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Conflicts increased in Africa shortly after COVID-19 lock downs, but welfare assistance reduced fatalities

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ABSTRACT

Understanding how rises in local prices affect food-related conflicts is essential for crafting adequate social welfare responses, particularly in settings with an already high level of food vulnerability. We contribute to the literature by examining how rises in local food prices and the lockdowns implemented to contain the first wave of the COVID-19 pandemic affected conflict. We analyze real-time conflict data for 24 African countries during 2015–2020, welfare responses to COVID-19, changes in local food prices, and georeferenced data on areas with cultivation, oil, mines, all associated with differentiated risk of conflict. We find that the probability of experiencing food-related conflicts, food looting, riots, and violence against civilians increased shortly after the first strict lockdowns of 2020. Increases in local prices led to increases in violence against civilians. However, countries that timely provided more welfare assistance saw a reduction in the probability of experiencing these conflicts and in the number of associated fatalities. Our results suggest that providing urgent aid and assistance to those who need it can help reduce violence and save lives.

1. Introduction

In response to the ongoing pandemic, several governments have implemented social distancing measures and lockdowns. Although these measures have shown to be effective in curbing the spread of the novel coronavirus, they have also caused significant economic, social and political disruption (Barrett, 2020; Senghore et al., 2020). The socio-economic disruption in the developing world risks increasing the already high levels of poverty even further. For instance, right before the pandemic outbreak, one in every five people was suffering from severe food insecurity in Africa, affecting nearly 277 million people. These vulnerable people had run out of food, most likely experienced hunger, even gone for days without eating, putting their well-being in great danger (FAO et al., 2019). As a result of the pandemic, several forecasts predict that between 60 and 240 million people worldwide could be pushed into poverty, depending on the efficiency in providing urgent and adequate relief to vulnerable citizens and struggling businesses (Gutiérrez-Romero and Ahamed, 2021; Sumner et al., 2020). The sudden loss of jobs and livelihoods for millions of people has caused food shortages and inflation - an explosive combination for uprisings.

Major food supply chains have been a catalytic feature of many historical conflicts ranging from the French Revolution until the violent unrest that eventually led to the Arab Spring (Barrett, 2020). Aid, food programs, and cash transfers have also historically been implemented to mitigate the risk of conflict, resulting in mixed findings. Sufficiently tailored conditional cash transfers have been shown to demobilize combatants (Crost et al., 2016; Pena et al., 2017). However, insurgent groups can also sabotage welfare interventions to maintain their influence and further increase violence and conflicts (Berman et al., 2011; Nunn and Qian, 2014). Given that the ongoing pandemic has spread so quickly around the globe, it is likely that some of the COVID-19 welfare assistance could be misused for clientelism and electoral purposes, putting at risk its efficiency for reducing conflicts (Birch et al., 2020).

This paper analyses three questions. First, we test whether social distancing measures, and the lockdowns implemented to contain the first wave of the COVID-19 pandemic increased the risks of internal conflicts. Second, we test the well-established hypothesis in the literature on whether rises in local commodity prices can contribute to rises in conflicts. Second, we test the well-established hypothesis in the literature on whether rises in local commodity prices can contribute to rises in...
food-related conflicts and violence against civilians. Third, we test the role of social welfare programs, implemented after COVID-19, in helping to reduce the risk of conflict increasing in the analyzed countries. We focus on the 24 African countries for which we have monthly data on local prices and real-time conflict data reported in the Armed Conflict Location and Event Data Project (ACLED) from January 1, 2015, until May 2, 2020. We analyze riots, food-related conflicts and violence against civilians, which refers to organized armed groups deliberately inflicting violence upon unarmed non-combatants civilians in non-related political violence.

To assess the role of food vulnerability and conflict, we construct a monthly index of local prices based on data from the Global Food Prices Database, which provides monthly commodity prices at a sub-country level in nearly 1000 local markets. We also construct an overall welfare and labor index based on 12 different types of interventions implemented worldwide to deal with COVID-19. We standardize this welfare and labor index to range from 0 (no intervention) up to 1 (the country has simultaneously implemented all 12 types of interventions). These 12 types of intervention, compiled by Gentilini et al. (2020), can broadly be grouped as those providing social assistance interventions, social insurance policies and labor market interventions. In our regression analysis we also control for a wide range of georeferenced socio-economic controls at the sub-country level for each country. The controls at cell level of 55 × 55 km within each country are nightlight, mobile phone coverage of 2G-3G, population size, percentage of mountains, percentage of forests, petroleum fields, mines, diamond mines, electricity coverage, primary roads coverage, and infant mortality rate. We also use the size of area and percentage of cultivated land, at district-level, as well as an index of ethnic diversity at country level.

We use panel random effects to estimate to what extent change in local prices and COVID-19 interventions (e.g. social distancing, lockdown, welfare and labor policies) affected the risk of internal conflicts. This panel random effects specification will yield unbiased effects assuming that there are no strong sources of endogeneity. These specifications could be biased if the analyzed government policies against COVID-19 were put into place in anticipation or response to ongoing conflict. In other words, our result will be biased if government response to the pandemic is not exogenous or independent from existing conflicts within each country. To address this endogeneity concern, as a robustness check, we also use panel specifications with instrumental variables.

As instruments we use the International Monetary Fund (IMF) overall commodity monthly price index which helps to denote the severity of external fluctuations that might affect how countries adopt different welfare and labor COVID-19 policies. We also include a series of dummy variables denoting whether the country is a former British, French, Portuguese, German, Belgian or American Colonization Society colony. We add information about the former colonizer as the extent of the generosity of the COVID-19 response packages depend on existing welfare structures and institutions likely shaped by colonial heritage (Nash and Patel, 2019). We also use the male mortality rate attributed to household and ambient air pollution and the percentage of diabetes prevalence among the adult population. These health indicators are known to increase the risk of experiencing severe COVID-19 symptoms (Pattorini and Regoli, 2020; Hussain et al., 2020), thus likely to influence the state’s decision as to when to impose lockdowns.

The paper offers three key findings. First, there is no evidence that the early social distancing measures implemented to mitigate the spread of COVID-19 fueled conflicts. These early interventions focused on containing the spread of COVID-19 without implementing partial or full lockdowns. Examples of these early social distancing measures include banning some international flights, banning large gatherings, closing restaurants, nightclubs, etc. In contrast, full local lockdowns increased the probability of the analyzed countries experiencing riots, food-related conflicts, and violence against civilians despite the global call for a ceasefire during the ongoing pandemic (UN News, 2020). Second, food vulnerability, proxied by increases in local prices is not associated to experiencing more riots or food-related incidents. However, rises in local prices increased the probability of countries experiencing violence against civilians, the state being involved in either instigating or responding to contain violence against civilians, and the number of fatalities of food-related conflicts. For instance, a 10% increase in the local price index is associated with a 0.7 percentage point increase in violence against civilians.

