495)	(0.026)	(0.794)	(0.017)	(0.972)	(0.031)
Sample	UCDP-GED		ACLED 1		ACLED 2	
Years	1989-2006	1989-2006	1989-2005	1989-2005	1997-2006	1997-2006
# of countries	39	45	12	12	41	44
Observations	27090	136026	6596	43435	14410	75520

^{c} significant at 10%; ^{b} significant at 5%; ^{a} significant at 1%. [1] ln distance to closest seaport.[2] distance to closest seaport relative to maximum distance, computed by country. Robust standard errors, clustered by administrative region in parentheses (see Table 18 in the appendix for robustness allowing for spatial serial correlation and other types of clustering). All estimations include year dummies and cell fixed effects.

heterogeneous across cells. The coefficient on the interaction between remoteness and our shock variable is always positive and significant, i.e. the probability of conflict in the least open locations is significantly less affected by changes in the world demand for the commodity produced by the cell. This result is extremely robust across datasets. Quantitatively, the effect is not negligible: for the seaport itself, a standard deviation increase in foreign demand decreases the conflict probability by 1 (column (4)) to 3 (column (6)) percentage points (to be compared with an unconditional probability of conflict comprised between 2 and 4% depending on the sample). Around 1000 kilometers from the seaport, however, no statistically significant effect can be detected in any of the estimations.[35]

In Panel C of Table 3, we test the robustness of our results using an alternative indicator of trade openness: the distance to the nearest seaport relative to the maximum distance computed by country. This prevents the variable to be systematically higher in large countries, as was the case with the level measure used in the baseline estimations. On the other hand, this ratio

[35] Section 15 of the online appendix provides an illustration of these results using specific examples of commodities and countries.

being by construction bounded between 0 and 1, it tends to underestimate the effect of large within-country distances. Qualitatively, our results are very similar: in the least open cells, conflict incidence is found to be significantly less affected by external changes in agricultural commodities demand. Note that the quantitative interpretation of our results is in this case straightforward: for instance, a standard deviation increase in foreign demand leads to a 4 to 10 percentage points decrease in conflict probability depending on the cells. On the contrary, summing the coefficients in columns (2), (4) or (6) we see that the effect is always statistically insignificant for the most remote locations.

Additional regressors. Our remoteness measures might be correlated with a number of characteristics of the cells affecting the way in which they react to external shocks. These include for instance economic size or the distance to the countries' political center. The correlation between the distance to seaports and distance to the capital city is indeed positive and statistically significant (around 0.45). One can argue that we might be identifying the effect of economic activity or political influence rather than the effect of trade openness.

Table 4: Agricultural commodities demand and conflict: robustness

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.	Conflict incidence		Conflict incidence		Conflict incidence	
Estimator	FE logit	FE-LPM	FE logit	FE-LPM	FE logit	FE-LPM
ln agr. shock	-6.537^b	-0.191^b	-7.170^c	-0.240^a	-13.701^a	-0.223^b
	(2.859)	(0.085)	(3.952)	(0.073)	(3.815)	(0.113)
ln agr. shock × remoteness[1]	0.321^b	0.032^a	0.388	0.020^a	0.510^b	0.042^a
	(0.144)	(0.010)	(0.305)	(0.007)	(0.251)	(0.011)
ln agr. shock × ln dist. to capital	-0.160	-0.010	0.326	0.004	0.371	0.008
	(0.184)	(0.008)	(0.287)	(0.010)	(0.279)	(0.010)
ln agr. shock × ln dist. to border	-0.286^b	-0.010^a	-0.264	-0.012^a	-0.418^b	-0.011
	(0.119)	(0.003)	(0.171)	(0.004)	(0.180)	(0.007)
ln agr. shock × ln dist. to nat. res.	0.314^b	0.014^a	0.506^a	0.017^a	0.716^a	0.037^a
	(0.138)	(0.005)	(0.179)	(0.004)	(0.210)	(0.010)
ln agr. shock × ln GDP area	-0.275^c	-0.002	-0.001	0.011^c	0.024	0.016^a
	(0.162)	(0.006)	(0.213)	(0.006)	(0.248)	(0.006)
ln agr. shock × ln pop. area	0.240	-0.003	0.028	0.008	0.460^c	-0.021^a
	(0.161)	(0.005)	(0.284)	(0.005)	(0.257)	(0.005)
Sample	UCDP-GED		ACLED 1		ACLED 2	
Years	1989-2006	1989-2006	1989-2005	1989-2005	1997-2006	1997-2006
# of countries	39	45	12	12	41	44
Observations	26784	130627	6511	43180	14230	72570

^{c} significant at 10%; ^{b} significant at 5%; ^{a} significant at 1%. [1] ln distance to closest seaport. dist. to nat. ress.: distance to nearest natural resource field (oil, gas or diamond). ln GDP and pop. area: PPP GDP and pop. of the area in 1990, from G-econ. Robust standard errors, clustered by administrative region in parentheses. All estimations include year dummies and cell fixed effects.

In Table 4, we add to our baseline estimations interactions terms between our shock variable and (i) the log of distance to the capital city[36]; (ii) the log of the distance to the closest international border; (iii) the log of distance to the closest natural resources field (oil, gas and diamond); (iv) the log of GDP of the area in 2000 and (v) the log of the population of the area in 2000. Two results are worth mentioning. First, the effect of our agricultural commodity shock, as well as its interaction with the distance to seaports, is very robust to the inclusion of these variables. The interaction terms between the shock variables and the distance to seaports remain significant in all specifications but column (3), and the estimated coefficients are quantitatively very close to our baseline estimates. Second and importantly, apart from distance to natural resources, none of the additional interaction terms are robust across estimations. This is in particular the case for the interactions with distance to the capital city and with the GDP of the area. This clearly suggests that we are capturing an income effect of external shocks on conflict that channels through international trade, rather than an effect related to the economic size or the political instability of the location.

Note that our shock has a larger effect in cells located close to a natural resource field (this is also the case when we consider exposure to crises). This suggests that income shocks play a more important role in more unstable cells. The online appendix contains a number of estimations consistent with this idea: we restrict the sample to "high-risk" cells (cells in which at least a conflict happens over the period, Table A.3) or we include interaction terms between our shocks and the level of past instability through the inclusion of the cumulated number of years in which a conflict was observed in the cell before year t (Table A.4). Qualitatively, our results are unchanged. But interestingly, we find that the effect of our shock is much higher in these cells these politically unstable cells.

Alternative measures of agricultural shocks. Both the FAO Agro-Maps data and the way in which we compute the shock have potential drawbacks, as already discussed in section 2.2. We perform two additional types of checks: the first use modified versions of our agricultural commodity shocks, but still focuses on the Agro-Maps data; the second use different data sources.

Our baseline estimates use the average share of each commodity in the total agricultural production value of the region over the available period. Using weights computed at the beginning of the sample period would result in an important loss of observations due to missing production data for most regions for early years. Missing production data is also a problem as it can create measurement error. We compute alternative versions of our shock variables (Table 15 in appendix). In Panel A, we use binary weights, i.e. weights which equal one if the commodity is produced by the region at some point over the period, zero otherwise. In Panel B, we use weights computed on the pre-1993 period. In this case, we run the estimations on the post-1993 period only. The sample size is drastically reduced in Panel B, but the results are very robust and stable – if anything they are slightly strengthened.

A second issue of our variable is that it might be endogenous to local conflicts if the cell is a large enough exporter or importer of the commodity to influence the world demand. Panel C of Table 15 shows that our results are robust to the exclusion of all commodities-countries

[36] Table A.7 in the online appendix reports very similar results using distances measures computed as ratios as in Table 3, Panel C.

which exports or imports represent more than 1% of world trade value. Finally, we also provide estimations based on a version of the shock which concentrates only on the commodities which are exported at some point by the countries over the sample period (Panel D). This drops 5 to 10% of the observations depending on the sample, but leaves the point estimates unchanged.

All these estimations are based on FAO Agro-maps data, which has the advantage to contain actual production data and to cover a long time-period. But it again has many missing values, it quite geographically aggregated, and actual production might be to some extent endogenous. Tables 16 and 17 in the appendix replicate our baseline results using two alternative data sources to measure the agricultural specialization of the cell. Table 16 uses M3-crop data, which contains more fine-grained data, is quasi-exhaustive in terms of geographical coverage but is only available for the year 2000. Table 17 shows the results using FAO-GAEZ data, which contains information on the suitability of the cell for producing each crop – instead of actual yield or production. Again, our results remain robust and quantitatively similar to our baseline estimations.

Additional robustness. Our results are robust to a variety of robustness checks, including: (i) modeling conflict onset, ending and intensity separately (section 8.3 of the appendix); (ii) allowing for cross-sectional spatial correlation and cell-specific serial correlation (Hsiang *et al.*, 2011), or alternatively for different levels of clustering of the standard-errors (Table 18 in the appendix); (iii) dropping potential outliers, i.e. countries or cells at the top or bottom of the distribution in terms of number of conflict events (Table A.21 of the online appendix); (iv) adding country-specific time trends or country-year dummies to control for country-specific temporal trends in the causes of conflict (online appendix, Tables A.23 and A.24); (vi) dropping each country separately from the estimations (results available upon request); (vii) adding non Sub-Saharan African countries contained in ACLED (Table A.27 in the online appendix) (viii) considering only deep-water seaports (Table A.25 in the online appendix); (ix) controlling for past instability through the inclusion of the cumulated number of years in which a conflict was observed in the cell before year t (Tables A.4 in the online appendix).

4.2 Long-lasting shock: financial crises

Baseline results. We now consider the exposure of the country to financial crises in its trading partners as an alternative, longer-lasting income shock. This variable has a negative impact on the country's income through lower exports (Table 13 in appendix). On the other hand, this impact on income should again affect regions heterogeneously, i.e. should be lower in regions located further away from the main seaports. Table 5 contains the baseline results. Again, we consider conflict incidence with both UCDP-GED dataset (estimations (1) and (2) of each panel), ACLED I dataset (estimations (3) and (4)) and ACLED II (estimations (5) and (6)). Panel A uses only the crisis variable, while we add interaction terms between exposure to crises and to the closest seaport, either in logarithm or as a ratio (Panel B and C).

On average across cells, the effect of exposure to financial crises in partner countries is generally statistically insignificant (Table 5, Panel A), which can be due to the fact that the impact is heterogeneous across regions. Introducing the interaction terms between exposure to crises and remoteness confirms this heterogeneity (Panel B). For the least remote cells, exposure to financial crises in partner countries increases conflict probability. The interaction term is negative and

Table 5: Exposure to crises and conflicts

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.	Conflict incidence		Conflict incidence		Conflict incidence	
Estimator	FE logit	FE-LPM	FE logit	FE-LPM	FE logit	FE-LPM
PANEL A						
Exposure to crises	-0.534	-0.010	-0.372	-0.027^b	1.846	0.039
	(0.507)	(0.011)	(1.030)	(0.011)	(1.465)	(0.035)
PANEL B						
Exposure to crises	6.376^a	0.276^a	10.766^a	0.075	16.852^a	0.783^a
	(1.967)	(0.076)	(2.635)	(0.055)	(5.271)	(0.296)
Exp. to crises × remoteness[1]	-1.107^a	-0.044^a	-1.899^a	-0.015^c	-2.221^a	-0.111^a
	(0.319)	(0.012)	(0.521)	(0.008)	(0.770)	(0.041)
PANEL C						
Exposure to crises	1.895^a	0.058^a	1.559	-0.018	8.030^a	0.186^b
	(0.668)	(0.018)	(0.983)	(0.016)	(1.939)	(0.088)
Exp. to crises × remoteness[2]	-4.635^a	-0.123^a	-4.456^b	-0.016	-9.783^a	-0.259^b
	(1.154)	(0.035)	(2.149)	(0.023)	(2.395)	(0.110)
Sample	UCDP-GED		ACLED 1		ACLED 2	
Years	1989-2006	1989-2006	1980-2005	1980-2005	1997-2006	1997-2006
# of countries	39	45	12	12	41	44
Observations	27126	137556	11128	66430	14420	76370

^{c} significant at 10%; ^{b} significant at 5%; ^{a} significant at 1%. [1] ln distance to closest seaport.[2] distance to closest seaport relative to maximum distance, computed by country. Robust standard errors, clustered by administrative region in parentheses (see Table 18 in the appendix for robustness allowing for spatial serial correlation and other types of clustering). All estimations include year dummies and cell fixed effects.

significant, i.e. distance to seaports dampens the effect of negative income shocks on conflict incidence. This is the case both when using non linear (FE Logit) or linear (OLS) estimators. Note that in some cases we find that for the most remote locations, being exposed to foreign financial crises actually has a *negative* and significant effect on conflict probability in some cases (adding up the coefficients in columns (2) and (6), Panel C). This result is however not robust, in particular to the inclusion of additional interaction terms between the shocks and cell-specific characteristics.

Robustness. As for our agricultural commodity shocks, the results presented in Table 5 are remarkably robust to a number of sensitivity tests, including: (i) modeling conflict onset, ending and intensity separately (section 8.3 of the appendix); (ii) allowing for cross-sectional spatial correlation and cell-specific serial correlation (Hsiang *et al.*, 2011), or alternatively for different levels of clustering of the standard-errors (Table 18 in the appendix); (iii) including additional cell-specific controls (Table A.8 of the online appendix); (iii) dropping potential outliers, i.e. countries or cells at the top or bottom of the distribution in terms of number of conflict events (Table A.22 of the online appendix); (iv) adding country-specific time trends or country-year dummies to control for country-specific temporal trends in the causes of conflict (online appendix, Tables A.23 and A.24)[37]; (vi) dropping each country separately from the estimations (results available upon request). (vii) adding non Sub-Saharan African countries contained in ACLED (Table A.28 in the online appendix) (viii) considering only deep-water seaports (Table A.25 in the online appendix) (ix) controlling for past instability through the inclusion of the cumulated number of years in which a conflict was observed in the cell before year t (Tables A.3 and A.4 in the online appendix).

5 Discussion and theoretical interpretation

As mentioned in the introduction, the effect of income shocks on conflicts is theoretically ambiguous.[38] Our results can be understood using contest theories, in which the probability of conflict depends on a trade-off between production and expropriation. In these models (Haavelmo, 1954 and Hirshleifer, 1989 among others), appropriation is modeled as a contest success function in which the probability of winning depends on the fighting technology, which is defined broadly and may include for instance the geographical conditions. In case of success, the individuals appropriate the opponent's economic production, which represents an opportunity to gain. But individual participation also depends on the opportunity cost of fighting, which is itself a positive function of income (Grossman, 1991, Besley and Persson, 2011). A positive income shock (say, an increase in production) therefore has two opposite effects: on the one hand, it increases the "prize", i.e. the resources that can be appropriated by exerting violence[39]; on the other hand, it decreases the individuals' incentives to fight by increasing the opportunity cost of insurrection.

Is our result that positive income shocks decrease conflict probability within cell sufficient to argue in favor of the opportunity cost mechanism? It isn't: conflict risk might as well decrease when a country experiences good shocks because they provide the state with the financial means to strengthen the control of opponents or buy off opposition (Fearon and Laitin, 2003). In principle, our results could reflect this *state capacity* effect. This section details the reasons which incite us to favor the opportunity cost interpretation.

The first reason is that distance to the capital city does not seem to play a role in our estimations. Intuitively, the state capacity effect should indeed be more prevalent in regions located close to the political center of the country, where the influence of the state is stronger. This would be consistent with Buhaug (2010), who finds that conflicts are more likely to be located far from the capital in countries with more powerful regimes. However, we have already seen in Table 4 that the coefficient on the interaction term between distance to capital city and our shock is not significant. It is also the case when using alternative shocks such as financial crises.

[37] When country-year dummies are included, the coefficients on the interaction term (the effect of the shock alone cannot be identified in this case, as it is country-year specific) display the expected sign but fail to reach significance with ACLED I dataset. These specifications are however very demanding. Given that we focus on relatively rare events in these estimations and only 12 countries, these results should probably be interpreted with caution.

[38] For more exhaustive surveys on the theories of conflict, see Garfinkel and Skaperdas (2007) or Blattman and Miguel (2010).

[39] See Fearon (2006) for a theoretical contribution using a contest model, or Chassang and Padro-i Miquel (2009) who use a bargaining approach. For empirical evidence, see Cotet and Tsui (2013), Lei and Michaels (2011) or Ross (2006).