Third, we also find that the urgent welfare and labor anti-poverty initiatives implemented in response to COVID-19 reduced the probability of conflicts from emerging and the associated fatalities. A wide range of COVID-welfare response policies were implemented, with at least five simultaneous anti-poverty initiatives in the most active countries analyzed here. Thus, it is not possible to disentangle in our analysis which specific action (if cash transfers, relief for utility bills, extended pension benefits, etc.) was the most efficient in reducing conflict. We nonetheless can ascertain that for every additional COVID-welfare measure implemented, the probability of experiencing violence against civilians, riots and food-related conflicts declined by approximately 0.2 percentage points. Our evidence resonates with other studies that suggest welfare assistance can reduce the incidence of violent conflicts if adequately tailored to local contexts (Crost et al., 2016).

Thus, our findings offer important insights on managing the short- and likely long-term effects of the pandemic on poverty and conflict.

2. Literature review

2.1. Social unrest and crime during lockdowns

The immediate concern for millions of people living in poverty during the first phase of the pandemic, before the availability of vaccines for COVID-19, was not the new coronavirus disease itself but surviving the economic hardship imposed by the lockdowns. In early March 2020, lockdowns were implemented worldwide. Shortly after, some crimes and conflicts declined substantially such as urban crimes, although others increased such as domestic violence and cybercrimes, exhibiting an important variation across cities worldwide (Nivette et al., 2021). In some sub-Saharan Africa countries such as the Democratic Republic of Congo, Kenya, Uganda, and South Africa, there were reports that the police and army used in some instances excessive force against citizens to implement lockdowns and disperse people to reduce crowding (Bujakera and Ayenat, 2020). Even Senegal, where clashes between police and civilians are rare, the first night of a national curfew was met with resistance from some citizens leading to violence (AFP, 2020; France 24, 2020). There were also reports of clashes over food shortages in countries such as Lesotho, South Africa, and Zimbabwe, as citizens that suddenly lost their livelihoods due to lockdowns desperately tried to get access to food parcels handed out by authorities (Burke, 2020). This type of food vulnerability and heavy-handed implementation of lockdowns is a volatile combination that risks increasing grievances and social unrest.

2.2. Food vulnerability

Lockdowns also imposed tight mobility restrictions on workers in various sectors, including farmers whose efforts to deliver essential food and basic staples were hampered in at least 33 of Africa’s 54 countries (Mutsaka, 2020). Although the first wave of the pandemic did not

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1 For instance, robbery, assault and urban crime decreased soon after the lockdowns in the Americas, Europe, the Middle East and Asia, as the restrictions imposed on population mobility facilitated the spotting and arresting of suspects (Nivette et al., 2021; The Economist, 2020). In contrast, increase in domestic violence after lockdowns was associated with increased economic uncertainty, additional stress induced by prolonged co-habiting in confined spaces, and reduced options for support (Usher et al., 2020).
Some rebel groups might have lost substantial revenues from the sudden humanitarian support to struggling families during quarantines and to, such as oil. With such falls in profits, rebel groups have higher in drop in prices of natural resources, which they might have illegal access food to households in townships (BBC, 2020). An extensive literature has described how sudden food insecurity can lead directly or indirectly to violent riots and social unrest (Brück and d’Errico, 2019; Jones et al., 2017; Raleigh et al., 2015; Rezaaedar-yakerni et al., 2020). According to this literature, at least three critical channels explain how food vulnerability could increase riots and violence against civilians. These mechanisms are also likely to play a role during the ongoing pandemic. First, at the individual level, food vulnerability deprives people of their most basic human rights, increases grievances and highlights differences in food entitlements among the population (Hendrix and Brinkman, 2013; Jones et al., 2017). Survival instincts and grievances reduce the opportunity costs of engaging in riots, food looting or joining rebel groups that criminal groups exploit. For instance, during the pandemic, mafias in Italy and Mexico offered food and “COVID-19 support packages” to potential recruits (Jones and Hale, 2020; Tondo, 2020). Similar tactics exploiting food vulnerability have been adopted in the sub-Saharan African context (Humphreys and Weinstein, 2008). In South Africa, for instance, gangs negotiated an unprecedented truce in Cape Town to stop their conflicts and provided food to households in townships (BBC, 2020).

Second, at the rebel group level, food vulnerabilities also directly impact the group’s ability to mobilize resources to support activities. Some rebel groups might have lost substantial revenues from the sudden drop in prices of natural resources, which they might have illegal access to, such as oil. With such falls in profits, rebel groups have higher incentives to victimize ordinary citizens seeking resource appropriation, such as food. The areas with the largest share of cultivation are most susceptible to such rebel tactics, particularly during food shortages (Rezaaedar-yakerni et al., 2020). Third, at the national level, the government has a crucial role in dealing with food vulnerability and food-related conflicts. Governments might use excessive violence against civilians to prevent further violent clashes and enforce strict lockdowns, depending on their ability to provide adequate and urgent humanitarian support to struggling families during quarantines and tactfully manage potential unrest.2 Based on the above discussion, we formulate the following two hypotheses on conflict.

H1. The lockdowns implemented to contain the first wave of the pandemic increased the probability of riots, violence against civilians and food-related conflicts.

H2. Rises in local commodity prices increased the probability of riots, violence against civilians and food-related conflicts.

2 Theoretically, producers could benefit from an increase in prices, but most producers are net consumers of food in the African context. Hence rises in local and international prices make producers worse off, given the higher net cost of the food basket (Lee and Nduku, 2011). This negative effect is likely to be more dominant for most African states since they are neither major importers nor exporters (Raleigh et al., 2015).

23. COVID-19 welfare assistance

From the vast literature on conflict we know a great deal about how economic crises and shocks increase civil conflicts, riots and violence against civilians (Blattman and Miguel, 2010; Miguel et al., 2004). Related literature offers mixed evidence on the extent to which foreign aid can reduce the incidence of conflicts. Various studies have found that aid can reduce conflicts as it increases popular support for governments and increases the cost of opportunity of joining rebel and insurgent groups (Berman et al., 2011; de Ree and Nillesen, 2009; Nielsen et al., 2011). However, other studies have also found that (food) aid can increase the incidence and the duration of civil conflicts (Nunn and Qian, 2014). Anti-poverty transfers such as community-driven programs and food aid supplies have also been found to increase the intensity of conflicts (Crost et al., 2014) as insurgent groups sabotage these programs to prevent weakening their ability to recruit future members. A similar positive association has been found between increased conflict and rural employment programs (Khanna and Zimmermann, 2014).

A small but growing strand of the literature has also studied the link between conditional cash transfers and conflict. The evidence is again somewhat mixed. The literature suggests that anti-poverty programs that are sufficiently tailored to local contexts can reduce the capacity of insurgents to recruit combatants from villages (Labonne, 2013), and increase the cost of opportunity of joining illegal activities in settings with long-entrenched civil conflicts (Pena et al., 2017). Nonetheless, it is unclear the extent to which countries with high rates of extreme poverty and exacerbated food vulnerability due to lockdowns will respond to the urgent and wide range of welfare and labor COVID-19 assistance packages. Many of the urgent welfare packages introduced are unconditional cash transfers that have been shown to reduce food vulnerabilities and poverty in sub-Saharan Africa and other developing regions, but with a lesser-known effect on conflict (Chakrabarti et al., 2020; Tiwari et al., 2016). Based on this analysis, we draw the following hypothesis.

H3. Rapid welfare and labor response to COVID-19 reduced the probability of riots, violence against civilians and food-related conflicts.

3. Data

3.1. Data on conflict

To analyze conflict events we use the Armed Conflict Location and Event Data Project (ACLED). ACLED provides georeferenced data at the sub-country level. This information is available by day and month on all reported political violence and protests around the globe. Specifically, ACLED provides information about six types of conflicts: battles, explosions (suicide bombs, grenades), violence against civilians, protests, riots and strategic developments (e.g. non-violent actions on agreements, arrests and disrupted weapons use). The sources of ACLED include government reports, local media, humanitarian agencies, and research publications (Raleigh and Dowd, 2016).

We analyze exclusively three of types of conflict events: Riots, violence against civilians, and food-related conflicts. Our period of analysis is limited to January 1, 2015 to May 2, 2020. Riots, as defined by ACLED, are violent forms of demonstrations. Violence against civilians is defined as an armed or violent group deliberately attacking unarmed civilians in non-related political violence (Raleigh and Dowd, 2016). Governments, rebels, militias, and rioters can be involved in these violent acts against civilians, including attacks, abductions, forced disappearances, and sexual violence. We identify food-related conflicts based on the detailed description of each of the events reported in ACLED. These events refer to conflicts related to food including, livestock, cattle, and agriculture.

We analyze all the riots, violence against civilians and food-related conflicts reported in ACLED on a daily basis. This fine level of granularity as to when and where the conflicts took place allows us to exploit the variation with which early social distancing measures, lockdowns and welfare/labor COVID-19 policy responses were implemented across countries during the first wave of the pandemic.

3.2. Dates of early social distancing and full lockdowns

We take into account the exact date on which the first social distancing measure was implemented in each of our analyzed countries.
These earlier social distancing measures consisted mostly of banning some international flights, having additional health screening at borders, banning large gatherings, closing restaurants, nightclubs, etc. We also include the date in which full lockdowns were introduced in each country. The dates from the first early social distancing and lockdowns are taken from the publicly available data on COVID-19 Government Response Tracker (OxCGRT) by Hale et al. (2020). At the time of writing this paper, OxCGRT did not include data on social distancing measures for 13 African countries (Benin, Burundi, Central African Republic, Equatorial Guinea, Eritrea, Guinea, Guinea-Bissau, Ivory Coast, Liberia, Republic of Congo, Senegal, Somalia and Togo). For all these 13 countries, we took information on the exact date of early social distancing and lockdowns from ACAPS (2020). From this database, we also took the period of the lockdown in Nigeria. Table A1, in the Appendix, lists the date when early social distancing and lockdowns were introduced for each of the analyzed countries.

3.3. Constructing a monthly local index of prices at the market level

To measure the link between food vulnerability and conflict we use the Global Food Prices Database (WFP) data. This dataset reports monthly commodity prices at a sub-country level, across 985 local markets, in 23 African countries from the 1990s until May 2020, for which there is also information on conflicts in ACLED. We add information for Zimbabwe not included in WFP from the USAID FEWS-NET dataset that provides monthly local food prices. We focus our analysis on the 24 African countries listed in Table A1 that shows the countries for which we have data on local prices from January 1, 2015 until May 2, 2020.

There is a wide range of variance in the type of goods that each local market sells. This variance in goods reflects partly differences in consumers’ diet, staple food, preferences, budget, trading barriers, and seasonal produce in each area. This variance in produce sold at local markets should be considered if seeking to assess how changes in local prices affect consumers and local violence. An alternative approach could be to set the same basket of staple goods such as wheat, rice, beans, etc. across all countries analyzed. Unfortunately, such a homogenous basket of staple food will not represent the wide variance in commodity goods consumed within and across countries. For that reason, the literature has preferred to analyze instead the change in prices of the most frequent commodity sold within each local market (Raleigh et al., 2015). We follow such an approach here by constructing an index of monthly prices of the most frequent commodity within each market. In our econometric analysis, we take January 2015 as the base for the index for each market, which allows us to assess to what extent the index of local prices has changed since then on a monthly basis. For each conflict reported in ACLED, we add the local price index of their closest food market within the same month, year and country where the conflict took place.

3.4. Constructing an index of welfare and labor COVID-19 policy

By the period of our analysis, May 1, 2020, a total of 159 countries had implemented some sort of welfare and labor COVID-19 policy. We constructed an overall welfare and labor index based on 12 different types of interventions implemented worldwide to deal with COVID-19 (See Fig. 1). These interventions can be grouped broadly into three broad categories. The first one, social assistance interventions include: cash-based transfers, public works, in-kind/school feeding and utility/financial support. The second, social insurance policies include: paid leave/unemployment, health insurance support, pensions and disability benefits and social security contributions. The last one, labor market interventions, include wage subsidy, training, labor regulation and reduced work time subsidy. We use a simple additive unweighted index to measure the whole range of various welfare and labor COVID-19 policy responses. We standardize this index to range from 0 (no intervention) up to 1 (the country has simultaneously implemented all 12 types of interventions). In practice, the overall index ranges from 0 to slightly above 0.4 (with five ongoing policies).

We use Gentilini et al. (2020) to identify which welfare and labor policy each of the countries analyzed had implemented in response to COVID. We use this source as it offers the most extensive list of actions and programs taken in each country. Gentilini et al. (2020) do not report the date on when these interventions were first put into place. So instead, we identify the date when the first economic intervention against COVID-19 was implemented, as reported by Hale et al. (2020).

Table A2 in Appendix lists the welfare and labor policies implemented in each of the 24 African countries analyzed. From the 19

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3 OxCGRT provides information on eight types of social distancing measures implemented in response to COVID-19 across 149 countries, since January 2020. These measures include international travel restrictions, limitations on internal movement, closure of schools, closure of workplaces, cancellations of public events, restrictions of large gatherings, requirements to stay at home, and restrictions on public transport. OxCGRT includes the date on when each of the social distancing measures were implemented. This database also provides an ordinal value of 1–4 to each of the eight social distancing measures that helps to ascertain the level of their severity (Hale et al., 2020).

4 We do not have data on local prices for all these additional countries, but the dates of their lockdowns help doing the preliminary spatial analysis as well as the regression discontinuity plots presented.

5 For each market we construct a consumer price index as the sum of the total expenditure of most common items sold by multiplying price by quantity and adding them. The basket compared in each market is such that it can be comparable over time. Then we divide the monthly consumer price index by the value of the index in the base year (January 2015).

6 Various methods can be used to create composite indices such as additive, multiplicative and weighting some aspects with principal components analysis (Hale et al., 2020). We use the additive method as there are few interventions which might not merit using principal component analysis. We are not interested either in which policy explains the most variance in responses, rather to simply come with an index that measures the whole range of interventions in each country, which has the advantage of being simpler to interpret.

7 Hale et al. (2020) also report the type of economic interventions that countries implemented to help their population in response to COVID-19, but in a much more aggregated way than Gentilini et al. (2020), and aggregating these actions broadly as income support, debt and contract relief for households, and other fiscal measures.