The second argument is that our variables are indeed significantly correlated with local GDP per capita. In Table 6, columns (1) and (2), we regress the log of GDP per capita of the cells on our shock variable (agricultural commodities demand and exposure to financial crises) and their interaction with remoteness. These estimations include year dummies, cell fixed effects and additional interactions between our shocks and distances to capital city, border and natural resource fields. The data on GDP per capita comes from G-econ, which contains geo-localized economic data by slightly more aggregated cells (1×1 degree), for four years in our sample (1990 to 2005, every five years). Of course, local GDP per capital data is extremely difficult to measure, which is why these results should be interpreted cautiously. We however find that our two shocks have respectively strong positive and negative effects for the least remote locations. A larger distance to seaports dampens these effects, although the coefficient on the interaction term is significant only in the case of the agricultural commodity shock.[40]

Table 6: Channels of transmission

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Dep. Var.	ln GDP per cap.		Military spending				Conflict incidence			
Shock	Agr. com.	Crises	Agr. com.	Crises	Agr. com.	Crises	Agr. com.		Crises	
Shock	0.442^a	-0.444^a	-0.152	-0.464^b	0.060	-0.288^c	-0.025	-0.145^a	0.005	0.259^b
	(0.049)	(0.142)	(0.133)	(0.180)	(0.128)	(0.159)	(0.036)	(0.056)	(0.052)	(0.113)
Shock × remoteness[1]	-0.022^a	0.004						0.018^a		-0.034^b
	(0.005)	(0.013)						(0.006)		(0.014)
Shock × Rev. mobilization							0.001	0.004	-0.004	-0.014
							(0.009)	(0.009)	(0.014)	(0.014)
Sample	-		-				UDCP-GED			
Estimator	FE-LPM		FE-LPM				FE-LPM			
Observations	27416	29766	597	626	615	645	117324	117324	117378	117378

^{c} significant at 10%; ^{b} significant at 5%; ^{a} significant at 1%. [1] ln distance to closest seaport. Robust standard errors in parentheses, clustered by cell in columns (1) and (2), by country-year in columns (3) to (6) and by administrative region in columns (7) to (10). All estimations include year dummies and individual fixed effects (cell in columns (1), (2) and (7) to (10)), country in columns (3) to (6)). Estimations (1) and (2) include interactions between the shock variable and distance to the capital city, distance to border, and distance to natural resource fields. GDP per cap.: GDP per capita from G-Econ. Military spending: country-level military spending from SIPRI, in level in columns (2) and (3), as a share of GDP in columns (4) and (5). Rev. mobilization: efficiency of revenue mobilization from QOG.

Another way to test for the relevance of the state capacity mechanism is to use country-level proxies for state capacity. In the spirit of Cotet and Tsui (2013), we first consider the effect of our shocks on military spending. If the negative effect of income shock on conflict probability that we observe was due to an improvement of state capacity, we should observe an increase in the level of military spending at the country-level. We use data from Stockholm International Peace Research Institute (SIPRI). In columns (3) and (4), we consider the level of expenditures, while columns (5) and (6) uses spending as a share of GDP. The estimated coefficients are either statistically insignificant or *negative*.

The last test we consider is the following: the state capacity effect should be more prevalent in countries characterized by a more efficient system of revenue mobilization. We proxy the efficiency of revenue mobilization using data from the World Banks's IDA Resource Allocation Index (IRAI), which is itself built from the results of the annual Country Policy and Institutional

[40] The interaction term becomes significant in the case of exposure to crises when we restrict the sample to countries contained in ACLED I.

Assessment. We interact this variable with our income shock proxies. As shown in columns (7) to (10), these interaction terms are systematically insignificant.

All in all, we can rule out the state capacity mechanism in our case because (i) distance to capital city does not matter; (ii) local GDP per capita is correlated with our shocks; (iii) our shocks do not affect military expenditures; (iv) our shocks do not have stronger effect in states where revenue mobilization is more efficient. This is not to say that state capacity is an irrelevant mechanism in general. It might be more relevant in the case of large income changes driven by resource booms, for instance, which affect more directly the revenues of the state (Cotet and Tsui, 2013).

6 Country-level results

The results presented in the previous sections suggest that external income shocks affect the probability of conflict within cells and that their effect is heterogeneous across cells. This implies that these shocks affect the geography of conflict and conflict *intensity* at the country-level. However, they do not allow us to determine whether they are significant determinants of conflict *outbreak* at the country-level. In this subsection, we consider the effect of our external demand shocks on conflict at the country-level (equation (6)). We pursue two alternative methodologies. In the first one, we aggregate our geo-localized conflict data and we construct time-varying country-specific measures of conflict incidence, outbreak, ending and intensity (the total number of events observed in a country a given year). We use the UCDP-GED dataset, which maximizes the number of years and countries, but the results are similar with ACLED I and ACLED II datasets. Alternatively, we directly use country-level data on civil conflicts from UCDP/PRIO data. This maximizes the number of countries (all Sub-Saharan Africa) and years (from 1980).

Table 7: Macro-level results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dep. Var.	Incidence		Onset		Ending		Intens.
Source	UCDP-GED	PRIO	UCDP-GED	PRIO	UCDP-GED	PRIO	UCDP-GED
Estimator	FE-LPM		FE-LPM		FE-LPM		FE-LPM
PANEL A							
ln agr. com. shock	-0.160	0.098	-0.098	0.042	0.245^{b}	-0.081	-44.577^{a}
	(0.122)	(0.078)	(0.149)	(0.048)	(0.121)	(0.268)	(17.204)
Observations	774	774	443	733	509	122	774
PANEL B							
Exposure to crises	-0.115	0.012	0.065	0.039	0.123	0.146	-0.627
	(0.080)	(0.047)	(0.090)	(0.038)	(0.094)	(0.213)	(8.473)
Observations	1262	1262	930	1180	541	182	1262

^{c} significant at 10%; ^{b} significant at 5%; ^{a} significant at 1%. Robust standard errors, clustered by country-year in parentheses. All estimations include year dummies and country fixed effects.

We start by considering agricultural commodities shock (Table 7, Panel A). Consistent with our micro-level results, commodity demand has a significant impact on the conflict intensity (column (7)) and ending (column (5)). However, we cannot detect any effect on conflict incidence or onset (columns (1) to (4))[41]. These results are globally consistent with Bazzi and Blattman (2013). Similarly, exposure to crisis plays no significant role on any of the outcome considered (Panel B). As the number of observations is logically much smaller than in our previous estimations, however, this lack of significance might also be the result of a less efficient estimation.

Table 8: Country-level conflict outbreak: micro-results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. Var.	Incidence		Intensity		Incidence		Intensity	
Condition	Country-level onset				Country-level onset			
Estimator	FE-LPM		FE-LPM		FE-LPM		FE-LPM	
ln agr. com. shock	0.016	-1.280^c	0.221	-14.320				
	(0.069)	(0.772)	(0.379)	(11.607)				
ln agr. shock × ln dist. to closest port		0.184^c		2.064				
		(0.105)		(1.657)				
Exposure to crises					0.508	1.153^b	-0.385	1.219
					(0.392)	(0.502)	(2.649)	(2.701)
Exp. to crises × ln dist. to closest port						-0.097^b		-0.242^b
						(0.045)		(0.121)
Observations	3729	3729	3729	3729	3729	3729	3729	3729

^{c} significant at 10%; ^{b} significant at 5%; ^{a} significant at 1%. [1] ln distance to closest seaport. Robust standard errors, clustered by administrative region in parentheses. All estimations include year dummies and cell fixed effects. All estimations are based on UCDP-GED dataset.

In Table 8, we run our estimations at the cell-level, but under the condition that no other cell experiences a civil conflict in the same country the year before (as in equation (5)). In other words, we are considering the outbreak of new conflicts at the country level, but at a geographically disaggregated level, which improves the efficiency of the estimations. We focus only on the UCDP-GED sample as it is the only one containing enough observations on conflict outbreak for this kind of exercise.

On average, our shocks do not have a significant effect on conflict outbreak, i.e. they do not seem to trigger new conflicts at the country-level (columns (1), (3), (5) and (7) of Table 8). When we interact them with distance to seaports, however, a different picture emerges. Both changes in demand for agricultural commodities and exposure to financial crises have a significant effect on conflict outbreak in the most opened locations (columns (2), (4)). In other words, conditional on country-level outbreak, conflicts are more likely to start in the most open locations following negative income shocks. While this is true for both shocks, the result seems slightly more robust when looking at exposure to crisis, i.e. a large and longer-lasting shock.

How can we interpret these findings? First, they illustrate the need to consider fine-grained conflict data. In its search for exogenous changes in income, the conflict literature (including the

[41] Note that these insignificant results could be due to measurement error stemming from missing production data in the computation of the agricultural shocks. However, concentrating on countries with the highest coverage, or using alternative sources for agricultural specialization leads to the same conclusion.

present paper) has focused on foreign shocks, such as commodity prices changes. These being related to international trade, their effect naturally depends on trade openness, which varies both across and within countries. Considering geographically disaggregated data allows shows that these shocks do matter once we allow for spatial heterogeneity. A second – purely statistical – reason why running estimations at the country-level might be misleading is that, civil conflicts being rare events, the identification is made on a small number of switches of the dependent variable, which leads to an important loss of efficiency.[42] Using disaggregated data lessen this problem by improving the efficiency of the estimations.

Overall, our results suggest that external income shocks are not the main determinants of conflict *outbreak*, but that they have a significant effect on conflict intensity and the geography of conflict, i.e. on the number and on the location of violent events after the start of the conflict. Therefore, while there are probably other, deeper, underlying causes of conflicts, such as long term institutional issues, ethnic problems or inequalities, income shocks (even small ones) might importantly affect the geography and intensity of conflicts. In that sense, they might act as threat multipliers, just like the boom in food prices accelerated and intensified the protests during the recent Arab Spring. At this stage, these interpretations are of course only tentative. An interesting extension of this work, which we leave for future research, would be to determine whether conflict outbreak is affected by the interaction between income shocks and with long-term institutional or ethnic issues.

7 Conclusion

We used in this paper detailed information on the location of conflicts within Sub-Saharan African countries to study the effect of external shocks both within and across countries. In order to reconcile the seemingly contradictory results found by micro- and macro-level studies, we have proposed a number of alternative ways to identify exogenous income shocks through international trade patterns. First, we have improved the usual measure of temporary commodity shock using a region-specific measure of agricultural specialization. We also went further by considering a long-lasting shocks with the number of banking crises in the country's partners. Second, we have combined these shocks with location-specific information reflecting their "natural" level of trade openness.

Our results are manifold. At the micro-level, we find that income shocks are generally negatively and significantly correlated with the incidence, intensity and onset of conflicts within locations. However the relationship between external shocks and conflict is significantly weaker for locations that are naturally less open, as these are precisely the ones in which income is less affected by foreign demand. These results are robust to the use of various conflict data, measures of income shocks, estimation techniques, samples or to the inclusion of a number of location-specific additional controls. We argue that our findings can be interpreted as evidence in favor of the opportunity cost mechanism, rather than of the state capacity. This has interesting indirect consequences: the opportunity cost argument is a purely economic one, which means that in-

[42] Indeed, to detect an effect of commodity price shocks on conflict incidence at the country level, we need commodity prices shocks to affect conflict onset or ending, as with country fixed effects, the identification of an effect is only possible when the dependent variable switches from zero to one or inversely.

dividual engaging into rebellions because of external shocks affecting their income are probably different in that they do not (only) enter in the conflict due to political convictions or agenda. The specificity of this motive for rebelion might be important to understand the evolution and the outcome of conflict.

In nutshell, this paper suggests that external income shocks are important to understand the geography and intensity of ongoing conflicts, and might affect the outbreak of new country-wide conflicts if they are large and persistent. Further research is however needed on this point, and more generally on the way in which income shocks may interact with other long-term issues such as inequality or ethnic problems. The boom in food prices was not the primarily cause of the recent Arab spring, but many analysts emphasized its role in accelerating and magnifying the protests. Likewise, income shocks may act as a "threat multiplier", and certainly explain an important part of the timing, geography and intensity of conflicts around the world.

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8 Appendix

8.1 Additional descriptive statistics

Table 9: Summary statistics: UCDP-GED sample

Country	# events	Max. # events	Share	Country	# events	# events	Share
Angola	1722	43	0.47	Malawi	0	0	0.00
Benin	21	14	0.07	Mali	66	5	0.08
Botswana	0	0	0.00	Mauritania	18	4	0.03
Burkina Faso	2	1	0.01	Mauritius	0	0	0.00
Burundi	1448	103	0.92	Mozambique	240	11	0.28
Cameroon	41	4	0.10	Namibia	19	6	0.03
Cape Verde	0	0	0.00	Niger	47	4	0.08
Central African Republic	48	8	0.11	Nigeria	314	18	0.26
Chad	237	9	0.13	Republic of Congo	291	45	0.17
Comoros	6	3	1.00	Rwanda	416	67	1.00
Congo (Democratic Republic of the)	1060	32	0.22	Sao Tome and Principe	0	0	0.00
Cote D'Ivoire	149	14	0.17	Senegal	220	14	0.20
Djibouti	35	5	0.88	Sierra Leone	1448	72	1.00
Equatorial Guinea	0	0	0.00	Somalia	775	60	0.32
Eritrea	109	13	0.43	South Africa	2759	126	0.28
Ethiopia	874	13	0.44	Sudan	1358	31	0.22
Gabon	0	0	0.00	Swaziland	2	2	0.20
Ghana	24	4	0.11	Tanzania	16	3	0.02
Guinea	49	9	0.16	The Gambia	4	2	0.50
Guinea-Bissau	52	10	0.46	Togo	80	47	0.56
Kenya	178	6	0.25	Uganda	1663	49	0.73
Lesotho	3	1	0.25	Western Sahara	7	2	0.05
Liberia	513	53	0.91	Zambia	11	2	0.02
Madagascar	30	11	0.03	Zimbabwe	9	1	0.05

Period 1989-2006. # events: total number of events in country over the sample period. Max. # events: maximum number of events by year over the sample period. Share: share of grid cells affected by at least one conflict over the sample period.

Table 10: Summary Statistics: ACLED I sample

Country	# events	Max. # events	Share
Angola	307	9	.17
Burundi	484	36	1
Central African Republic	4	1	.02
Cote D'Ivoire	6	2	.02
Congo (Democratic Republic of the)	787	80	.23
Republic of Congo	193	27	.25
Guinea	18	4	.07
Liberia	250	19	.71
Rwanda	261	68	1
Sudan	59	11	.02
Sierra Leone	677	30	.96
Uganda	1093	32	.91

Period 1980-2005. # events: total number of events in country over the sample period. Max. # events: maximum number of events by year over the sample period. Share: share of grid cells affected by at least one conflict over the sample period.

Table 11: Summary statistics: ACLED II

Country	# events	Max. # events	Share	Country	# events	# events	Share
Angola	2213	294	0.41	Malawi	2	2	0.03
Benin	0	0	0.00	Mali	26	5	0.04
Botswana	2	1	0.00	Mauritania	5	2	0.01
Burkina Faso	14	3	0.07	Mozambique	5	2	0.01
Burundi	1520	181	0.92	Namibia	58	36	0.03
Cameroon	32	7	0.07	Niger	73	10	0.05
Central African Republic	119	8	0.23	Nigeria	624	20	0.38
Chad	161	20	0.10	Republic of Congo	301	79	0.25
Congo (Democratic Republic of the)	2175	93	0.30	Rwanda	224	47	0.75
Cote D'Ivoire	303	24	0.34	Senegal	156	19	0.27
Djibouti	6	1	0.38	Sierra Leone	952	59	1.00
Equatorial Guinea	1	1	0.08	Somalia	881	156	0.36
Eritrea	274	76	0.33	South Africa	82	15	0.06
Ethiopia	741	23	0.38	Sudan	1237	35	0.22
Gabon	5	1	0.03	Swaziland	8	2	0.20
Ghana	18	3	0.12	Tanzania	47	7	0.04
Guinea	158	20	0.25	The Gambia	7	4	0.50
Guinea-Bissau	126	51	0.46	Togo	7	4	0.11
Kenya	489	26	0.44	Uganda	1805	80	0.83
Lesotho	4	3	0.17	Western Sahara	2	1	0.02
Liberia	548	92	0.68	Zambia	18	4	0.04
Madagascar	6	2	0.02	Zimbabwe	126	9	0.28

Period 1997-2006. # events: total number of events in country over the sample period. Max. # events: maximum number of events by year over the sample period. Share: share of grid cells affected by at least one conflict over the sample period.

Table 12: Summary Statistics: all three samples, overlapping countries and time period

Sample Country	UCDP-GED	ACLED I # events	ACLED II	UCDP-GED	ACLED I Max. # events	ACLED II	UCDP-GED	ACLED I Share	ACLED II
Angola	676	78	2211	34	7	294	0.32	0.07	0.41
Burundi	1088	259	1439	103	22	181	0.92	0.92	0.92
Central African Republic	14	4	86	3	1	6	0.05	0.02	0.19
Cote D'Ivoire	128	0	294	14	0	24	0.16	0.00	0.34
Congo (Dem. Rep. of the)	790	680	1975	32	80	93	0.20	0.22	0.29
Republic of Congo	229	148	294	45	27	79	0.17	0.22	0.25
Guinea	36	11	157	9	4	20	0.14	0.05	0.25
Liberia	124	86	543	28	11	92	0.62	0.59	0.65
Rwanda	154	61	198	36	16	47	0.88	0.63	0.75
Sudan	872	43	1141	31	11	35	0.18	0.01	0.20
Sierra Leone	749	393	951	72	30	59	1.00	0.96	1.00
Uganda	1283	621	1660	49	32	80	0.64	0.71	0.81

Period 1997-2005. # events: total number of events in country over the sample period. Max. # events: maximum number of events by year over the sample period. Share: share of grid cells affected by at least one conflict over the sample period.