Fig. 1. COVID-19 policy response index across Africa, as of May 1, 2020
Note. Own estimates using Gentilini et al. (2020).
countries with an ongoing COVID-19 welfare and labor policy, 12 have provided cash transfers (among other policies), while the other seven have provided utility and financial support. Labor interventions are the least used thus far. Among the 24 countries analyzed, only Egypt has adopted recent labor regulations.

3.5. Other controls

We also include a wide range of control variables to mitigate potential confounding or unobserved characteristics based on the extensive literature on conflict. In Table A3, we list the sources, sub-country level for each variable particularly if taken from satellite data which allowed us to get controls for small cell grid of 55 × 55km within each country. Focusing on small-area cells within countries, instead of administrative boundaries, offers wider array of socio-economic, population, and other geographical characteristics, that might explain the reasons behind local conflict events at small-area scale reported in ACLED. The controls at cell level, drawn from the publicly available georeferenced data from Manacorda and Tesei (2020) within each country are: mobile phone coverage of 2G-3G, population size, percentage of mountains, percentage of forests, petroleum fields, mines, diamond mines, electricity coverage, primary roads coverage, and infant mortality rate. Mobile phone coverage has been found crucial for political mobilization and riots as it facilitates mass political mobilization (Manacorda and Tesei, 2020). Similarly, poor density of roads has been found important for triggering conflicts in Sub-Saharan Africa as it hinders the ability of the security forces to quickly react to outbursts of violence and disrupt rebel and communal conflicts (Detges, 2016). Uneven provision of infrastructure could trigger social unrest as it also signals favouritism to certain regions by the government (Burgess et al., 2015). Similarly, high infant mortality could increase conflict due to increased grievances among the population (Collier and Hoeffler, 2014).

Population size and mountains are important controls used in the empirical conflict literature (Miguel et al., 2004). These variables reflect the size of the potential population that can engage in conflict, and potential areas where rebels could hide if conflict is triggered (Collier and Hoeffler, 2014). All of our other natural resource controls help us to assess the increased risk of conflict due to greed, increased in the presence of natural resources (Berman et al., 2017; Collier and Hoeffler, 2014; Fenske and Zurimendi, 2017).

We also use a proxy for indicator of wealth, at the cell level for each country. Given the lack of detailed income or consumption by household surveys in the region, we use satellite data on nighttime. Nightlight has been used by several other studies as a proxy of economic activity, functionality of critical infrastructure, and income levels, particularly for countries where there is no reliable data at small-area level (Atsant, 2015; Bonardi et al., 2021; Sathe et al., 2021). We use the monthly average of the stable nightlight luminosity from the DMSP-OLS Nighttime Light at the district level, from the USA Air Force Weather Agency. To avoid potential endogeneity issues due to reverse causality, we use the monthly nightlight for 2015 only.

We also use the logarithm of the cultivated district and size of the area (district) taken from the publicly available data from Rezaedaryakenari et al. (2020). We include these because with economic shocks as pronounced as those seen during the pandemic, some rebel groups might have higher incentives to victimize ordinary citizens seeking resource appropriation, particularly food. Thus, the areas with the largest share of cultivation are most susceptible to such rebel tactics (Rezaedaryakenari et al., 2020). Lastly, at the country level, we include the ethnolinguistic fractionalization index, which measures the probability that two randomly drawn individuals within a country are not from the same ethnic group. We add this variable as several studies have found that ethnic diversity increases the risk of incidence of armed conflict and civil conflicts (Collier and Hoeffler, 1998; Wegenast and Basedau, 2013), although this evidence is not conclusive across all studies (Miguel et al., 2004). Still, ethnic diversity is an important element to consider as it could have triggered conflict if government response to COVID-19 was biased toward certain groups.

3.6. Instrumental variables

Social distancing measures, lockdowns and welfare/labor COVID-19 policy responses have been implemented to mitigate the spread of COVID-19, and in some countries potentially to mitigate the risk of violence erupting or escalating. For this reason, policy responses to COVID could be endogenous dependent on exiting conflicts, and unlikely to be exogenous interventions. To mitigate potential endogeneity concerns our econometric specification uses instrumental variables.

Our panel specifications use four instruments. We use the male mortality rate attributed to household and ambient air pollution per 100,000, based on standardized age, at the national level for the year 2016. Another instrument is the percentage of diabetes prevalence among the adult population (aged 20–79) at the national level over the years 2015–2019. These two health indicators increase the risk of experiencing severe COVID-19 symptoms (Fattorini and Regoli, 2020; Hussain et al., 2020), and could have influenced governments’ decisions on when to implement lockdowns. We also include the IMF overall commodity monthly price index over the years 2015–2020. This index is representative of the global commodity market, including food, agriculture, fuel and non-fuel prices, and is determined by the largest import market of a given commodity. This overall index helps to denote the severity of external fluctuations that might have affected how countries adopted different welfare and labor COVID-19 policies. The extent of the
3.7. Conflicts

Before we present our econometric analysis, we make a pause to show the trend in the conflicts reported in ACLED for the entire African continent from January 1, 2015, until May 2, 2020.

We present these conflicts using regression discontinuity plots. Figs. 2–4 show the polynomial fit that represents the behavior of the underlying conditional expectation of the outcome variable, in our case, the incidence of conflict before and after the lockdown. The red vertical line represents the beginning of the lockdown. As standard in this kind of regression discontinuity plots, each dot represents a collection of local sample means of the outcome variable within each bin (Calonico et al., 2015). These figures show that riots, violence against civilians, and food-related conflicts had a flat and slight downward trajectory in the previous five years before the lockdowns. However, there is a clear jump in the incidence of these conflicts immediately after the lockdowns were implemented.

In Fig. 5 we illustrate instead the spatial distribution of riots, violence against civilians and food-related violence for the entire African continent. We focus on three periods. The panel at the top shows the episodes of violence that occurred between the date of the first lockdown of 2020 (around March 2020), and May 2020. The panel in the middle shows the episodes of violence for exactly the same dates as the panel on top, but for the previous year of 2019 (around March–May 2019). The panel at the bottom shows the episodes of violence that occurred from January 1, 2015, until the first lockdown of 2020.

Fig. 5 reveals two patterns. First, regions that experienced conflicts soon after the 2020 lockdowns tended to have conflicts in the past. This spatial correlation suggests that there are underlying conditions in these areas that makes them more vulnerable to violence. Second, conflicts that erupted after lockdowns are more spatially concentrated in areas with a higher share of cultivated land (denoted by a darker color in the right-hand maps). This spatial correlation between conflict and cultivated land had been noted earlier, in a pre-COVID study by Rezaee-daryakenari et al. (2020). These authors explain that areas with more cultivation tend to have more conflict because they provide greater utility for forcible appropriation by rebels to acquire food.

Since we are concerned with the role of food vulnerability, the rest of our analysis focuses exclusively on the 24 African countries for which we have data on local food prices. Table A4 summarizes the incidence of ACLED conflicts across these 24 countries from January 1, 2015, until May 2, 2020. During that period, there were 42,010 conflicts reported, including battles, explosions (e.g. suicide bombs, grenades), violence against civilians, protests, riots, and strategic developments. Just over a quarter (28%) of these events were violence against civilians, and 13% were riots, with a minority of food-related conflicts and food looting (2%). The state was reported to be involved as an actor in these conflicts, either instigating or responding to contain violence, in nearly 32% of all reported ACLED conflict cases. The state involved as an actor refers to military, police, government or government guard interventions. The total and average number of the fatalities per event are also reported in Table A4. There were 169,454 fatalities associated with any conflict reported in ACLED, from January 1, 2015 until May 2, 2020. There were 4552 fatalities related to riots, 50,506 fatalities related to violence against civilians, 6888 fatalities associated with any food-related conflicts (including food looting), and 4344 fatalities related to food looting.

Fig. 6 plots the relationship between violence against civilians and local food prices and the IMF global commodity index. That figure also reports the Pearson correlation coefficient between violence against civilians and local prices (correlation represented by parameter r) and with IMF global commodity index (correlation represented by parameter s). Again, we focus only on the 24 countries for which we have information on local food prices. Only for Fig. 6, we aggregate the data at monthly level for each country. We also standardize each of the three depicted variables such that their monthly average is divided by the maximum value of each variable for the entire series. Thus, the y-axis
shows how much the monthly series fluctuates from the highest level achieved within each country. The x-axis shows the beginning of each year from 2015 to 2020. The labels of the x-axis for all countries are shown only for the bottom panel of Fig. 6 (to avoid over-cluttering the information).

The IMF global commodity index, denoted by the dotted line in Fig. 6, is the same for all countries, thus has the same trends for all countries. In contrast, the local food price index exhibits different variation within countries. In some cases, like Mauritania, the index of local food prices has very little variation. In other countries, such as Ghana or Zimbabwe, local prices exhibit an erratic pattern of ups and downs. The difference in variation in local prices is likely due to a wide range of local factors such as weather fluctuations, changes in local demand and supply of food. Fig. 6 also shows that for some countries, such as Central African Republic, Ethiopia, and Mali there is a particularly strong correlation between local food prices and violence against civilians. This correlation coefficient for such countries is −0.35, 0.36, and 0.40 respectively. However, there are many cases where there is a much weaker correlation between local prices and violence against civilians. That is the case of Mauritania, Guinea, and Malawi, with correlation coefficients is −0.04, 0.02, and 0.06 respectively. This evidence might suggest that raises in food prices might have contributed to some conflicts.

4. Method

We use two econometric specifications to estimate the impact of price volatility, early social distancing measures, full lockdowns, and COVID-19 welfare policy response on conflict. First, we use a random panel effects (RE) model, as shown in equation (1). We use the RE model because it can simultaneously model both time-variant and time-invariant effects (Bell and Jones, 2015). The panel RE specification also has the main advantage of handling hierarchical data, in our case, having repeated observations in sub-country level cells, nested within countries, the higher-level fixed units. Being able to model this kind of panel data is the reason why the RE model is also known as the
We focus on the incidence of four types of conflicts ($\text{conflict}_{jit}$): riots, violence against civilians, food-related conflict incidents and food looting that occurred at the cell area $j$ (with reported latitude and longitude in ACLED) located in country $i$ at time $t$ (which includes the day, month and year). Our dependent variable is binary for each of the four types of conflicts analyzed.

$S_{it}$ is a vector that includes the three COVID-19 interventions we focus on: the date of the first social distancing measure implemented in the country, a lockdown dummy variable that takes the value of 0 or 1 depending on if the conflict occurred before or after the local lockdown implemented in each country, and the welfare and labor COVID-19 policy index in country $i$ implemented at day, month, year $t$. As mentioned before, this policy index has been normalized to take the value of 0 when no intervention has been implemented up to 1 if the country has simultaneously implemented all potential 12 welfare/labor interventions reported worldwide post-COVID. Since this index is a continuous variable, we can ascertain whether increases in the value of the index, leads to a change in the probability of experiencing conflict.

The monthly local price index measured in logarithm (log local price) at cell $j$ in country $i$ ranges from January 2015 until May 2, 2020. $X_{ji}$ is a vector that captures our controls at the cell $j$ located in country $i$ and includes: the percentage of mountains, forests, whether the cell has petroleum fields, mines, diamond mines, and area size (district level). In addition, vector $X_{ji}$ includes some key variables lagged in time to mitigate potential endogeneity issues. These lagged variables are the stable nighttime (measured in logarithm for the year 2015), the percentage of mobile phone coverage in 2G-3G, the percentage of electricity coverage, primary roads coverage, population, infant mortality, percentage of land cultivated. Vector $C_{i}$ includes the ethnolinguistic fractionalization index, for country $i$. This ethnolinguistic index is time-invariant for countries. The reason why we are unable to include further country-fixed effects dummy variables in the regression is they get eliminated due to multicollinearity with our other time-invariant controls. ($\eta_{ji} + \epsilon_{jit}$) denotes the time-invariant and time-variant error term. The results of the RE specifications are shown in Table 1, columns 1–4.

We also use a linear RE model to measure the change in probability of change in conflict as it is the best way to practically address the hierarchical structure of our panel data, and test for endogeneity simultaneously. Unfortunately, modern statistical software such as Stata do not have packages capable to estimate logit or probit models using instrumental variables, and deal with hierarchical data with panel random or fixed effects. The only way to estimate logit or probit models and test for endogeneity with panel data would be to pool the data and cluster the standard errors by countries. Unfortunately, this approach is very likely to introduce important biases as we have very few countries, 24, below the recommended number to cluster errors. Pooling the data also has the main shortcoming of treating observations as independent of each other. Thus, pooling the data would ignore, for instance, the date in which conflicts are occurring over time, and would be impossible to detect within unit variation.

Fig. 6. Monthly prices and ACLED’s violence against civilians

Note: $r =$ correlation between incidence of violence against civilians and local food price. $s =$ correlation between incidence of violence against civilians and IMF commodity price.

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8 We also use a linear RE model to measure the change in probability of change in conflict as it is the best way to practically address the hierarchical structure of our panel data, and test for endogeneity simultaneously. Unfortunately, modern statistical software such as Stata do not have packages capable to estimate logit or probit models using instrumental variables, and deal with hierarchical data with panel random or fixed effects. The only way to estimate logit or probit models and test for endogeneity with panel data would be to pool the data and cluster the standard errors by countries. Unfortunately, this approach is very likely to introduce important biases as we have very few countries, 24, below the recommended number to cluster errors. Pooling the data also has the main shortcoming of treating observations as independent of each other. Thus, pooling the data would ignore, for instance, the date in which conflicts are occurring over time, and would be impossible to detect within unit variation.