8.2 Financial crises and trade

Table 13: Exposure to financial crises and international trade

	(1)	(2)	(3)
Dep. Var.	Bilateral trade		ln GDP
Estimator	FE		FE
Banking crisis, importer	-0.123^{a}	-0.085^{a}	
	(0.033)	(0.032)	
ln GDP origin		0.541^{a}	
		(0.056)	
ln GDP destination		0.524^{a}	
		(0.078)	
Exposure to crises			-0.602^{c}
			(0.312)
Observations	37238	38730	1110
Bilateral FE	Yes	Yes	-
Country FE	-	-	Yes

^{c} significant at 10%; ^{b} significant at 5%; ^{a} significant at 1%. Robust standard errors in parentheses, clustered by dyad in columns (1) and (2), by country in column (3). All estimations include year dummies. Estimations based on Sub-Saharan African exporting countries, over the period 1980-2006.

8.3 Results on onset, ending and intensity

Our baseline estimations consider conflict incidence as a dependent variable. This section shows that our results are robust to the use of three alternative conflict variables: *conflict onset*, *conflict ending* and *conflict intensity*.

Conflict onset. We estimate a probabilistic model of the form:

$$\Pr(\text{Conflict}_{c,t} > 0|\text{Conflict}_{c,t-1} = 0) = \beta_1\text{shock}_{i,t}+\gamma_1\text{shock}_{i,t}\times\text{remoteness}_c+\eta_t+\mu_c+\xi_{it}+\varepsilon_{c,t} \quad (7)$$

where the dependent variable is conflict the *onset* of a civil conflict, i.e. conflict occurrence conditional on $\text{Conflict}_{c,t-1} = 0$. This variable is coded as "missing" for ongoing conflicts.

Conflict ending. Our model becomes:

$$\Pr(\text{Conflict}_{c,t} = 0|\text{Conflict}_{c,t-1} > 0) = \beta_1\text{shock}_{i,t}+\gamma_1\text{shock}_{i,t}\times\text{remoteness}_c+\eta_t+\mu_c+\xi_{it}+\varepsilon_{c,t} \quad (8)$$

where the dependent variable is conflict the *ending* of a civil conflict. Note that, as mentioned earlier, conflict are not persistent at the cell-level, which makes the study of conflict ending more difficult than at the country level. The fact that these results are less stable is therefore not surprising.

Conflict intensity. As a measure of conflict intensity, we use the number of conflict events observed in cell c during the calendar year t, $N^c_{c,t}$, as a dependent variable and estimate:

$$N^c_{c,t} = \beta_1\text{shock}_{i,t} + \gamma_1\text{shock}_{i,t} \times \text{remoteness}_c + \eta_t + \mu_c + \xi_{it} + \varepsilon_{c,t} \quad (9)$$

Table 14 contains the results using the UCDP-GED dataset a linear estimator. Complete results using the other conflict datasets (ACLED I and ACLED II), all our shock variables as well as non-linear estimator (FE logit and Poisson Pseudo-Maximimum Likelihood) are shown in the online appendix, section 8, Tables A.9 to A.20.

Table 14: Conflict onset, ending and intensity

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.	Onset	Onset	Ending	Ending	Intensity	Intensity
Shock	Agr. com.	Crises	Agr. com.	Crises	Agr. com.	Crises
PANEL A						
Shock	-0.026^a	-0.008	0.116^a	0.029	-0.252^c	-0.075
	(0.005)	(0.006)	(0.034)	(0.033)	(0.151)	(0.052)
PANEL B						
Shock	-0.103^a	0.095^b	0.280^a	-0.257	-1.836	1.762^b
	(0.019)	(0.041)	(0.066)	(0.221)	(1.191)	(0.802)
Shock × remoteness[1]	0.013^a	-0.016^b	-0.030^a	0.048	0.267	-0.284^b
	(0.003)	(0.007)	(0.010)	(0.033)	(0.179)	(0.128)
Observations	134375	135904	13688	13782	131274	132804

^{c} significant at 10%; ^{b} significant at 5%; ^{a} significant at 1%. [1] ln distance to closest seaport. Robust standard errors, clustered by administrative region in parentheses. All estimations include year dummies and cell fixed effects. FE-LPM. Conflict events data from UCDP-GED.

8.4 Agricultural commodities shocks: more robustness

Table 15: Agricultural commodities shocks: further robustness

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.	Conflict incidence		Conflict incidence		Conflict incidence	
Dataset	UCDP		ACLED 1		ACLED 2	
Estimator	FE logit	FE-LPM	FE logit	FE-LPM	FE logit	FE-LPM
PANEL A: binary weights						
ln agr. shock	-5.460^a	-0.230^a	-7.674^a	-0.104^b	-7.403^a	-0.387^a
	(1.563)	(0.061)	(2.099)	(0.043)	(2.083)	(0.092)
ln agr. shock × remoteness[1]	0.624^a	0.032^a	1.126^a	0.016^a	0.877^a	0.054^a
	(0.157)	(0.008)	(0.226)	(0.006)	(0.298)	(0.014)
Observations	27126	137556	6596	43435	14420	76370
PANEL B: weights before 1993						
ln agr. shock	-10.827^a	-0.366^a	-9.315^a	-0.515^c	-5.391^a	-0.234^a
	(1.618)	(0.105)	(2.437)	(0.303)	(1.897)	(0.082)
ln agr. shock × remoteness[1]	1.588^a	0.054^a	1.412^a	0.072^c	0.945^a	0.037^a
	(0.253)	(0.016)	(0.349)	(0.043)	(0.310)	(0.013)
Observations	6708	49712	1908	7032	6180	38240
PANEL C: dropping large players						
ln agr. shock	-5.136^a	-0.241^a	-5.110^a	-0.075^c	-4.476^a	-0.255^a
	(1.103)	(0.064)	(1.510)	(0.044)	(1.624)	(0.073)
ln agr. shock × remoteness[1]	0.582^a	0.034^a	0.774^a	0.013^b	0.677^a	0.040^a
	(0.160)	(0.009)	(0.227)	(0.006)	(0.244)	(0.011)
Observations	27090	136026	6596	43435	14410	75520
PANEL D: only exported products						
ln agr. shock	-5.009^a	-0.242^a	-6.022^a	-0.108^b	-5.673^a	-0.321^a
	(1.073)	(0.064)	(1.574)	(0.043)	(1.646)	(0.081)
ln agr. shock × remoteness[1]	0.468^a	0.032^a	0.837^a	0.018^a	0.675^a	0.047^a
	(0.155)	(0.009)	(0.247)	(0.007)	(0.252)	(0.012)
Observations	26982	127692	6596	43435	14380	70890

^{c} significant at 10%; ^{b} significant at 5%; ^{a} significant at 1%. [1] ln distance to closest seaport. Robust standard errors, clustered by administrative region in parentheses. All estimations include year dummies and cell fixed effects. Estimations cover only the post-1993 time-period in Panel D.

Table 16: Agricultural commodities shocks: M3-crop data

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.	Conflict incidence		Conflict incidence		Conflict incidence	
Estimator	FE logit	FE-LPM	FE logit	FE-LPM	FE logit	FE-LPM
PANEL A						
ln agr. shock, M3-crop	-0.339	-0.011	-1.553^{c}	0.003	-1.326^{c}	-0.057^{c}
	(0.448)	(0.013)	(0.941)	(0.014)	(0.757)	(0.032)
PANEL B						
ln agr. shock, M3-crop	-3.746^{a}	-0.219^{a}	-6.288^{a}	-0.114^{b}	-4.273^{b}	-0.338^{a}
	(1.253)	(0.064)	(1.746)	(0.056)	(1.864)	(0.105)
ln agr. shock × remoteness[1]	0.593^{a}	0.035^{a}	0.872^{a}	0.018^{b}	0.545^{c}	0.048^{a}
	(0.167)	(0.010)	(0.234)	(0.008)	(0.295)	(0.017)
PANEL C						
ln agr. shock, M3-crop	-2.197^{a}	-0.083^{a}	-3.625^{a}	-0.053^{b}	-2.159^{b}	-0.118^{a}
	(0.688)	(0.025)	(1.123)	(0.021)	(0.981)	(0.043)
ln agr. shock × remoteness[2]	3.224^{a}	0.128^{a}	3.410^{a}	0.082^{a}	2.043^{c}	0.122^{b}
	(0.633)	(0.030)	(0.934)	(0.025)	(1.094)	(0.049)
Sample	UCDP-GED		ACLED 1		ACLED 2	
Years	1989-2006	1989-2006	1989-2005	1989-2005	1997-2006	1997-2006
# of countries	39	42	12	12	41	42
Observations	24714	103662	6086	33405	13120	57590

^{c} significant at 10%; ^{b} significant at 5%; ^{a} significant at 1%. [1] ln distance to closest seaport. [2] distance to closest seaport relative to maximum distance, computed by country. Robust standard errors, clustered by administrative region in parentheses. All estimations include year dummies and cell fixed effects. Agricultural commodities shock computed M3-crop dataset.

Table 17: Agricultural commodities shocks: GAEZ Suitability data

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.	Conflict incidence		Conflict incidence		Conflict incidence	
Estimator	FE logit	FE-LPM	FE logit	FE-LPM	FE logit	FE-LPM
PANEL A						
ln agr. shock, GAEZ	0.122	0.007	-0.567	0.001	-0.514	-0.004
	(0.340)	(0.010)	(0.558)	(0.009)	(0.454)	(0.019)
PANEL B						
ln agr. shock, GAEZ	-3.744^a	-0.216^a	-4.812^a	-0.084^b	-3.834^a	-0.258^a
	(1.237)	(0.061)	(1.337)	(0.038)	(1.466)	(0.084)
ln agr. shock × remoteness[1]	0.651^a	0.035^a	0.774^a	0.013^b	0.548^b	0.040^a
	(0.186)	(0.010)	(0.173)	(0.005)	(0.217)	(0.013)
PANEL C						
ln agr. shock, GAEZ	-1.550^a	-0.063^a	-1.888^b	-0.020	-1.677^b	-0.069^b
	(0.563)	(0.018)	(0.838)	(0.015)	(0.714)	(0.032)
ln agr. shock × remoteness[2]	3.302^a	0.126^a	2.939^a	0.037^b	2.192^b	0.116^b
	(0.747)	(0.031)	(0.994)	(0.017)	(0.954)	(0.046)
Sample	UCDP-GED		ACLED 1		ACLED 2	
Years	1989-2006	1989-2006	1989-2005	1989-2005	1997-2006	1997-2006
# of countries	36	41	12	12	38	41
Observations	16902	75294	4794	28356	9230	41830

^{c} significant at 10%; ^{b} significant at 5%; ^{a} significant at 1%. [1] ln distance to closest seaport.[2] distance to closest seaport relative to maximum distance, computed by country. Robust standard errors, clustered by administrative region in parentheses. All estimations include year dummies and cell fixed effects. Agricultural commodities shock computed FAO-GAEZ data.

8.5 Serial and spatial correlation: robustness

Table 18: Shocks and conflicts: spatial serial correlation

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.	Conflict incidence			Conflict incidence		
Shock var.	ln Agr. com. shock			Exp. to crises		
Estimator	FE-LPM			FE-LPM		
Shock	-0.234	-0.106	-0.263	0.276	0.075	0.783
Spatial: 100km; Time: 2 years	$(0.022)^a$	$(0.038)^a$	$(0.050)^a$	$(0.046)^a$	$(0.034)^b$	$(0.117)^a$
Spatial: 100km; Time: 10 years	$(0.022)^a$	$(0.037)^a$	$(0.047)^a$	$(0.045)^a$	$(0.034)^b$	$(0.108)^a$
Spatial: 1000km; Time: 2 years	$(0.043)^a$	$(0.064)^c$	$(0.085)^a$	$(0.079)^a$	(0.063)	$(0.286)^a$
Spatial: 1000km; Time: 10 years	$(0.043)^a$	$(0.063)^c$	$(0.083)^a$	$(0.078)^a$	(0.063)	$(0.283)^a$
Clustering: Country-year level	$(0.036)^a$	(0.067)	$(0.080)^a$	$(0.078)^a$	(0.058)	$(0.253)^a$
Shock × remoteness[1]	0.031	0.017	0.039	-0.044	-0.015	-0.111
Spatial: 100km; Time: 2 years	$(0.003)^a$	$(0.006)^a$	$(0.007)^a$	$(0.007)^a$	$(0.005)^a$	$(0.017)^a$
Spatial: 100km; Time: 10 years	$(0.003)^a$	$(0.006)^a$	$(0.007)^a$	$(0.007)^a$	$(0.005)^a$	$(0.016)^a$
Spatial: 1000km; Time: 2 years	$(0.006)^a$	$(0.010)^c$	$(0.013)^a$	$(0.012)^a$	(0.009)	$(0.041)^a$
Spatial: 1000km; Time: 10 years	$(0.006)^a$	$(0.010)^c$	$(0.013)^a$	$(0.012)^a$	(0.009)	$(0.040)^a$
Clustering: Country-year level	$(0.005)^a$	$(0.010)^c$	$(0.012)^a$	$(0.012)^a$	$(0.009)^c$	$(0.035)^a$
Sample	UCDP-GED	ACLED 1	ACLED 2	UCDP-GED	ACLED 1	ACLED 2
Observations	136026	43435	75520	137556	66430	76370

[c] significant at 10%; [b] significant at 5%; [a] significant at 1%. [1] ln distance to closest seaport. Robust standard errors, adjusted for various levels of serial and spatial correlation in parentheses. All estimations include year dummies and cell fixed effects.

External shocks, internal shots: the geography of civil conflicts
Online appendix (not for publication)

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Contents

1 Additional data description

Structure of the dataset. Our dataset is a full grid of 0.5×0.5 degrees cell covering all Sub-Saharan African countries, i.e. 8378 cells. This is the exact same structure as PRIO-GRID.[1] All conflict events variable are aggregated at the level of the cell. We assign to each cell a main country and a SALB-ADM1 region. When a cell contains multiple countries or administrative regions, we assign it to the countries or regions which represent the larger share of the area of the cell. Administrative borders are taken at the end of our sample period. These main countries and regions are also used for the clustering of the standard errors in our estimations.

Conflict events data. We make use of three different datasets containing the geo-location of conflict events in Sub-Saharan Africa: two versions of the Armed Conflict Location and Event dataset[2] (ACLED), and the recently released UCDP-Georeferenced Event dataset (UCDP-GED). These datasets cover different countries and time periods. The first ACLED dataset[3] – ACLED I hereafter – contains only 12 African countries – which have all known large civil war episodes over the period of study -, but covers a long time period (1960-2005). The second ACLED dataset[4] – ACLED II hereafter – covers all African countries, plus a small number of non African countries, but the data only starts in 1997. Finally, the UCDP-GED dataset [5] covers African countries and the period 1989-2010.

In each dataset, the unit of observation is the event. They contain information about the date (precise day most of the time), longitude and latitude of conflicts events within each country. These events are obtained from various sources, including press accounts from regional and local news, humanitarian agencies or research publications. The three datasets mainly differ in the rules they apply for the inclusion of events. ACLED I and UCDP-GED consider only events pertaining to conflicts reaching at least 25 battle-related deaths per year, which makes them comparable with the country-level data commonly used in the literature. Note that UCDP-GED includes all events related to a given conflict – defined by a dyad of actors – even if the during a specific year, this conflict didn't cause more than 25 deaths. All the events related to a given conflict are included as soon as this conflict caused 25 deaths or more in any given year of the sample period. UCDP-GED uses arguably the clearest definition of an event: "The incidence of the use of armed force by an organized actor against another organized actor, or against civilians, resulting in at least 1 direct death in either the best, low or high estimate categories at a specific location and for a specific temporal duration". ACLED II, on the other

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

[2] See Michalopoulos and Papaioannous (2011), Besley and Reynal-Queyrol (2013) and Harari and La Ferrara (2013) for recent contributions using ACLED data.

[3] http://www.prio.no/CSCW/Datasets/Armed-Conflict/Armed-Conflict-Location-and-Event-Data/

[4] Raleigh *et al.* (2010) and the website: http://www.acleddata.com/

[5] See Sundberg *et al.* (2010) and Melander and Sundberg (2011) for more details. Data available at http://www.ucdp.uu.se/ged/.

hand, records all political violence including violence against civilians, rioting and protesting within and outside a civil conflict, without specifying a battle-related deaths threshold. To be consistent with the other two sources, we concentrate on events related to violent conflicts, i.e. categories 1 to 5 in the ACLED II dataset. The broader definition of conflict however makes the comparison with the country-level literature more difficult. In general, the rule for an event to be considered is therefore the most stringent for ACLED I, followed by UCDP-GED, and finally ACLED II.