9 An alternative way to analyze this policy index is to construct a categorical variable, by for instance focusing on those countries implementing exclusively social assistance, insurance policies or labor market interventions. Unfortunately, most countries implemented a combination of these policies simultaneously, and with different amounts of cash or benefits. Thus, it is not possible to create meaningful mutually exclusive categories of policy responses across countries.
The RE estimates may be unbiased if there are no strong sources of endogeneity, such as omitted variables due to unobserved heterogeneity. However, we suspect that the RE specifications could be biased given that governments might have implemented social distancing measures, lockdowns and COVID-19 welfare responses in anticipation or response to ongoing conflicts. To address this endogeneity concern, we use panel RE with instrumental variables. Equation (2) shows the first-stage regression, where we instrument our three likely endogenous variables: the date of the first social distancing measure, whether the conflict event occurred before or after the lockdown and the welfare and labor COVID-19 policy index, all denoted by vector $Z_t$. Our instruments are represented by vector $S_t$. These instruments are male mortality rate attributed to household and ambient air pollution per 100,000 (lagged for the year 2016); diabetes prevalence (% of population ages 20 to 79, years 2015–2019); the IMFs commodity price index (years 2015–2019); the IMF commodity price index (years 2015–2019); and the country is a former British, French, Portuguese, German, Belgian or American Colonization Society colony.

$$S_{it} = \gamma + \mu_t Z_t + \mu_t \log \text{local price}_{it} + \mu_t X_{it} + \mu_t C_t + \nu_t$$

Equation (3) shows the second-stage regression of estimating the impact of the instrumented endogenous variables on the incidence of conflict. The terms $(\xi_t + \varphi_t)$ in equation (3) represent the time-invariant and time-variant error terms.

$$\text{conflict}_{it} = \kappa + \beta_1 S_{it} + \beta_2 \log \text{local price}_{it} + \beta_3 X_{it} + \beta_4 C_t + (\xi_t + \varphi_t)$$

Table A5 in the Appendix shows the first-stage regression, and all instruments are strongly correlated to the instrumented variables. The F-statistic of the excluded instruments is well above 10 for all regressions. The results of the second-stage IV-2SLS regression are reported in Table 1, in columns 5–8. At the bottom of that table, the Sargan-Hannsen overidentification tests suggest that the instruments are valid. Table 1, also shows the Hausman endogeneity tests which suggest there is evidence of endogeneity in columns 6 and 7 (violence against civilians and
food-related incidents). This endogeneity test suggest that the second-stage IV 2SLS panel RE regressions should be preferred to the panel RE without instruments.

5. Results

5.1. Riots, violence against civilians and food-related conflict

Table 1 shows that the early social distancing measures do not affect the probability of conflicts occurring. That is the case if using random specifications RE with and without instrumental variables (Table 1, columns 1–8). This non-statistically significant effect is unsurprising since many of these early measures did not impose any mobility restrictions on the population but mostly focused on having some travel restrictions on journeys from abroad and avoiding overcrowding. The stricter lockdown measures to contain the first wave of the COVID-19 pandemic yield different results. If focused on the IV-2SLS results, Table 1, columns 5–8, show that the probability of experiencing riots, violence against civilians, food-related conflicts and food looting increased after lockdowns, as our earlier Figs. 2–4 had shown. Thus, these findings support our first hypothesis.

With regards to food vulnerability, we find that a 10% increase in the value of the local price index is associated with a 0.71 percentage point increase in violence against civilians. The same results are obtained when using the panel RE specifications with or without instrumenting (Table 1 columns 2 and 6). To depict more clearly this association, Fig. 7 shows the marginal effects between local prices and violence and incidence of violence against civilians. This figure shows a positive association between rises in local prices and violence against civilians is present regardless of the value of the index of local price, whether at low or high value across all our sample.10

Our evidence also suggests that rises in local prices is not associated with riots, food-related incidents or food looting. The same results are obtained when using the RE specifications with or without instrumenting (Table 1 columns 1, 3, 4, 5, 7 and 8). Thus, we find mixed support for our second hypothesis. Our findings suggest that riots obey factors other than rises local prices. For instance, riots are more likely to occur in more urbanized settings with higher levels of stable nightlife, electricity coverage, population, and mobile phone coverage (Table 1, columns 1 and 5). The reason why these urbanized areas might be more likely to experience riots can perhaps be found in Manacorda and Tesei (2020). These authors in a pre-COVID study in sub-Saharan Africa conclude that mobile phone coverage is instrumental for mass mobilization. But this type of mobilization only occurs during economic downturns as it accentuates existing grievances and the cost of

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10 It is worth noting that the logarithm of a positive number may be negative or zero. In our case, the logarithm of the local price index ranges from –5.0 to nearly 9.0.
stable nightlight, less electricity coverage, primary roads, but more
concentrated in less urbanized settings as they have lower levels of
spending in public infrastructure or across groups (Burgess et al., 2015).

Our results also suggest that riots also are more likely
to emerge in areas with potential grievances, as proxied by less density
citizens seeking resource appropriation, such as food, when the profits of
cultivated areas are more at risk of experiencing these events. Earlier
literature has suggested that highly cultivated areas are at higher risk of
conflict as rebel groups have increased incentives to victimize ordinary
citizens seeking resource appropriation, such as food, when the profits of
these rebel groups fall (Rezaedaryakanoi et al., 2020).

The IV-2SLS specifications show that the welfare and labor COVID-
19 policy index has reduced the probability of riots, violence against
citizens and food-related conflicts, including food looting. Thus, our