The latitude and longitude associated with each event define a geographical "location". The three datasets contain information on the precision of the geo-referencing of the events. In all datasets, the geo-precision is at least the municipality level in at least 80% of the cases (more than 95% in ACLEDs datasets), and is even finer (village) for more than 65% of the observations (more than 80% in ACLEDs). The geo-precision is generally at the level of the province for the rest of the events. We drop the observations in the UCDP-GED dataset where the event cannot be localized at a finer level than the country (less than 2% of the observations). For each data source, we aggregate the data 0.5×0.5 degree cell and by year. In most cases, we have information on the temporal precision of the event: for most events, the precise day it took place is known, but in a few case only the week, the month or even the year is know. ACLEDs do not consider events for which the precision is lower than a month, but UCDP-GED include some events for which we only know the year. Given that we aggregate the information over time, at the yearly frequency, this has however no impact on our results. We concentrate on Sub-Saharan African countries are this is the zone covered by all three datasets. Our final sample between 12 and 48 countries depending on the conflict data we use. We however show robustness checks using the ACLED II data available for other regions, including some MENA, Asian and European countries.

Note that when we assign each grid cell to a country or region, or in the computation of our shocks, we consider the end-of-the-period boundaries. We do not consider changes in international or regional borders as these are potentially endogenous to conflict. However, distance to capital and to international borders, which are taken from PRIO-GRID are time-varying, i.e. take into account changes in international borders, which occurred in Erithrea (1993), Ethiopia (1993), Namibia (1990) and South Africa (1990) during our period of study.

Agricultural commodities: FAO-Agromaps. First, we use FAO Agro-maps information to obtain a region-specific measure of agricultural specialization. The FAO Agro-maps data[6] contains information on the volume of production of different agricultural commodities at the sub-national level, for a number of years. It uses the Second Administrative Level Boundaries (SALB) defined by the UN

[6]http://kids.fao.org/agromaps

based on national administrative units. These administrative units appear in light grey on maps A.1 to A.8 below. We focus on the years 1989-2006 to be able to match the product classification with HS trade data from UN-COMTRADE.

The FAO Agro-Maps database follows the internal product classification of FAO-STAT, which contains 173 crops.[7] This classification groups crops by family, genius or some other common characteristics.[8] We match each of the commodities with an HS4 product category. To be able to compute production shares, we convert the volumes of productions to values using unit values computed from UN-Comtrade data. The main sources of the FAO are the official statistics of the FAO member countries, which mainly collect data through surveys. To be included in the dataset, a crop has to be produced in the region ("including on-holding losses and wastage, quantities consumed directly on the farm and marketed quantities") and should belong to one of the categories defined by the FAO.

The FAO-agromaps data covers the period 1982-2011, but the data is generally available only for a smaller number of years within this time period for each country. The years for which the production data is available for each country, as well as the countries for which the source of the production data is clearly documented appear in Table A.2 below. 27% of cells-year are missing, but only 43 cells out of 7475 are missing over the entire period. Missing production data does not seem to be a consequence of conflict occurring in the region: Table A.1 shows the results of regressing a dummy for "missingness" on conflict variables, controlling for year and cell fixed effects. Put differently, we have tried to determine whether if experiencing a conflict during year t increases the probability that the FAO-agromaps data is missing. As shown in Table A.1 , this is only the case in the ACLED I sample. In the two other samples, there is no significant correlation.

Agricultural commodities: M3-Crops. The M3-CROPS data from Monfreda *et al.* (2008) contains information on the harvested area in hectares for 137 different crops for grid-cells 5 arc minutes$\times$5 arc minutes resolution for the year 2000. This dataset has a different approach than the FAO Agro-map data. It focuses on the land use and do not provide information on the production. This dataset has the advantage of being more fine-grained and to include more crops than FAO Agro-maps (Monfreda *et al.* (2008)). On the other hand, it is only available for the year 2000.

[7] The following list of commodities is in included in FAO-Agromaps data for Sub-Saharan African countries: Apples; Avocados; Bambara Beans; Bananas; Barley; Beans, Dry; Beans, Green; Broad Beans, Dry; Broad Beans, Green; Cabbages; Cantaloupes & other Melons; Cashew Nuts; Cassava; Chick-Peas; Chillies & Peppers, Green; Citrus Fruit nes; Cloves, Whole and Stems; Cocoa Beans; Coffee, Green; Cow Peas, Dry; Cucumbers and Gherkins; Eggplants; Fonio; Garlic; Ginger; Grapes; Groundnuts in Shell; Lentils; Maize; Mangoes, mangosteens, guavas; Melonseed; Millet; Natural Rubber; Oats; Oil Palm Fruit; Okra; Olives; Onions and Shallots, Green; Onions, Dry; Oranges; Peas, Dry; Peas, Green; Pepper, White/Long/Black; Pigeon Peas; Pimento, Allspice; Pineapples; Pistachios; Plantains; Potatoes; Pulses nes; Pumpkins, Squash, Gourds; Rice, Paddy; Seed Cotton; Sesame Seed; Sorghum; Soybeans; Sugar Beets; Sugar Cane; Sunflower Seed;Sweet Potatoes; Tang.Mand.Clement.Satsma; Taro (Coco Yam); Tobacco Leaves; Tomatoes; Vanilla; Vegetables Fresh nes; Watermelons; Wheat; Yams; Yautia (Cocoyam).

[8] For more details on the classification, see: http://www.fao.org/waicent/faoinfo/economic/faodef/faodefe.htm

Table A.1 : Correlation between missingness and conflict

	(1)	(2)	(3)
Sample	UCDP-GED	ACLED 1	ACLED 2
Conflict	-0.003	0.034^a	0.007
	(0.008)	(0.011)	(0.007)
Observations	7217	3721	3969
R^2	0.045	0.011	0.020

Robust standard errors in parentheses. ^{c} significant at 10%; ^{b} significant at 5%; ^{a} significant at 1%. Cell fixed effects included in each regression.

Agricultural commodities: FAO-GAEZ. We consider also the suitability of a location for cultivating 45 crops from the FAO's Global Agro-Ecological Zones (GAEZ).[9] This data is constructed from models that use location characteristics such as climate information (rainfall and temperature for instance) and soil characteristics. This information is combined with crops' characteristics (in terms of growing requirements) to generate a global GIS raster of the suitability of a grid cell for cultivating each crop. Suitability is then defined as the percentage of the maximum yield that can be attained in each grid cell. Many scenarii are possible to evaluate whether a crop can grow or not. We only consider cases where crop production has been considered with *low input level conditions* that mean that the production is based on the use of traditional ways without use of chemicals, nutrients or modern irrigation (only rain fed). The climate information is based on the average information over the period 1961-1990. Following Nunn and Qian (2011) and Alesina *et al.* (2011), we define a cell as suitable for a crop if it can achieve at least 40% of the maximum yield. This alternative data has two main advantage. First, the inputs used in the construction of the data are exogenous characteristics and not affected by conflicts, as they are not based on actual production. Second, it is not affected by the consumption patterns of the location.

Crises. The crisis data comes from Reinhart and Rogoff (2011). According to Reinhart and Rogoff (2011: 1680), a banking crisis is marked by two types of events: "(1) bank runs that lead to the closure, merging, or takeover by the public sector of one or more financial institutions; and (2) if there are no runs, the closure, merging, takeover, or large-scale government assistance of an important financial institution (or group of institutions), that marks the start of a string of similar outcomes for other financial institutions." Reinhart and Rogoff (2011)'s data set combines various sources. Our final data set include both, in their classification, severe and systemic banking crises.

[9]http://gaez.fao.org/Main.html. See Nunn and Qian (2011) for an excellent discussion of the GAEZ data.

Trade data. Aggregate bilateral trade data comes from the Direction of Trade Statistics (DOTS). Bilateral trade data disaggregated by HS4 digit products is from UN-COMTRADE.

Distance to seaports. The major seaports are identified using http://www.e-ships.net/ports.php and Couttenier and Vicard (2012). We retain the main ports of each country with a maximum draft of at least 10 meters. We now provide in Table A.25 robustness checks using an alternative minimum draft of 12 meters. This is a meaningful alternative as it is the threshold used internationally to consider a port as a "deep-water" one. These ports are defined as deep-water because they can accommodate loaded "Panamax" ships, which dimensions are determined by the ones allowed by the Panama Canal's lock chambers. Table A.25 contains only our baseline estimations, but we have checked that all our results are unchanged when using this alternative size threshold for seaports. We consider 10 meters as the baseline as a number of ports have a draft comprised between 10 and 12 meters, but are still widely used for international trade, especially at a regional level (the port of Durban (South Africa), the port of Lobito (Angola), the port of pointe noir (Congo), the port of Libreville (Gabon) or the port of Lagos (Nigeria) are major ports but with a draft comprise between 10 and 12 for instance). The location of seaports can be seen in maps A.1 to A.6 below. Distances to the closest seaport have been computed using Stata routine *geodist*.

Other location-specific data. Distance between the cell's centroid and international borders and to capital city are taken directly from PRIO-GRID. Cell-specific GDP and population data are also available in PRIO-GRID, and originally come from G-econ 4.0 data[10]. We also compute the distances to the nearest natural resource field (diamond, oil or gas) using information from PRIO.[11]

Military spending. The data on military spending comes from the Stockholm International Peace Research Institute (SIPRI).[12] Data come mainly from official data reported by national governments and are available since 1988 for 172 countries. They consider as military spending all current and capital expenditure on armed forces, operations or military research and development.

Revenue Mobilization. We use as proxy for revenue mobilization data from the World Bank Resource Allocation Index (IRAI). The IRAI is a criterium of the *Country Policy and Institutional Assessment* (CPIA) from the World Bank and give a picture of the country's revenue mobilization

[10]http://gecon.yale.edu/

[11]For oil, http://www.prio.no/Data/Geographical-and-Resource-Datasets/Petroleum-Dataset. For diamonds, http://www.prio.no/Data/Geographical-and-Resource-Datasets/Diamond-Resources/.

[12]http://www.sipri.org/research/armaments/milex/milex_database

that include tax policy and tax administration.

Commodity prices. We use the commodity prices indexes computed by Bazzi and Blattman (2013).[13]

AGOA. List of eligible countries, products and dates in which the preferences were granted are available at: http://www.agoa.gov/AGOAEligibility/index.asp. We combine these data with trade flow data from Comtrade to compute the country-specific exposure to the AGOA as the share of trade in the product for which preferences will be granted by the AGOA. These shares are computed over the pre-AGOA period (1995 to the year in which the country enters the AGOA).

Country level conflict data. We use the UCDP/PRIO Armed Conflict Dataset (v4-2013). We use the civil war incidence dummy variable, which is equal to 1 for years with a number of battle deaths greater than 1000, and 0 otherwise; and civil conflict dummy which is equal to 1 for years with a number of battle deaths greater than 25, and 0 otherwise.

Table A.2 : FAO Agromaps: years covered

Country	Years covered	Country	Years covered
Angola	1999-2012	Malawi	1982-1998, 2001-2006
Botswana	1993, 2004	Mali	1984-1998, 2001-2011
Burkina Faso	1984-2009	Mauritania	1992, 1998, 2004-2007
Burundi	1998, 2010-2012	Mauritius*	-
Cameroon	1989, 2001-2007	Mozambique*	1999, 2002-2003, 2005-2008
Cape Verde*	1998-2001	Namibia*	1995
Central African Republic*	1992, 1993	Niger	2007-2011
Chad*	1983-1995, 1998	Nigeria	1994-2005
Congo*	1990	Rwanda*	1984-1990, 1997, 1999-2001
Congo, Dem Republic of	1994-1996	Sao Tome and Principe	1998
Cote d'Ivoire	1993-2007	Senegal	1990-1999, 2001, 2007
Djibouti*	1989	Sierra Leone	1986
Eritrea*	2002-2004	Somalia	1994-1995
Ethiopia	1991, 2001-2011,	South Africa	1990-1996, 1998, 2002
Gambia	1994, 1998, 2000, 2005-2011	Sudan*	1994-2001
Ghana	1997-2011	Swaziland*	1994-1995, 1997-1998, 2000
Guinea	1998, 2001	Togo	1994, 1998, 2001-2011
Guinea-Bissau	1995-1997, 2000-2010	Tunisia	1994, 2000
Kenya	1991, 1994-2000, 2005-2008	Uganda	1981-1999
Lesotho	1990, 1994, 1997, 2006-2009	Tanzania	1991-2001
Liberia	1995-1997	Zambia	1987-2011
Madagascar	1993-1997	Zimbabwe	1994

*: production data source *not* documented. Removing these countries from the sample does not alter our results.

[13]http://econ.ucsd.edu/ sbazzi/Research.html.

2 Conflict data: maps

Figure A.1 : Conflict locations, UCDP-GED, 1989-2010

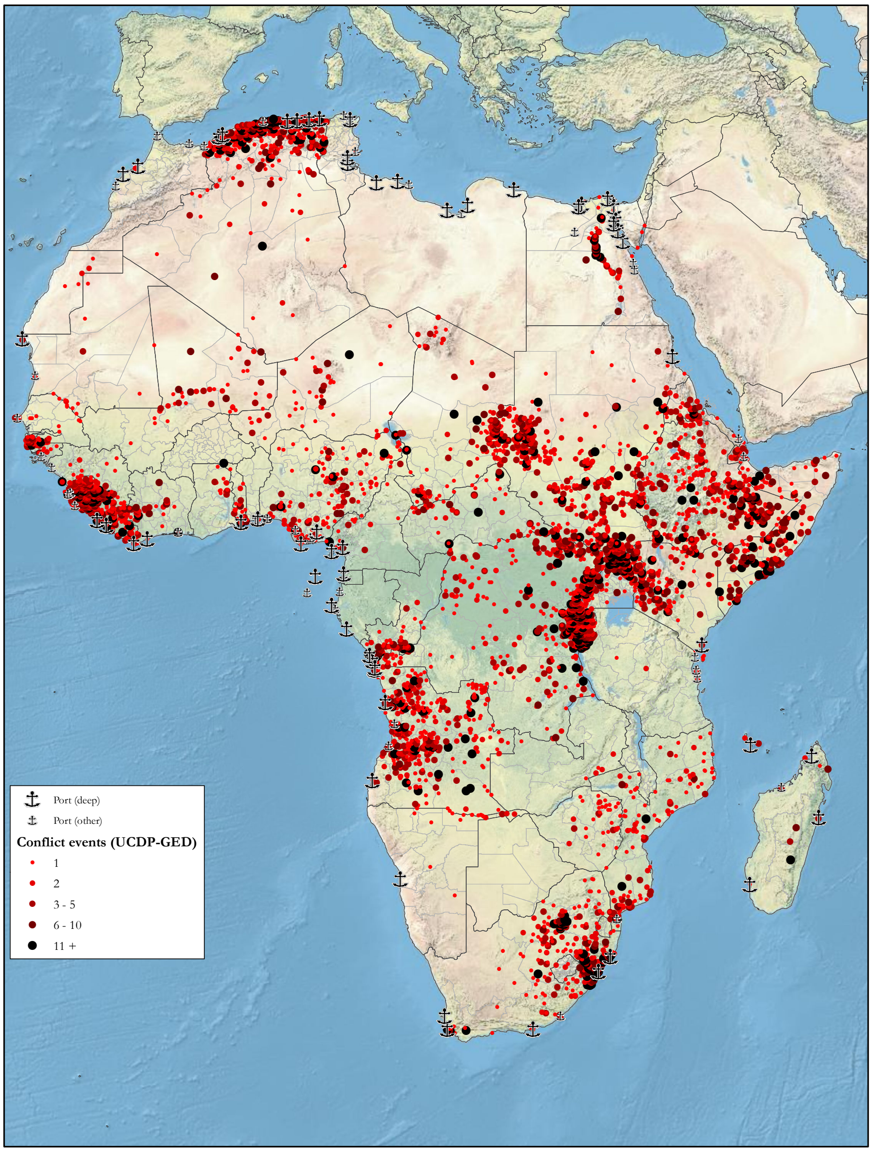


Figure A.2 : Conflict locations, ACLED ver. I, 1980-2005

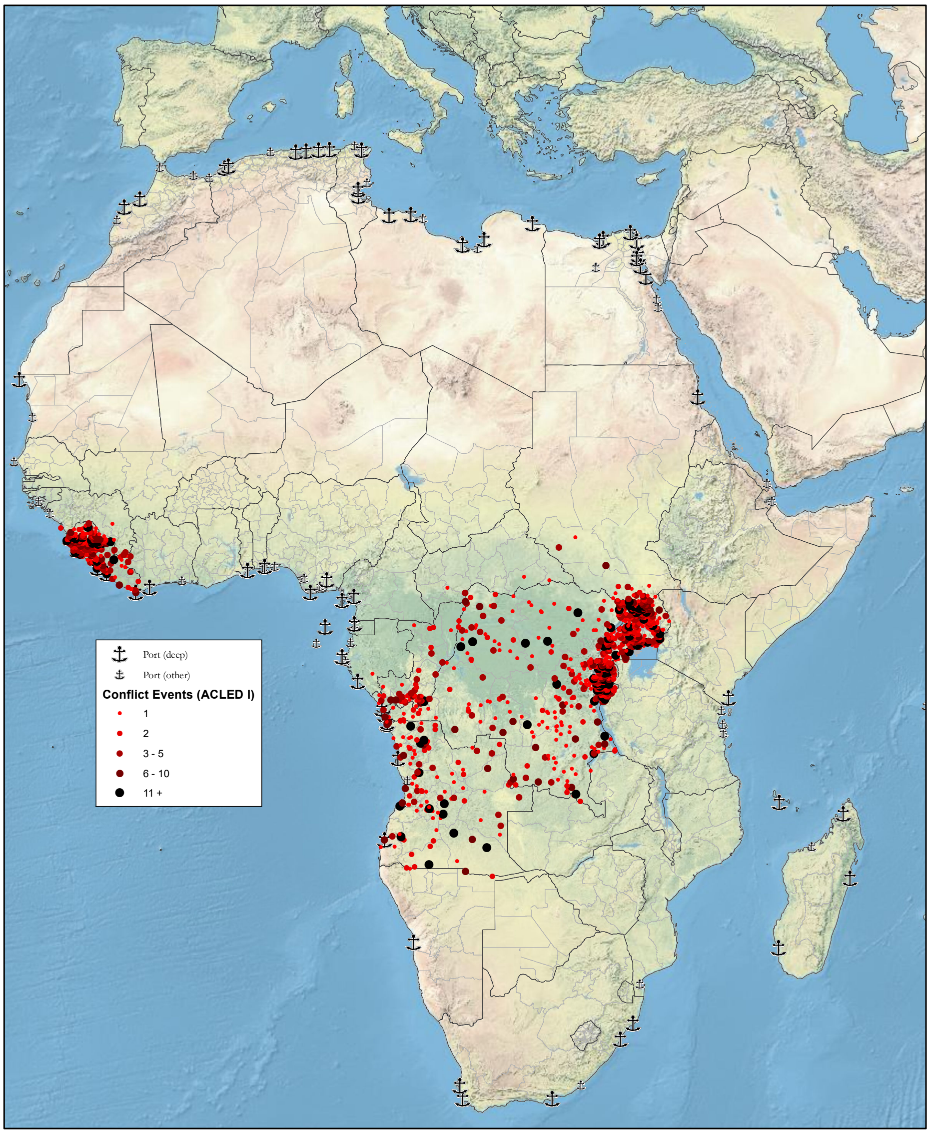


Figure A.3 : Conflict locations, ACLED ver. II, 1997-2010

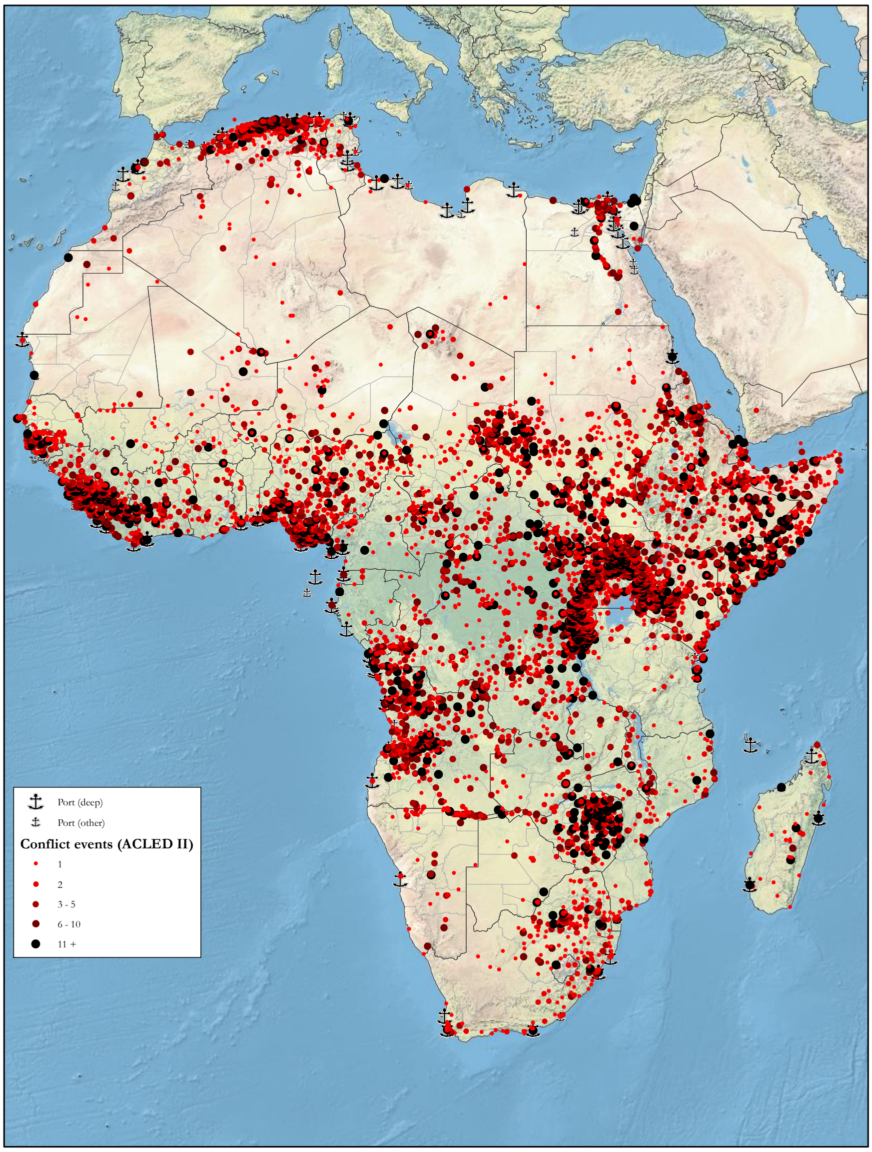


Figure A.4 : Conflict locations, UCDP-GED, 1997-2005

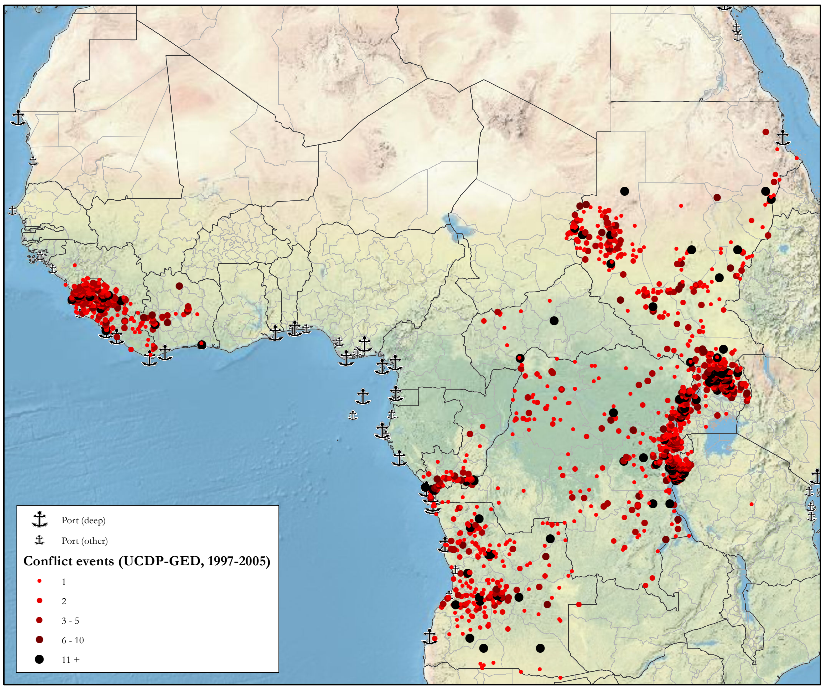


Figure A.5 : Conflict locations, ACLED ver. I, 1997-2005

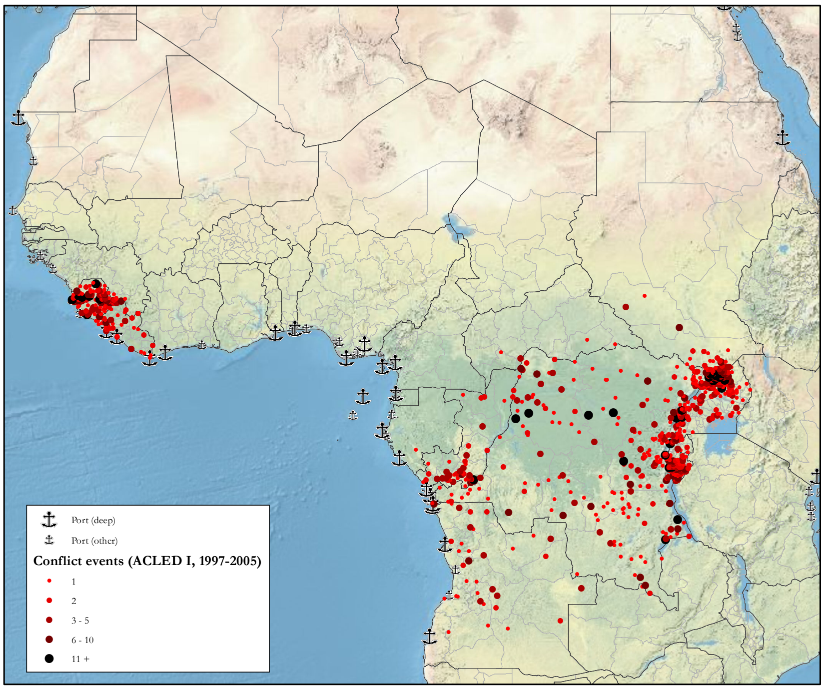
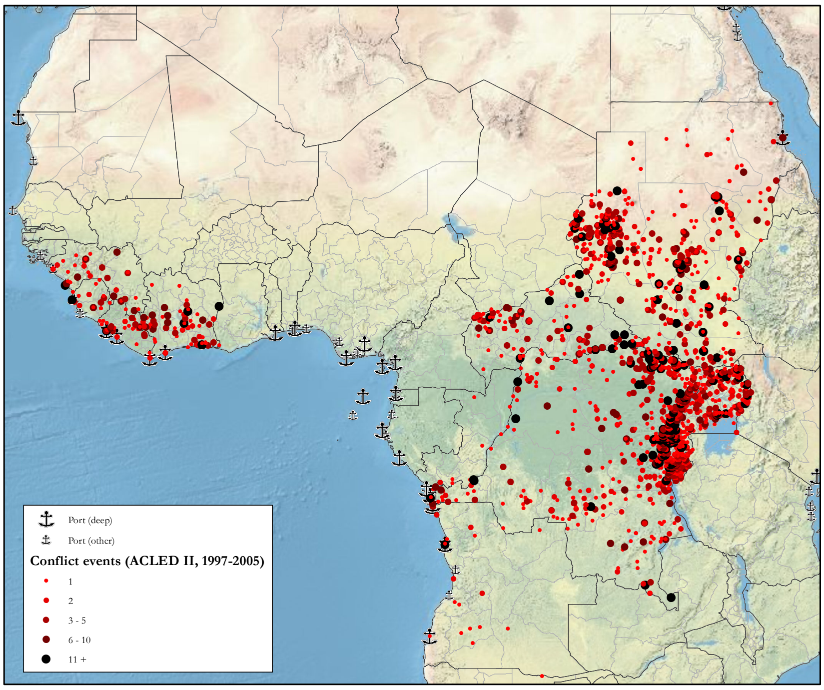


Figure A.6 : Conflict locations, ACLED ver. II, 1997-2005



3 Effect of income shocks on conflict-prone cells

Table A.3 : Agricultural commodities shocks and conflict incidence, high risk cells

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.	Conflict incidence		Conflict incidence		Conflict incidence	
Estimator	FE logit	FE-LPM	FE logit	FE-LPM	FE logit	FE-LPM
PANEL A						
ln agr. shock	-2.534^a	-0.263^a	-1.749^a	-0.108^b	-1.563^b	-0.233^a
	(0.628)	(0.055)	(0.583)	(0.045)	(0.675)	(0.086)
PANEL B						
ln agr. shock	-5.054^a	-0.675^a	-5.860^a	-0.463^a	-5.500^a	-0.876^a
	(1.079)	(0.136)	(1.551)	(0.133)	(1.604)	(0.214)
ln agr. shock × remoteness[1]	0.495^a	0.076^a	0.758^a	0.062^a	0.676^a	0.110^a
	(0.153)	(0.020)	(0.225)	(0.019)	(0.243)	(0.033)
PANEL C						
ln agr. shock	-3.525^a	-0.405^a	-3.298^a	-0.258^a	-2.947^a	-0.426^a
	(0.567)	(0.060)	(0.872)	(0.063)	(0.880)	(0.116)
ln agr. shock × remoteness[2]	2.660^a	0.345^a	2.769^a	0.260^a	2.705^a	0.393^a
	(0.495)	(0.064)	(0.794)	(0.065)	(0.972)	(0.133)
Sample	UCDP-GED		ACLED 1		ACLED 2	
Years	1989-2006	1989-2006	1989-2005	1989-2005	1997-2006	1997-2006
# of countries	39	39	12	12	41	41
Observations	27090	27090	6596	6596	14410	14410

^{c} significant at 10%; ^{b} significant at 5%; ^{a} significant at 1%. Robust standard errors, clustered by administrative region in parentheses. All estimations include year dummies and cell fixed effects. [1] ln distance to closest seaport.[2] distance to closest seaport relative to maximum distance, computed by country.

Table A.4 : Robustness: control for past-instability

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.	Conflict incidence		Conflict incidence		Conflict incidence	
Estimator	FE logit	FE-LPM	FE logit	FE-LPM	FE logit	FE-LPM
PANEL A						
ln agr. shock	-4.411^a	-0.198^a	-5.055^a	-0.073	-4.836^a	-0.249^a
	(1.019)	(0.049)	(1.638)	(0.053)	(1.527)	(0.068)
ln agr. shock × remoteness[1]	0.443^a	0.027^a	0.748^a	0.014^c	0.601^b	0.037^a
	(0.149)	(0.007)	(0.257)	(0.008)	(0.234)	(0.010)
# past years in conflict	0.332^a	0.049^a	0.516^b	0.092^a	0.243^a	0.027^b
	(0.078)	(0.007)	(0.214)	(0.031)	(0.080)	(0.011)
ln agr. shock × # past years in confl.	-0.031^a	-0.005^a	-0.051^b	-0.009^a	-0.024^a	-0.003^b
	(0.007)	(0.001)	(0.020)	(0.003)	(0.008)	(0.001)
Sample	UCDP-GED		ACLED 1		ACLED 2	
Observations	27090	136026	6596	43435	14410	75520
PANEL B						
Exposure to crises	5.616^a	0.228^a	10.345^a	0.056	13.703^a	0.671^b
	(1.840)	(0.068)	(2.499)	(0.045)	(4.565)	(0.272)
Exp. to crises × remoteness[1]	-1.042^a	-0.038^a	-1.955^a	-0.013^c	-1.910^a	-0.095^b
	(0.297)	(0.011)	(0.508)	(0.007)	(0.666)	(0.038)
# past years in conflict	0.000	0.000	0.004	0.004^a	-0.012	-0.001^c
	(0.004)	(0.001)	(0.004)	(0.001)	(0.008)	(0.001)
Exp. to crises × # past years in confl.	0.273^a	0.034^a	0.195^a	0.055^a	1.090^a	0.040^a
	(0.053)	(0.006)	(0.060)	(0.016)	(0.224)	(0.011)
Sample	UCDP-GED		ACLED 1		ACLED 2	
Observations	27126	137556	11128	66430	14420	76370

^{c} significant at 10%; ^{b} significant at 5%; ^{a} significant at 1%. Robust standard errors, clustered by administrative region in parentheses. All estimations include year dummies and cell fixed effects. [1] ln distance to closest seaport.[2] distance to closest seaport relative to maximum distance, computed by country. *Past instability*: cumulative number of events in cell since the start of the sample period.

4 Conflict and distances: correlations

Table A.5 : Conflicts and cell-specific characteristics: correlations

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.	Conflict incidence		Conflict incidence		Conflict incidence	
remoteness[1]	-0.014^a	-0.012^a	-0.002	-0.001	-0.013^a	-0.011^a
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
ln dist. to capital city	-0.002^c	0.010^a	-0.005^a	-0.001	-0.009^a	0.006^a
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
ln distance to border	-0.004^a	-0.001^a	-0.002^a	-0.001	-0.008^a	-0.005^a
	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
ln dist. to nat. ress.	-0.008^a	-0.006^a	0.000	0.003^a	-0.007^a	-0.004^a
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
ln GDP area		-0.003^a		-0.004^a		-0.004^a
		(0.001)		(0.001)		(0.001)
ln population area		0.014^a		0.012^a		0.019^a
		(0.001)		(0.001)		(0.001)
Sample	UCDP-GED		ACLED 1		ACLED 2	
Observations	145351	144883	69888	69810	80750	80490

^{c} significant at 10%; ^{b} significant at 5%; ^{a} significant at 1%. [1] ln distance to closest seaport. dist. to nat. ress.: distance to nearest natural resource field (oil, gas or diamond). ln GDP and pop. area: PPP GDP and pop. of the area in 1990, from G-econ. Robust standard errors in parentheses. All estimations include year dummies and country fixed effects.