### Table 2
COVID-19 interventions, local prices and fatalities.

| Fatalities of: | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---------------|-----|-----|-----|-----|-----|-----|-----|-----|
| Panel Random Effects (RE) | Any ACLED conflict | Riots | Violence against civilians | Food-related conflict | Any ACLED conflict | Riots | Violence against civilians | Food-related conflict |
| First social distancing implemented | -0.024*** | 0.001 | -0.014*** | -0.002*** | -0.033 | 0.000 | 0.007 | -0.002*** |
| Strict lockdown | 0.310 | 0.017 | -0.111 | 0.021 | 5.997*** | 0.192 | 2.396*** | 0.061 |
| Index of welfare and labor | -2.057 | -0.052 | -0.864 | 0.102 | -26.693*** | -0.345 | -13.333*** | -0.809 |
| COVID19 response (1.266) | (0.134) | (0.948) | (0.160) | 7.337 | (0.804) | (5.692) | (1.048) |
| Log index local market price | -0.240*** | 0.018 | 0.951*** | 0.033*** | -0.240 | 0.019 | -0.020 | 0.035*** |
| Log stable nighttime (year 2015) | -0.037 | 0.010 | 0.103 | 0.001 | -0.001 | 0.010 | 0.145** | 0.011 |
| Log mobile phone coverage | -0.692*** | 0.017*** | -0.105*** | -0.043*** | -0.708*** | 0.018*** | 0.085** | -0.040*** |
| 2G-3G | (0.029) | (0.006) | (0.038) | (0.006) | (0.061) | (0.006) | (0.045) | (0.007) |
| % Mountains | 0.113 | -0.053*** | 0.049 | 0.149 | 0.077 | -0.055*** | -0.155 | 0.001 |
| % Forests | -0.218*** | -0.010 | -0.433*** | -0.157*** | -2.174*** | -0.016 | -0.754*** | -0.166*** |
| Petroleum fields | (0.188) | (0.027) | (0.161) | (0.027) | (0.272) | (0.028) | (0.202) | (0.031) |
| Mines | 0.098 | 0.015*** | 0.018 | -0.013 | 0.094 | -0.015* | 0.113* | -0.010 |
| Diamond mines | 0.312*** | 0.004 | 0.243*** | 0.009 | 0.360** | 0.003 | 0.289*** | 0.015 |
| Size of area | 0.000*** | 0.000 | 0.000*** | 0.000 | 0.000*** | 0.000 | 0.000*** | 0.000 |
| Electricity | 0.012 | 0.067*** | -0.018 | -0.040** | 0.072 | 0.066*** | 0.014 | -0.036** |
| Primary roads | 0.062 | -0.021*** | -0.043 | -0.011** | 0.083 | -0.018*** | -0.040 | -0.016** |
| Log population | -0.433*** | 0.005 | -0.175*** | 0.000 | -0.444*** | 0.004 | -0.265*** | -0.004 |
| Log infant mortality rate | 1.198*** | 0.040*** | 0.931*** | 0.038*** | 1.294*** | 0.066 | 0.937*** | 0.007*** |
| Log cultivated | 0.351*** | 0.002 | 0.396*** | 0.034*** | 0.321*** | 0.001 | 0.211*** | 0.029*** |
| Ethnolinguistic fractionalization index (0.732) | -0.075 | -0.013 | -0.113 | -0.093*** | 0.137 | -0.024 | 0.105 | -0.143*** |
| Constant | 538.073*** | -15.911 | 302.793*** | 39.856*** | 725.467 | -10.325 | 153.514 | 53.199*** |
| Observations | 42,010 | 42,010 | 42,010 | 42,010 | 42,010 | 42,010 | 42,010 | 42,010 |
| Number of countries | 24 | 24 | 24 | 24 | 24 | 24 | 24 | 24 |
| Test of overidentification restrictions: | Sargan-Hansen statistics Chi-sq(1) | 4.099 | 3.081 | 2.140 | 4.716 |
| P-value | 0.998 | 0.799 | 0.906 | 0.581 |
| Hausman test | Chi2 | 40.080 | 11.960 | 104.990 | 18.850 |
| Prob > chi2 | 0.001 | 0.803 | 0.000 | 0.337 |

Note. Significant at the ***p < 0.01, **p < 0.05 and *p < 0.1 levels.

participation fall. Our results also suggest that riots also are more likely
to emerge in areas with potential grievances, as proxied by less density
of primary roads as this low density could reflect low government spending in public infrastructure or across groups (Burgess et al., 2015).

Table 1 also suggests that violence against civilians seems to be
concentrated in less urbanized settings as they have lower levels of
stable nighttime, less electricity coverage, primary roads, but more
cultivated land and mines (Table 1, columns 2 and 6). Similarly, food-
related incidents and food looting are more likely to occur in areas
with a greater density of cultivated land (column 7 and 8), as Fig. 5
suggested earlier. This is an important finding. Although the volatility
of local prices is not associated with food-related conflicts, these high
cultivated areas are more at risk of experiencing these events. Earlier
literature has suggested that highly cultivated areas are at higher risk of
conflict as rebel groups have increased incentives to victimize ordinary
citizens seeking resource appropriation, such as food, when the profits of
these rebel groups fall (Rezaedaryakanoi et al., 2020).

The IV-2SLS specifications show that the welfare and labor COVID-
19 policy index has reduced the probability of riots, violence against
citizens and food-related conflicts, including food looting. Thus, our
findings support our third hypothesis. For instance, Figs. 8–10 show the marginal effect of the probability of experiencing riots, violence against civilians, and food-related conflicts with the welfare and labor COVID-19 policy index values. These marginal effects depict the IV-2SLS specifications in Table 1, columns 5–7. The effect of the index is negative and linearly associated with the probability of experiencing riots. Specifically, with a 0.1 unit increase in the welfare/labor COVID-19 policy index, the likelihood of experiencing these conflicts declines by nearly 0.2 percentage points.

6. Robustness checks

We perform two robustness checks to validate the strength of the results. First, we assess whether lockdowns and COVID-19 welfare policy responses affect the number of fatalities associated with the conflicts analyzed. Second, we assess what factors increase the probability of the state being directly involved in riots, violence against civilians and food-related conflicts either instigating or responding to contain violence.

6.1. Fatalities

We next analyze the total number of fatalities. Our new dependent variable is the number of fatalities reported in ACLED from January 1, 2015 until May 2, 2020, associated with any conflict. We also analyze the number of fatalities exclusively related to riots, violence against civilians and food-related conflicts (including food looting). As before, we use two specifications: panel random effects (RE) and panel random effects with IV-2SLS. Table 2 reports the results. At the bottom of Table 2, we show the Sargan-Hansen overidentification test and the Hausman endogeneity tests. The first-stage regression results are the same as already reported in Table A5 since we have the same endogenous variables as in the earlier IV RE specification. These first-stage regressions suggest the instruments are relevant and valid. Again, we find evidence of endogeneity, particularly for all ACLED fatalities and fatalities due to violence against civilians (Table 2, columns 5 and 7). The IV-2SLS specifications show that early social distancing measures have no increased association with fatalities (Table 2, columns 5–8). However, the number of fatalities increased substantially after lockdowns for all ACLED fatalities (column 5) and fatalities associated with violence against civilians (column 7). There is no evidence of increased fatalities associated with food-related conflict. For this type of conflict, we added any fatalities related to food looting.

There is evidence that countries with a higher welfare and labor COVID-19 policy index experienced lower levels of overall ACLED's fatalities and a lower level of fatalities due to violence against civilians (Table 2, columns 5 and 7). Fig. 11 shows these marginal effects. For instance, the number of total fatalities decreases by nearly five casualties when comparing a country with no welfare and labor COVID-19 policy response versus one with an index of 0.4.

As mentioned earlier (Table 1), higher local prices are not associated with a higher probability of experiencing food-related conflicts. However, Table 2 reveals there is a statistically significant association between rises in local prices and fatalities derived from food-related conflicts. For instance, for a 10% increase in the local price index (measured in natural logarithm) the number of food-related conflict fatalities increases nearly by 0.35 percentage point increase. Very similar results are obtained when using the RE specifications with or without instrumenting (columns 4 and 8). Fig. 12 illustrates these marginal effects between rises in local prices and number of food-related conflict fatalities. The positive association between these variables is positive, regardless of the initial value of the index of local price.