5 External validity

Are our external income shocks triggering specific types of conflicts? For instance, if open regions are systematically located away from international borders, our results might be less likely to identify an effect on separatists events. This sections argues on the contrary that our shocks are not triggering specific types of conflicts.

First, it is true that we identify an effect on relatively opened cells, but these cells are not cells in which few conflict happen on average. This can be seen in Figures A.1 to A.6 or in Table A.5 : many conflicts happen along the coastlines (and close to borders – distance to capital has a more ambiguous role). On the other hand, the correlation between distance to the seaport and distance to border is roughly zero in our sample, and statistically insignificant at common confidence levels. Therefore, we are identifying the impact of trade shocks on a subset of all conflicts – those which are indeed best connected to the peripheries – but it is not clear these are different from the conflicts generally considered by the literature.

Are conflict erupting in open regions different? While our data lacks information on the type of conflict (separatist, ethnic), we have done the following. We have merged our dataset with Fearon and Laitin (2003) data on conflict types. They have information (up to 1999) on whether (i) a conflict is ethnic or not; (ii) the rebels aim at the center or at autonomy. The data contains many missing values, and the match with our dataset is very poor, as we end up with only 150 events matched with a type of conflict. The results we get are therefore to be considered with caution. We find that the average distance to seaports is similar for ethnic and non-ethnic conflicts, while it is actually lower for separatist conflicts.

Finally, our data includes information on the actors of each event. This information is available on all three datasets. We can therefore try to determine whether our shocks influence the probability of conflict occurring *within* a particular dyad of actors, and whether this effect varies across cells depending on trade openness. The results are provided in Table 2 below (do we put that in the appendix?). We have run estimations at the cell-dyad level. The dataset is considerably bigger as it contains all possible cell-dyad-years combinations. The unconditional conflict probability is also considerably lower, which explains the small values of the coefficients. We find however consistent results across our three datasets: positive income shocks decrease conflict probability, and less so in remote locations, even *within a specific dyad*, i.e. a specific conflict. This comforts us about the fact that our shocks are not identifying particular types of conflicts.

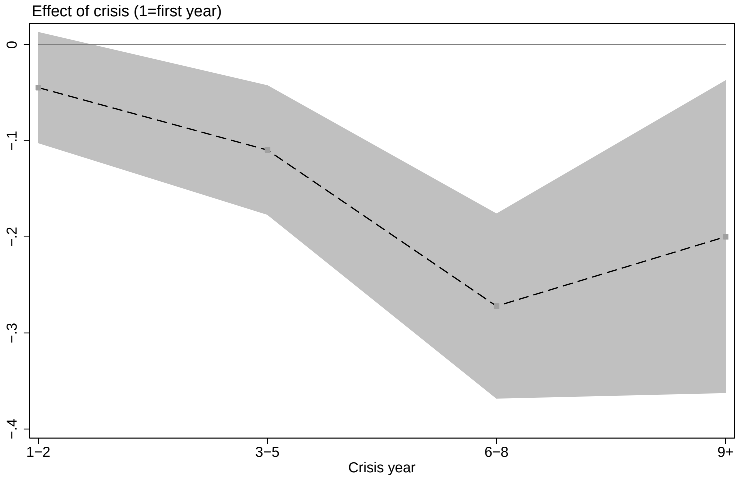
Table A.6 : External income shocks and conflict incidence: cell-dyad estimations

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.	Conflict incidence		Conflict incidence		Conflict incidence	
Estimator	FE-LPM		FE-LPM		FE-LPM	
Sample	UCDP-GED		ACLED 1		ACLED 2	
PANEL A						
ln agr. com. shock	-0.001^{a}	-0.004^{a}	-0.000	-0.004^{b}	-0.001^{a}	-0.006^{a}
	(0.000)	(0.001)	(0.000)	(0.002)	(0.000)	(0.001)
ln agr. shock × remoteness[1]		0.000^{a}		0.001^{b}		0.001^{a}
		(0.000)		(0.000)		(0.000)
Observations	9751248	9751248	1741176	1741176	6842050	6842050
PANEL B						
Exposure to crises	-0.000	0.003^{a}	-0.001^{a}	0.004^{c}	0.000	0.006^{c}
	(0.000)	(0.001)	(0.000)	(0.002)	(0.000)	(0.004)
Exp. to crises × remoteness[1]		-0.001^{a}		-0.001^{b}		-0.001^{c}
		(0.000)		(0.000)		(0.001)
Observations	9759240	9759240	2611764	2611764	6850580	6850580

^{c} significant at 10%; ^{b} significant at 5%; ^{a} significant at 1%. Robust standard errors, clustered by administrative region in parentheses. All estimations include year dummies and cell-actor dyad fixed effects. [1] ln distance to closest seaport.[2] distance to closest seaport relative to maximum distance, computed by country.

6 Exposure to crises and trade: more results

Figure A.7 : Cumulative effect of financial crises in importer countries on bilateral exports



This figure represents the effect of crises on bilateral trade. The specification is similar to Table 13 of the appendix of the paper, column (2), except that we replace the crisis variable by a set of dummies representing the number of years since the crisis started. We split our crisis variable into four dummies which equal 1 respectively if the importer country is (i) in the first or second year of the crisis; (ii) in the third to fifth year; (iii) in the sixth to the ninth year; (iv) if the crisis started more 10 years before or more. The grey area depicts 90% confidence intervals.

7 Additional interaction terms

Table A.7 : Agricultural commodities shocks and conflict: robustness (distance ratio)

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.	Conflict incidence		Conflict incidence		Conflict incidence	
Estimator	FE logit	FE-LPM	FE logit	FE-LPM	FE logit	FE-LPM
ln agr. shock	-7.319^{a}	-0.144^{b}	0.697	-0.106^{c}	-8.651^{b}	0.080
	(1.810)	(0.057)	(3.832)	(0.054)	(3.370)	(0.061)
ln agr. shock × remoteness^{2}	2.080^{a}	0.091^{a}	2.286^{b}	0.113^{a}	2.427^{b}	0.096^{a}
	(0.575)	(0.026)	(0.910)	(0.026)	(1.117)	(0.032)
ln agr. shock × rel. dist. to capital	0.192	-0.007	-0.665	-0.061^{b}	0.794	-0.030
	(0.253)	(0.006)	(0.956)	(0.030)	(1.100)	(0.034)
ln agr. shock × rel. dist. to border	0.417^{c}	0.012	-1.416^{c}	-0.044^{a}	-2.026^{b}	-0.075^{b}
	(0.240)	(0.010)	(0.788)	(0.015)	(0.886)	(0.034)
ln agr. shock × rel. dist. to nat. res.	1.328^{b}	0.049^{b}	2.939^{a}	0.094^{a}	1.367	0.076^{b}
	(0.624)	(0.019)	(0.958)	(0.020)	(0.946)	(0.031)
ln agr. shock × ln GDP area	-0.243	-0.006	0.115	0.009^{b}	-0.029	0.002
	(0.157)	(0.005)	(0.261)	(0.004)	(0.275)	(0.006)
ln agr. shock × ln pop. area	0.262^{c}	0.001	-0.346	0.006	0.487^{c}	-0.014^{a}
	(0.147)	(0.004)	(0.313)	(0.005)	(0.273)	(0.005)
Sample	UCDP-GED		ACLED 1		ACLED 2	
Years	1989-2006	1989-2006	1989-2005	1989-2005	1997-2006	1997-2006
# of countries	39	45	12	12	41	44
Observations	26784	130645	6511	43180	14230	72580

^{c} significant at 10%; ^{b} significant at 5%; ^{a} significant at 1%. Robust standard errors, clustered by administrative region in parentheses. All estimations include year dummies and cell fixed effects. ^{2} distance to closest seaport, relative to maximum distance computed by country. rel. dist. to nat. ress.: distance to nearest natural resource field (oil, gas or diamond), relative to maximum distance. ln GDP and pop. area: PPP GDP and pop. of the area in 1990, from G-econ.

Table A.8 : Exposure to crises and conflict: robustness

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.	Conflict incidence		Conflict incidence		Conflict incidence	
Estimator	FE logit	FE-LPM	FE logit	FE-LPM	FE logit	FE-LPM
PANEL A						
Exposure to crises	19.091^a	0.581^a	16.262^c	0.431^a	33.944^a	1.401^a
	(4.863)	(0.168)	(8.337)	(0.093)	(8.850)	(0.426)
Exp. to crises × remoteness[1]	-1.039^a	-0.050^a	-1.243^b	-0.021^b	-1.937^b	-0.135^a
	(0.314)	(0.014)	(0.533)	(0.009)	(0.804)	(0.040)
Exp. to crises × ln dist. to capital	-0.583^c	-0.021	-1.330^b	-0.020^b	0.155	0.040
	(0.309)	(0.013)	(0.642)	(0.009)	(0.835)	(0.039)
Exp. to crises × ln dist. to border	0.235	0.008	-0.145	-0.000	0.131	0.010
	(0.196)	(0.005)	(0.420)	(0.004)	(0.351)	(0.015)
Exp. to crises × ln dist. to nat. res.	-0.552^c	-0.026^a	-0.934^a	-0.031^a	-1.333^a	-0.098^a
	(0.309)	(0.008)	(0.306)	(0.007)	(0.513)	(0.022)
Exp. to crises × ln GDP area	0.160	-0.007	-0.798	-0.012^b	0.774	0.027
	(0.198)	(0.006)	(0.485)	(0.006)	(0.892)	(0.025)
Exp. to crises × ln pop. area	-0.692^b	-0.006	0.287	-0.007	-1.113^c	-0.009
	(0.286)	(0.005)	(0.647)	(0.005)	(0.672)	(0.016)
PANEL B						
main						
Exposure to crises	10.648^a	0.215^a	-5.783	0.167^b	24.601^a	0.765^b
	(3.767)	(0.071)	(7.149)	(0.070)	(8.551)	(0.325)
Exp. to crises × rel. dist. to closest port	-4.818^a	-0.130^a	-3.968	-0.083^c	-10.285^a	-0.380^a
	(1.637)	(0.039)	(2.510)	(0.048)	(3.543)	(0.115)
Exp. to crises × rel. dist. to capital	-0.364	-0.022	0.228	0.009	0.072	0.134
	(1.517)	(0.040)	(2.567)	(0.046)	(3.229)	(0.101)
Exp. to crises × rel. dist. to border	-0.163	0.006	1.237	0.016	-0.040	0.036
	(0.784)	(0.023)	(1.809)	(0.017)	(1.995)	(0.087)
Exp. to crises × rel. dist. to nat. res.	-2.039	-0.063^b	-3.667^c	-0.115^a	-4.478^c	-0.259^a
	(1.430)	(0.030)	(2.077)	(0.035)	(2.564)	(0.077)
Exp. to crises × ln GDP area	0.274	0.004	-0.667	-0.005	0.694	0.052^c
	(0.211)	(0.005)	(0.603)	(0.005)	(0.783)	(0.027)
Exp. to crises × ln pop. area	-0.664^b	-0.011^b	0.657	-0.013^b	-1.277^b	-0.031
	(0.322)	(0.005)	(0.662)	(0.006)	(0.641)	(0.020)
Sample	UCDP-GED		ACLED 1		ACLED 2	
Years	1989-2006	1989-2006	1980-2005	1980-2005	1997-2006	1997-2006
# of countries	38	43	12	12	40	43
Observations	26820	132157	10998	66040	14240	73420

^{c} significant at 10%; ^{b} significant at 5%; ^{a} significant at 1%. Robust standard errors, clustered by administrative region in parentheses. All estimations include year dummies and cell fixed effects. [1] ln distance to closest seaport. dist. to nat. ress.: distance to nearest natural resource field (oil, gas or diamond). [2] distance to closest seaport, relative to maximum distance computed by country. rel. dist. to nat. ress.: distance to nearest natural resource field (oil, gas or diamond), relative to maximum distance. ln GDP and pop. area: PPP GDP and pop. of the area in 1990, from G-econ.

8 Additional results on conflict onset, ending and intensity

Table A.9 : Agricultural commodities shocks and conflict onset

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.	Conflict onset		Conflict onset		Conflict onset	
Estimator	FE logit	FE-LPM	FE logit	FE-LPM	FE logit	FE-LPM
PANEL A						
ln agr. shock	-2.673^a	-0.026^a	-1.714^a	-0.014^c	-1.121^c	-0.012^b
	(0.549)	(0.005)	(0.503)	(0.008)	(0.574)	(0.006)
PANEL B						
ln agr. shock	-5.571^a	-0.103^a	-5.671^a	-0.098^a	-3.189^b	-0.113^a
	(0.875)	(0.019)	(1.457)	(0.028)	(1.409)	(0.039)
ln agr. shock × remoteness[1]	0.545^a	0.013^a	0.720^a	0.014^a	0.352^c	0.016^a
	(0.130)	(0.003)	(0.207)	(0.004)	(0.209)	(0.006)
Sample	UCDP-GED		ACLED 1		ACLED 2	
Observations	23520	134375	6062	42901	12281	74248

^{c} significant at 10%; ^{b} significant at 5%; ^{a} significant at 1%. Robust standard errors, clustered by administrative region in parentheses. All estimations include year dummies and cell fixed effects. [1] ln distance to closest seaport. Conflict onset is defined as conflict incidence, conditional on no conflict happening in the same cell in year $t-1$.

Table A.10 : Agricultural commodities shocks and conflict ending

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.	Conflict ending		Conflict ending		Conflict ending	
Estimator	FE logit	FE-LPM	FE logit	FE-LPM	FE logit	FE-LPM
PANEL A						
ln agr. shock	0.969^b	0.116^a	0.332	0.070	0.324	0.079
	(0.377)	(0.034)	(0.369)	(0.093)	(0.559)	(0.084)
PANEL B						
ln agr. shock	2.989^a	0.280^a	5.519^a	0.913^a	0.839	0.441
	(0.990)	(0.066)	(1.743)	(0.236)	(1.636)	(0.277)
ln agr. shock × remoteness[1]	-0.374^b	-0.030^a	-0.871^a	-0.145^a	-0.087	-0.060
	(0.162)	(0.010)	(0.265)	(0.041)	(0.253)	(0.043)
Sample	UCDP-GED		ACLED 1		ACLED 2	
Observations	7450	13688	1778	1804	5975	12434

^{c} significant at 10%; ^{b} significant at 5%; ^{a} significant at 1%. Robust standard errors, clustered by administrative region in parentheses. All estimations include year dummies and cell fixed effects. [1] ln distance to closest seaport. Conflict ending is defined as conflict incidence, conditional on a conflict happening in the same cell in year $t-1$.

Table A.11 : Agricultural commodities shocks and conflict intensity

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.	Conflict intensity		Conflict intensity		Conflict intensity	
Estimator	FE logit	FE-LPM	FE logit	FE-LPM	FE logit	FE-LPM
PANEL A						
ln agr. shock	-2.140^a	-0.252^c	-1.043^b	0.063	-0.783	-0.057
	(0.366)	(0.151)	(0.460)	(0.062)	(0.496)	(0.060)
PANEL B						
ln agr. shock	-4.860^a	-1.836	-3.168^a	-0.192	-5.378^a	-1.645^a
	(0.666)	(1.191)	(1.145)	(0.283)	(1.398)	(0.582)
ln agr. shock × remoteness[1]	0.547^a	0.267	0.437^b	0.043	0.784^a	0.257^a
	(0.114)	(0.179)	(0.182)	(0.040)	(0.244)	(0.093)
Sample	UCDP-GED		ACLED 1		ACLED 2	
Observations	27090	131274	6596	43435	14540	75520

^{c} significant at 10%; ^{b} significant at 5%; ^{a} significant at 1%. Robust standard errors, clustered by administrative region in parentheses. All estimations include year dummies and cell fixed effects. [1] ln distance to closest seaport. Conflict intensity is defined as the number of events in the cell during year t.

Table A.12 : Exposure to crises and conflict onset

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.	Conflict onset		Conflict onset		Conflict onset	
Estimator	FE logit	FE-LPM	FE logit	FE-LPM	FE logit	FE-LPM
PANEL A						
Exposure to crises	-0.438	-0.008	-0.861	-0.017^a	1.336	0.022
	(0.571)	(0.006)	(0.817)	(0.005)	(1.292)	(0.020)
PANEL B						
Exposure to crises	6.155^a	0.095^b	8.963^a	0.044	18.022^a	0.346^b
	(2.257)	(0.041)	(2.735)	(0.032)	(6.368)	(0.162)
Exp. to crises × remoteness[1]	-1.013^a	-0.016^b	-1.682^a	-0.009^c	-2.446^a	-0.048^b
	(0.342)	(0.007)	(0.502)	(0.005)	(0.904)	(0.023)
Sample	UCDP-GED		ACLED 1		ACLED 2	
Observations	23555	135904	10483	65811	12291	75098

^{c} significant at 10%; ^{b} significant at 5%; ^{a} significant at 1%. Robust standard errors, clustered by administrative region in parentheses. All estimations include year dummies and cell fixed effects. [1] ln distance to closest seaport. Conflict onset is defined as conflict incidence, conditional on no conflict happening in the same cell in year $t-1$.

Table A.13 : Exposure to crises and conflict ending

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.	Conflict ending		Conflict ending		Conflict ending	
Estimator	FE logit	FE-LPM	FE logit	FE-LPM	FE logit	FE-LPM
PANEL A						
Exposure to crises	0.921^b	0.029	-0.314	0.007	-0.952	-0.188
	(0.439)	(0.033)	(0.595)	(0.099)	(0.791)	(0.123)
PANEL B						
Exposure to crises	-0.404	-0.257	-1.922	-0.385	-5.040	-1.278^b
	(1.862)	(0.221)	(2.001)	(0.345)	(5.357)	(0.562)
Exp. to crises × remoteness[1]	0.207	0.048	0.287	0.067	0.636	0.164^b
	(0.257)	(0.033)	(0.360)	(0.059)	(0.761)	(0.078)
Sample	UCDP-GED		ACLED 1		ACLED 2	
Observations	7461	13782	2604	4749	5978	12521

^{c} significant at 10%; ^{b} significant at 5%; ^{a} significant at 1%. Robust standard errors, clustered by administrative region in parentheses. All estimations include year dummies and cell fixed effects. [1] ln distance to closest seaport. Conflict ending is defined as conflict incidence, conditional on a conflict happening in the same cell in year $t-1$.

Table A.14 : Exposure to crises and conflict intensity

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.	Conflict intensity		Conflict intensity		Conflict intensity	
Estimator	FE logit	FE-LPM	FE logit	FE-LPM	FE logit	FE-LPM
PANEL A						
Exposure to crises	-0.571^c	-0.075	-0.303	-0.082^b	2.992^a	0.382
	(0.324)	(0.052)	(0.726)	(0.040)	(0.768)	(0.270)
PANEL B						
Exposure to crises	5.682^a	1.762^b	8.423^a	0.139	19.878^a	6.795^b
	(0.810)	(0.802)	(2.133)	(0.204)	(6.831)	(3.144)
Exp. to crises × remoteness[1]	-1.091^a	-0.284^b	-1.422^a	-0.033	-2.565^a	-0.953^b
	(0.150)	(0.128)	(0.349)	(0.029)	(0.968)	(0.435)
Sample	UCDP-GED		ACLED 1		ACLED 2	
Observations	28584	132804	11336	66430	15390	76370

^{c} significant at 10%; ^{b} significant at 5%; ^{a} significant at 1%. Robust standard errors, clustered by administrative region in parentheses. All estimations include year dummies and cell fixed effects. [1] ln distance to closest seaport. Conflict intensity is defined as the number of events in the cell during year t.

Table A.15 : Agricultural commodities shocks (M3-crop) and conflict onset

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.	Conflict onset		Conflict onset		Conflict onset	
Estimator	FE logit	FE-LPM	FE logit	FE-LPM	FE logit	FE-LPM
PANEL A						
ln agr. shock, M3-crop	-0.627^c	-0.012^c	-1.282	-0.008	-0.826	-0.032
	(0.372)	(0.006)	(0.816)	(0.008)	(0.666)	(0.020)
PANEL B						
ln agr. shock, M3-crop	-4.250^a	-0.105^a	-6.221^a	-0.106^a	-2.626^c	-0.144^b
	(1.068)	(0.026)	(1.737)	(0.036)	(1.548)	(0.061)
ln agr. shock × remoteness[1]	0.644^a	0.016^a	0.872^a	0.015^a	0.334	0.019^b
	(0.148)	(0.004)	(0.207)	(0.005)	(0.245)	(0.009)
Sample	UCDP-GED		ACLED 1		ACLED 2	
Observations	21299	102094	5557	32876	11137	56384

^{c} significant at 10%; ^{b} significant at 5%; ^{a} significant at 1%. Robust standard errors, clustered by administrative region in parentheses. All estimations include year dummies and cell fixed effects. [1] ln distance to closest seaport. Conflict onset is defined as conflict incidence, conditional on no conflict happening in the same cell in year $t-1$.

Table A.16 : Agricultural commodities shocks (M3-crop) and conflict ending

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.	Conflict ending		Conflict ending		Conflict ending	
Estimator	FE logit	FE-LPM	FE logit	FE-LPM	FE logit	FE-LPM
PANEL A						
ln agr. shock, M3-crop	0.626	0.067	0.667	0.122	0.418	0.037
	(0.434)	(0.044)	(0.815)	(0.158)	(0.878)	(0.128)
PANEL B						
ln agr. shock, M3-crop	3.154^a	0.336^a	5.061^a	0.810^a	0.375	0.265
	(0.982)	(0.083)	(1.606)	(0.237)	(1.541)	(0.261)
ln agr. shock × remoteness[1]	-0.456^a	-0.044^a	-0.889^a	-0.136^a	0.008	-0.043
	(0.164)	(0.011)	(0.319)	(0.046)	(0.254)	(0.043)
Sample	UCDP-GED		ACLED 1		ACLED 2	
Observations	6898	11438	1699	1725	5513	10277

^{c} significant at 10%; ^{b} significant at 5%; ^{a} significant at 1%. Robust standard errors, clustered by administrative region in parentheses. All estimations include year dummies and cell fixed effects. [1] ln distance to closest seaport. Conflict ending is defined as conflict incidence, conditional on a conflict happening in the same cell in year $t-1$.

Table A.17 : Agricultural commodities shocks (M3-crop) and conflict intensity

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.	Conflict intensity		Conflict intensity		Conflict intensity	
Estimator	FE logit	FE-LPM	FE logit	FE-LPM	FE logit	FE-LPM
PANEL A						
ln agr. shock, M3-crop	0.691	0.048	-1.329^{c}	0.090	-2.287^{a}	-0.474^{c}
	(0.445)	(0.121)	(0.806)	(0.083)	(0.748)	(0.244)
PANEL B						
ln agr. shock, M3-crop	-3.260^{a}	-1.664	-4.008^{a}	-0.229	-4.880^{a}	-2.416^{a}
	(0.931)	(1.080)	(1.168)	(0.354)	(1.811)	(0.868)
ln agr. shock × remoteness[1]	0.719^{a}	0.288^{c}	0.577^{a}	0.049	0.501	0.332^{b}
	(0.130)	(0.170)	(0.160)	(0.047)	(0.307)	(0.148)
Sample	UCDP-GED		ACLED 1		ACLED 2	
Observations	25470	100926	6222	33405	13680	57590

^{c} significant at 10%; ^{b} significant at 5%; ^{a} significant at 1%. Robust standard errors, clustered by administrative region in parentheses. All estimations include year dummies and cell fixed effects. [1] ln distance to closest seaport. Conflict intensity is defined as the number of events in the cell during year t.

Table A.18 : Agricultural commodities shocks (GAEZ) and conflict onset

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.	Conflict onset		Conflict onset		Conflict onset	
Estimator	FE logit	FE-LPM	FE logit	FE-LPM	FE logit	FE-LPM
PANEL A						
ln agr. shock, GAEZ	0.145	0.004	0.141	0.010	-0.618	-0.014
	(0.349)	(0.006)	(0.620)	(0.006)	(0.482)	(0.014)
PANEL B						
ln agr. shock, GAEZ	-3.710^{a}	-0.088^{a}	-3.943^{a}	-0.047^{b}	-2.903^{b}	-0.145^{a}
	(1.057)	(0.024)	(1.178)	(0.023)	(1.319)	(0.055)
ln agr. shock × remoteness[1]	0.658^{a}	0.014^{a}	0.731^{a}	0.009^{a}	0.373^{c}	0.021^{b}
	(0.155)	(0.004)	(0.135)	(0.003)	(0.191)	(0.008)
Sample	UCDP-GED		ACLED 1		ACLED 2	
Observations	14604	74291	4504	28066	7875	41036

^{c} significant at 10%; ^{b} significant at 5%; ^{a} significant at 1%. Robust standard errors, clustered by administrative region in parentheses. All estimations include year dummies and cell fixed effects. [1] ln distance to closest seaport. Conflict onset is defined as conflict incidence, conditional on no conflict happening in the same cell in year $t-1$.

Table A.19 : Agricultural commodities shocks (GAEZ) and conflict ending

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.	Conflict ending		Conflict ending		Conflict ending	
Estimator	FE logit	FE-LPM	FE logit	FE-LPM	FE logit	FE-LPM
PANEL A						
ln agr. shock, GAEZ	0.560	0.082	-0.177	-0.052	0.437	0.106
	(0.401)	(0.050)	(0.693)	(0.148)	(0.636)	(0.091)
PANEL B						
ln agr. shock, GAEZ	2.271^{a}	0.330^{a}	2.644^{c}	0.518^{b}	2.091	0.645^{a}
	(0.879)	(0.076)	(1.391)	(0.244)	(1.437)	(0.230)
ln agr. shock × remoteness[1]	-0.307^{b}	-0.041^{a}	-0.579^{b}	-0.117^{b}	-0.290	-0.093^{b}
	(0.147)	(0.009)	(0.274)	(0.049)	(0.232)	(0.041)
Sample	UCDP-GED		ACLED 1		ACLED 2	
Observations	4661	7972	1166	1179	3808	7287

^{c} significant at 10%; ^{b} significant at 5%; ^{a} significant at 1%. Robust standard errors, clustered by administrative region in parentheses. All estimations include year dummies and cell fixed effects. [1] ln distance to closest seaport. Conflict ending is defined as conflict incidence, conditional on a conflict happening in the same cell in year $t-1$.

Table A.20 : Agricultural commodities shocks (GAEZ) and conflict intensity

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.	Conflict intensity		Conflict intensity		Conflict intensity	
Estimator	FE logit	FE-LPM	FE logit	FE-LPM	FE logit	FE-LPM
PANEL A						
ln agr. shock, GAEZ	1.126	0.327	-1.488^{a}	-0.090^{c}	-1.423^{b}	-0.153
	(0.772)	(0.327)	(0.526)	(0.052)	(0.574)	(0.214)
PANEL B						
ln agr. shock, GAEZ	-1.798^{c}	-0.895^{b}	-4.329^{a}	-0.359	-4.948^{a}	-2.261^{b}
	(1.048)	(0.391)	(0.918)	(0.231)	(1.045)	(0.934)
ln agr. shock × remoteness[1]	0.535^{a}	0.193^{c}	0.530^{a}	0.042	0.618^{a}	0.332^{b}
	(0.125)	(0.102)	(0.165)	(0.033)	(0.192)	(0.136)
Sample	UCDP-GED		ACLED 1		ACLED 2	
Observations	17388	73602	4879	28356	9630	41830

^{c} significant at 10%; ^{b} significant at 5%; ^{a} significant at 1%. Robust standard errors, clustered by administrative region in parentheses. All estimations include year dummies and cell fixed effects. [1] ln distance to closest seaport. Conflict intensity is defined as the number of events in the cell during year t.

9 Sensitivity to outliers

Table A.21 : Agricultural commodities shocks: outliers

	(1)	(2)	(3)
Dep. Var.		Conflict incidence	
Estimator		FE-LPM	
Dataset	UCDP	ACLED 1	ACLED 2
PANEL A: All but 5 countries with higher proportion of events			
ln agr. com. shock	-0.226^a	-0.079^a	-0.212^a
	(0.064)	(0.021)	(0.068)
ln agr. shock × ln dist. to closest port	0.030^a	0.012^a	0.031^a
	(0.009)	(0.004)	(0.010)
Observations	133200	40766	73950
PANEL B: Countries with less than 20% of the territory with events/year			
ln agr. com. shock	-0.214^a	-0.077^a	-0.154^a
	(0.062)	(0.019)	(0.058)
ln agr. shock × ln dist. to closest port	0.028^a	0.011^a	0.022^b
	(0.009)	(0.003)	(0.009)
Observations	133640	42075	73426
PANEL C: Countries with at least one event/year			
ln agr. com. shock	-0.283^a	-0.245^b	-0.331^a
	(0.076)	(0.110)	(0.085)
ln agr. shock × ln dist. to closest port	0.037^a	0.038^b	0.048^a
	(0.011)	(0.015)	(0.013)
Observations	92,607	29,505	61,306
PANEL D: Cells with less than 2 events/year			
ln agr. com. shock	-0.123^a	-0.060^a	-0.115^a
	(0.026)	(0.018)	(0.039)
ln agr. shock × ln dist. to closest port	0.016^a	0.009^a	0.017^a
	(0.004)	(0.003)	(0.006)
Observations	129,216	42,816	73,715

^{c} significant at 10%; ^{b} significant at 5%; ^{a} significant at 1%. Robust standard errors, clustered by administrative region in parentheses. All estimations include year dummies and cell fixed effects. [1] ln distance to closest seaport.

Table A.22 : Exposure to crisis: outliers

	(1)	(2)	(3)
Dep. Var.		Conflict incidence	
Estimator		FE-LPM	
Dataset	UCDP	ACLED 1	ACLED 2
PANEL A: All but 5 countries with higher proportion of events			
Exp. to crises	0.21^{a}	0.02	0.81^{a}
	(0.08)	(0.03)	(0.31)
Exp. to crises × ln dist. to closest port	-0.03^{a}	-0.01	-0.11^{a}
	(0.01)	(0.00)	(0.04)
Observations	134,730	62,348	74,800
PANEL B: Countries with less than 20% of the territory with events/year			
Exp. to crises	0.21^{a}	-0.02	0.56^{b}
	(0.08)	(0.03)	(0.23)
Exp. to crises × ln dist. to closest port	-0.03^{a}	-0.00	-0.08^{b}
	(0.01)	(0.00)	(0.03)
Observations	135,165	64,620	74,275
PANEL C: Countries with at least one event/year			
Exp. to crises	0.27^{a}	0.09	0.90^{b}
	(0.08)	(0.06)	(0.36)
Exp. to crises × ln dist. to closest port	-0.04^{a}	-0.02^{b}	-0.13^{b}
	(0.01)	(0.01)	(0.05)
Observations	93,049	42,318	61,569
PANEL D: Cells with less than 2 events/year			
Exp. to crises	0.13^{a}	0.04	0.33^{b}
	(0.04)	(0.03)	(0.14)
Exp. to crises × ln dist. to closest port	-0.02^{a}	-0.01^{b}	-0.05^{b}
	(0.01)	(0.00)	(0.02)
Observations	130,745	65,700	74,565

^{c} significant at 10%; ^{b} significant at 5%; ^{a} significant at 1%. Robust standard errors, clustered by administrative region in parentheses. All estimations include year dummies and cell fixed effects. [1] ln distance to closest seaport.

10 Country-specific trends and country-year fixed effects

Table A.23 : Robustness: country-specific time trends

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.		Conflict incidence			Conflict incidence	
Estimator		FE-LPM			FE-LPM	
PANEL A						
ln agr. shock	-0.143^{b}	0.044	-0.183^{a}			
	(0.066)	(0.075)	(0.058)			
ln agr. shock × remoteness[1]	0.021^{b}	-0.007	0.028^{a}			
	(0.010)	(0.010)	(0.009)			
Exposure to crises				0.084	0.057	0.447^{b}
				(0.063)	(0.049)	(0.190)
Exp. to crises × remoteness[1]				-0.016	-0.014^{c}	-0.061^{b}
				(0.010)	(0.007)	(0.026)
PANEL B						
ln agr. shock	-0.013	-0.040^{b}	-0.050^{a}			
	(0.017)	(0.018)	(0.015)			
ln agr. shock × remoteness[2]	0.025^{c}	0.060^{b}	0.067^{a}			
	(0.014)	(0.024)	(0.021)			
Exposure to crises				0.021	-0.030^{b}	0.149^{b}
				(0.015)	(0.012)	(0.066)
Exp. to crises × remoteness[2]				-0.066^{b}	-0.006	-0.179^{a}
				(0.029)	(0.015)	(0.065)
Sample	UCDP-GED	ACLED 1	ACLED 2	UCDP-GED	ACLED 1	ACLED 2
Observations	136026	43435	75520	137556	66430	76370

^{c} significant at 10%; ^{b} significant at 5%; ^{a} significant at 1%. Robust standard errors, clustered by administrative region in parentheses. All estimations include year dummies, country-specific trends and cell fixed effects. [1] ln distance to closest seaport. [2] distance to closest seaport, relative to maximum distance computed by country.

Table A.24 : Robustness: country-year fixed effects

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.	Conflict incidence			Conflict incidence		
Estimator	FE-LPM			FE-LPM		
PANEL A						
ln agr. shock	-0.209^a	-0.130^b	-0.049^b			
	(0.076)	(0.064)	(0.021)			
ln agr. shock × remoteness[1]	0.030^a	0.021^b	0.007^b			
	(0.012)	(0.010)	(0.003)			
Exp. to crises × remoteness[1]				-0.011	0.003	-0.029^c
				(0.008)	(0.005)	(0.016)
PANEL B						
ln agr. shock	-0.056^a	-0.014	-0.036^b			
	(0.017)	(0.013)	(0.018)			
ln agr. shock × remoteness[2]	0.067^a	0.018^c	0.060^b			
	(0.023)	(0.010)	(0.025)			
Exp. to crises × remoteness[2]				-0.082^a	0.007	-0.168^a
				(0.031)	(0.010)	(0.061)
Sample	UCDP-GED	ACLED 1	ACLED 2	UCDP-GED	ACLED 1	ACLED 2
Observations	136026	75520	43435	137556	66430	76370

^{c} significant at 10%; ^{b} significant at 5%; ^{a} significant at 1%. Robust standard errors, clustered by administrative region in parentheses. All estimations include country-year and cell fixed effects. [1] ln distance to closest seaport. [2] distance to closest seaport, relative to maximum distance computed by country.

11 Deep-water ports

Table A.25 : Robustness: deep water seaports (draft of min. 12 meters)

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.	Conflict incidence		Conflict incidence		Conflict incidence	
Estimator	FE logit	FE-LPM	FE logit	FE-LPM	FE logit	FE-LPM
PANEL A						
ln agr. shock	-6.486^a	-0.275^a	-8.592^a	-0.156^a	-0.232^a	-5.876^a
	(1.232)	(0.082)	(1.599)	(0.042)	(0.077)	(1.961)
ln agr. shock × remoteness[1]	0.699^a	0.037^a	1.161^a	0.025^a	0.033^a	0.705^b
	(0.176)	(0.012)	(0.224)	(0.006)	(0.012)	(0.302)
Sample	UCDP-GED		ACLED 1		ACLED 2	
Observations	27090	136026	6596	43435	75520	14410
PANEL B						
Exposure to crises	8.030^a	0.307^a	0.089	0.804^b	13.678^a	21.783^a
	(2.409)	(0.083)	(0.065)	(0.372)	(3.297)	(6.956)
Exp. to crises × remoteness[1]	-1.346^a	-0.049^a	-0.017^c	-0.113^b	-2.301^a	-2.897^a
	(0.373)	(0.013)	(0.009)	(0.052)	(0.600)	(0.992)
Sample	UCDP-GED		ACLED 1		ACLED 2	
Observations	27126	137556	66430	76370	11128	14420

^{c} significant at 10%; ^{b} significant at 5%; ^{a} significant at 1%. Robust standard errors, clustered by administrative region in parentheses. All estimations include year dummies and cell fixed effects. [1] ln distance to closest deep-water seaport, i.e. seaport with a minimum draft of 12 meters.

12 Alternative shock: African Growth Opportunity Act

This section considers an alternative external income shock, based on the African Growth Opportunity Act (AGOA). Starting in the early 2000s, the US granted free access to its market to a number of African countries, for a large range of products. The year in which these preferences were granted depends on the country.[14] As shown by Frazer and Biesebroeck (2010), the AGOA had a positive and significant effect on these countries' exports. We use a dummy (A_{it}) which equals 1 if the country belongs to the AGOA in year t. This variable is possibly less exogenous that the previous ones. A country becomes eligible to the AGOA only when it meets certain conditions, among which political stability may play a role (although it does not appear explicitly in the list of criteria defined by the agreement). To ensure that we are focusing on a shock that is exogenous, we refine the variable. First, as not all products are eligible to the AGOA, countries should be affected heterogeneously depending on their exposure to AGOA-eligible products, and depending on how much they trade with the US. We define the "exposure to AGOA" as follows:

$$\text{Exp}_{it}^{AGOA,1} = \beta_{ip}^{US} \times A_{it} \tag{1}$$

where β_{ip} is the average share of total exports of country i in AGOA-eligible products before the AGOA enters into force (from 1995 to the year in which the preferences are granted to the country). This variable does not only reflect the fact that a country entered the AGOA, but also the extent to which it is likely to be affected *ex-post* due to its *ex-ante* specialization. This variable is more exogenous to political conditions. We also interact A_{it} with the distance between the country's main seaport (see below for a discussion of the seaport data) and the US (New York City):

$$\text{Exp}_{it}^{AGOA,2} = \text{distance}_{i}^{US} \times A_{it} \tag{2}$$

We expect a country to be less affected by the AGOA if is it located further away from the US. This ensures again that we are identifying an exogenous shock: if a country's eligibility to the AGOA can plausibly be affected by political conditions, there is a priori no reason to believe that this bias is differently distributed according to the distance of the country to the US.

The results are given in Table A.26 below.

[14] For the list of eligible countries, products and dates in which the preferences were granted, see: http://www.agoa.gov/AGOAEligibility/index.asp. We do not consider other unilateral liberalization initiatives such as Everything but Arms in the EU, as these are generally granting free market access for the entire range of products, which limits the scope for identification. The countries included in our estimations entered the AGOA in 2000 (Chad, Congo, Rwanda, Uganda, Guinea), 2002 (Sierra Leone), 2003 (Democratic Republic of Congo), 2004 (Angola) and 2006 (Burundi, Liberia). Central African Republic was eligible from 2000 to 2003 and Ivory Coast from 2002 to 2005.

Table A.26 : Alternative shock: African Growth Opportunity Act

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.	Conflict incidence		Conflict incidence		Conflict incidence	
Estimator	FE logit	FE-LPM	FE logit	FE-LPM	FE logit	FE-LPM
PANEL A						
AGOA	-0.918^a	-0.024^a	-0.851^a	-0.006	-0.381^b	-0.023^a
	(0.322)	(0.008)	(0.309)	(0.006)	(0.166)	(0.006)
Share products AGOA	-0.733	-0.025	-1.267	-0.006	-1.253^a	-0.077^a
	(0.673)	(0.017)	(0.968)	(0.018)	(0.407)	(0.019)
PANEL B						
AGOA	-0.815^b	-0.019^b	-1.307^a	-0.014^c	-0.500^a	-0.018^a
	(0.335)	(0.007)	(0.389)	(0.008)	(0.179)	(0.006)
AGOA × ln dist. US	-0.087	-0.013	4.174^a	0.106^c	1.744^b	0.025
	(0.997)	(0.020)	(1.558)	(0.055)	(0.769)	(0.022)
PANEL C						
AGOA	-4.751^a	-0.205^a	-5.250^a	-0.141^b	-2.235^a	-0.169^a
	(1.115)	(0.057)	(1.746)	(0.058)	(0.785)	(0.057)
AGOA × remoteness[1]	0.646^a	0.029^a	0.712^a	0.021^b	0.309^b	0.024^a
	(0.166)	(0.008)	(0.267)	(0.009)	(0.122)	(0.008)
PANEL B						
AGOA	-1.895^a	-0.058^a	-2.096^a	-0.037^a	-0.877^a	-0.047^a
	(0.601)	(0.018)	(0.767)	(0.014)	(0.274)	(0.013)
AGOA × remoteness[2]	2.025^a	0.068^a	2.145^b	0.050^b	1.011^a	0.053^a
	(0.640)	(0.023)	(1.030)	(0.025)	(0.374)	(0.017)
Sample	UCDP-GED		ACLED 1		ACLED 2	
Years	1989-2006	1989-2006	1980-2005	1980-2005	1997-2006	1997-2006
# of countries	36	41	12	12	37	40
Observations	27126	137556	11128	66430	14420	76370

^{c} significant at 10%; ^{b} significant at 5%; ^{a} significant at 1%. Robust standard errors, clustered by administrative region in parentheses. All estimations include year dummies and cell fixed effects. [1] ln distance to closest seaport.[2] distance to closest seaport relative to maximum distance, computed by country.

13 Additional countries

Table A.27 : Agricultural commodities shocks and conflicts: all ACLED countries

Dep. Var.	Conflict incidence		Conflict onset		Conflict ending	
Estimator	FE logit	FE-LPM	FE logit	FE-LPM	FE logit	FE-LPM
PANEL A						
ln agr. com. shock	-3.010[a]	-0.046[a]	-2.250[a]	-0.025[a]	-0.362	-0.010
	(0.642)	(0.012)	(0.572)	(0.008)	(0.574)	(0.078)
PANEL B						
ln agr. com. shock	-6.322[a]	-0.275[a]	-3.769[a]	-0.116[a]	0.418	0.398
	(1.544)	(0.075)	(1.345)	(0.041)	(1.632)	(0.274)
ln agr. shock × remoteness[1]	0.567[b]	0.037[a]	0.256	0.015[b]	-0.131	-0.067
	(0.250)	(0.011)	(0.209)	(0.006)	(0.261)	(0.044)
Observations	18330	90608	15858	88993	6727	14221

[c] significant at 10%; [b] significant at 5%; [a] significant at 1%. Robust standard errors, clustered by administrative region in parentheses. All estimations include year dummies and cell fixed effects. [1] ln distance to closest seaport. These estimations include the same ACLED II countries as in the baseline estimations, plus Afghanistan, Haiti, Cambodia, Laos, Lebanon, Myanmar and Nepal.

Table A.28 : Exposure to crises and conflicts: all ACLED countries

Dep. Var.	Conflict incidence		Conflict onset		Conflict ending	
Estimator	FE logit	FE-LPM	FE logit	FE-LPM	FE logit	FE-LPM
PANEL A						
Exposure to crises	0.043	-0.026	0.523	-0.001	-0.506	-0.083
	(0.685)	(0.022)	(0.611)	(0.010)	(0.799)	(0.087)
PANEL B						
Exp. to crises	9.972[a]	0.209[a]	10.498[a]	0.108[a]	0.232	-0.750[b]
	(3.063)	(0.078)	(2.886)	(0.039)	(3.153)	(0.371)
Exp. to crises × remoteness[1]	-1.552[a]	-0.037[a]	-1.565[a]	-0.017[a]	-0.124	0.109[b]
	(0.470)	(0.013)	(0.432)	(0.006)	(0.477)	(0.055)
Observations	18340	91458	15868	89843	6730	14308

[c] significant at 10%; [b] significant at 5%; [a] significant at 1%. Robust standard errors, clustered by administrative region in parentheses. All estimations include year dummies and cell fixed effects. [1] ln distance to closest seaport.These estimations include the same ACLED II countries as in the baseline estimations, plus Afghanistan, Haiti, Cambodia, Laos, Lebanon, Myanmar and Nepal.

14 Transitory agricultural commodities shocks

Table A.29 : Transitory effect of agricultural demand shocks

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.	Δln agricultural com. shock$_t$					
Estimator	FE-LPM					
Δln agricultural com. shock$_{t-1}$	0.079	0.094^c	0.071	0.064	0.076	0.071
	(0.050)	(0.056)	(0.064)	(0.052)	(0.058)	(0.064)
Δln agricultural com. shock$_{t-2}$		-0.065	-0.098		-0.077	-0.098
		(0.051)	(0.063)		(0.055)	(0.063)
Δln agricultural com. shock$_{t-3}$			-0.011			-0.011
			(0.046)			(0.046)
Product-specific time trends	No	No	No	Yes	Yes	Yes
Observations	884	832	780	884	832	780
R^2	0.227	0.241	0.259	0.243	0.260	0.259

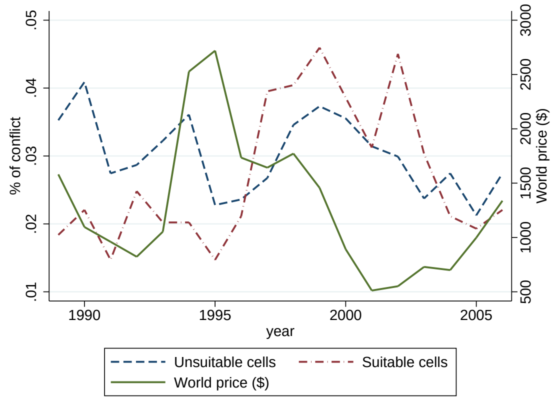
^{c} significant at 10%; ^{b} significant at 5%; ^{a} significant at 1%. Robust standard errors in parentheses. Product (HS4) and year fixed effects included in all specifications.

15 Agricultural Commodities and conflict: an illustration

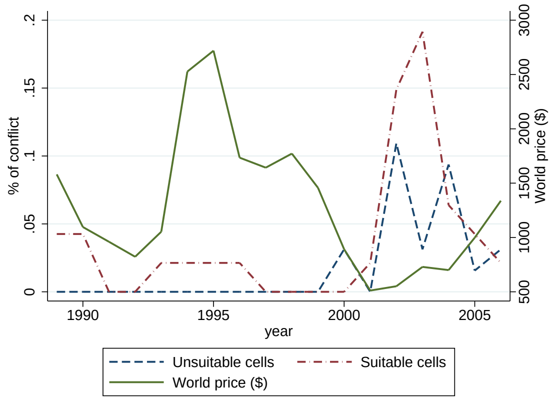
This section provides an illustration of our finding using specific commodities and countries. We have gathered data on the world price of three important commodities: coffee, sorghum and maize. For each country present in our sample and for each of these crops, we have separated the cells into two categories: those suitable and those unsuitable to produce the commodity (using the FAO-GAEZ data). Then, by year, we compute the share of suitable and unsuitable cells affected by conflict events. We expect decreases in the world price of the commodity to be negatively correlated with the share of cells experiencing conflicts, especially if in cells which are suitable to grow the crop. Figures A.8(a) to A.8(f) below are consistent with this. For each crop, we have included a Figure for the entire sample of countries, and another focusing on a large producer of the crop. While the correlation between the world price of the commodities and conflict propensity is generally not visible in unsuitable cells, there is a clear negative link between these prices and conflict propensity in suitable regions. In Cote d'Ivoire, for instance, the low prices of coffee observed between 1999 and 2005 is associated with a huge increase in conflict propensity in suitable cells. The negative correlation is also very clear in the case of sorghum in Kenya: sorghum-producing regions clearly see conflict propensity increasing systematically when prices are low, and decreasing when prices are high, while little change can be observed in the other cells.

Figure A.8 : World crop prices, crop suitability and conflicts

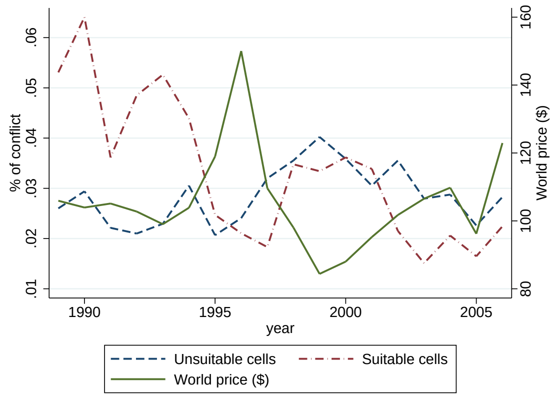
(a) All countries (coffee)



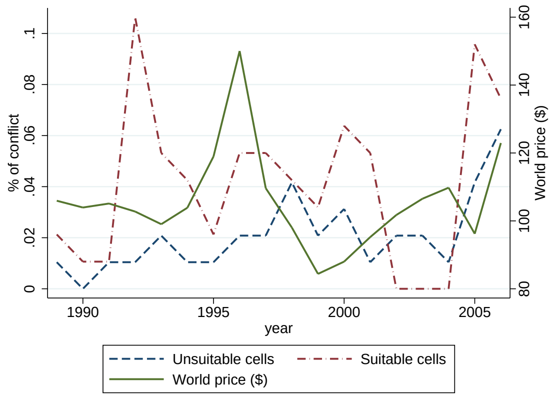
(b) Cote d'Ivoire (coffee)



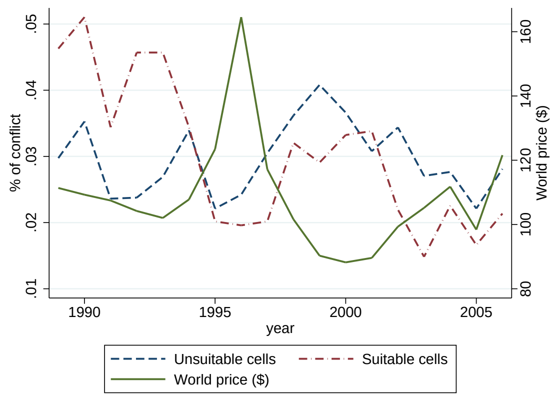
(c) All countries (sorghum)



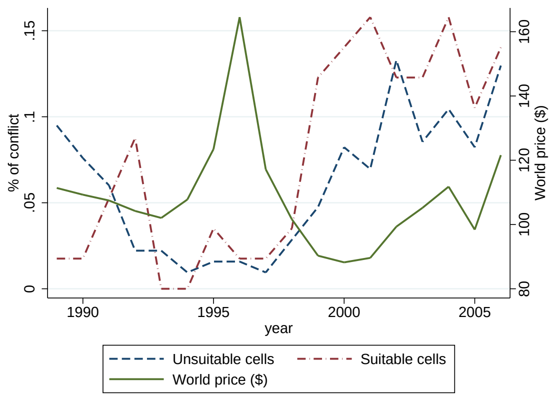
(d) Kenya (sorghum)



(e) All countries (maize)



(f) Ethiopia (maize)



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