6.2. The state as an actor in riots, violence against civilians and food-related conflicts

To conclude our analysis, we analyze the conflicts in which the state...
Table 3: COVID-19 interventions, local prices and the state as perpetrator of violence.

| State (military, policy, or government) involved as actor in: | Panel Random Effects (RE) specifications | Panel RE IV specifications |
|-------------------------------------------------------------|------------------------------------------|----------------------------|
|                                                            | Any ACLED conflict | Riots | Violence against civilians | Food-related conflict | Any ACLED conflict | Riots | Violence against civilians | Food-related conflict |
| First social distancing implemented                        | −0.002***          | 0.001 | −0.000                     | −0.000                | 0.001               | 0.001 | 0.000                     | −0.000                |
| Strict lockdown                                            | 0.071***           | 0.015 | 0.064***                    | 0.006**               | −0.300***           | 0.001 | −0.086***                 | 0.018***              |
| Index of welfare and labor COVID19 response                | 0.111              | −0.023 | 0.057*                     | −0.002                | 2.563***            | 0.104 | 0.486**                   | −0.126*               |
| Log index local market price                               | −0.041***          | 0.003 | 0.000***                    | 0.000                 | −0.017***           | 0.003 | 0.000***                  | 0.000***              |
| Log stable nighttime (year 2015)                           | 0.030***           | 0.017*** | −0.001                     | −0.001                | 0.025***            | 0.017*** | −0.002                     | 0.000                 |
| Log mobile phone coverage 2G-3G                            | −0.049***          | 0.011*** | 0.002                     | −0.000                | −0.049***           | 0.011*** | 0.002                     | −0.000                |
| % Mountains                                                | 0.047***           | −0.028*** | 0.035***                    | −0.000                | 0.044***            | −0.028*** | 0.033***                   | −0.000                |
| Petroleum fields                                           | −0.107***          | −0.012*** | 0.000***                    | −0.000                | −0.198***           | −0.012*** | 0.005                    | −0.004                |
| Mines                                                      | −0.007*            | −0.003* | −0.004*                     | −0.000                | −0.005              | −0.003* | −0.003*                    | −0.000                |
| Diamond mines                                              | 0.019**            | 0.000 | 0.003                        | 0.001                 | 0.014*              | −0.001 | 0.002                     | 0.001                 |
| Size of area                                               | −0.000             | 0.000*** | −0.000***                    | 0.000                 | −0.000              | 0.000*** | 0.000***                  | 0.000                 |
| Electricity                                                | 0.012              | 0.028*** | 0.005                      | −0.004***             | 0.005               | 0.028*** | 0.003                    | −0.004***             |
| Primary roads                                              | 0.021***           | −0.000 | 0.004*                      | −0.000                | 0.025***            | −0.000 | 0.004*                     | 0.000                 |
| Log population                                             | −0.026***          | −0.001 | 0.000                        | 0.000                 | −0.027***           | −0.001 | 0.000                     | −0.000                |
| Log infant mortality rate                                  | 0.079              | 0.001 | −0.018***                   | 0.000                 | 0.063***            | 0.001 | −0.018***                 | 0.000                 |
| Log cultivated                                             | −0.027***          | −0.004* | −0.017***                   | 0.001                 | −0.031***           | −0.004* | −0.017***                 | 0.002**               |
| Ethnolinguistic fractionalization index                    | −0.015             | 0.058 | −0.019                      | −0.007*               | 0.037               | 0.065  | 0.000                     | −0.005                |
| Constant                                                   | 43.927***          | −17.621 | 10.271                      | 1.157                 | 20.167              | 21.776 | 2.595                     | −0.004                |
| Observations                                               | 42.010             | 42.010 | 42.010                      | 42.010                | 42.010              | 42.010 | 42.010                     | 42.010                |
| Number of countries                                        | 24                 | 24    | 24                           | 24                   | 24                 | 24    | 24                        | 24                   |
| Test of overidentification restrictions:                   |                     |       |                              |                      |
| Sargan-Hansen statistics Chi-sq(1)                         |                     |       |                              |                      |
| P-value                                                    | 9.349              | 1.865 | 3.949                        | 5.014                |
| Hausman test                                               | 0.155              | 0.932 | 0.684                        | 0.542                |
| Prob > chi2                                                | 0.000              | 0.000 | 0.000                        | 0.012                |

Note: Significant at the ***p < 0.01, **p < 0.05 and * p < 0.1 levels.

has been directly involved as an actor (either instigating or responding to contain violence). As before, we focus on riots, violence against civilians, and food-related conflicts. We identify whether the state was involved as an actor, whether in its capacity as the military, the police, the government or government guards, according to ACLED’s database.

We present two specifications, panel RE without and with IV-2SLS. Table 3 presents the results of both specifications. The first-stage IV-2SLS regression results are the same as already reported in Table A5 since we have the same endogenous variables as in the earlier IV specifications.

The Sargan-Hansen overidentification tests show that the instruments satisfy the overidentification restrictions (see bottom of Table 3). Also, the Hausman tests suggest the IV-2SLS panel RE results should be preferred to those of panel RE results. According to the IV-2SLS panel RE specifications, the instances where the state is involved in food-related conflicts have increased since the local lockdowns (Table 3, column 8). However, in countries with a higher index of welfare and labor COVID政策 response, the state is less likely to be involved as an actor in food-related conflicts. In contrast, in these countries, the state is more likely to be involved in violence against civilians (column 7), but perhaps in enforcing lockdowns or preventing clashes.

Table 3, column 7, also shows that rises in local prices is associated with a slight increase of the state being involved as an actor in violence against civilians. This effect is statistically significant, and is similar whether using the RE without or with IV (columns 3 and 7). For
instance, a 10% rise in the index of a local price, leads to a rise of nearly 0.09 percentage point increase in the probability of the state being involved in violence against civilian conflicts. However, there is no evidence to suggest that a rise in local prices is associated with the state being involved as an actor for riots and food-related conflicts.

7. Conclusion

We analyzed the impact of lockdowns, food vulnerability, welfare, and labor COVID-19 policy responses on conflict. Our IV-2SLS panel random effects specifications revealed that riots, violence against civilians and food-related conflicts increased after lockdowns. We also found that food insecurity, measured in terms of rises in local prices, is associated with a higher probability of a country experiencing violence against civilians, the state being involved in violence against civilians, and a higher number of fatalities associated with food-related conflicts.

Our findings also revealed that increases in local prices are associated with increases in violence against civilians, the state being involved in instigating or responding to contain violence against civilians, and the number of fatalities of food-related conflicts. This vulnerability to local prices can be explained by the fact that most of the food consumed in Africa (90%) comes from domestic producers (Raleigh et al., 2015) and most producers in Africa are net food consumers (Lee and Ndulo, 2011). Nonetheless, we found no statistically significant association between rises in local prices and incidence of riots or incidence of food-related conflicts. Our analysis revealed that other factors increased the probability of experiencing these conflicts. Riots are more likely to emerge in areas with poorer density of roads, which can proxy grievances, and with high mobile phone coverage, thus an easier way to mass mobilize people (Manacorda and Tesei, 2020). We also found that areas experiencing more food-related conflicts are those with higher density of cultivated land. These findings support pre-COVID research that suggests these areas have increased risks of rebel groups instigating violence to steal food (Rezaeedaryakenari et al., 2020).

The implications of our analysis are important from a public policy perspective. Food vulnerability and price volatility are an explosive combination for certain types of conflicts. Another key finding is that countries with a higher index of welfare and labor COVID-19 policy response are less likely to have suffered these conflicts and less likely to have experienced fatalities as a result of violence against civilians. Since the lockdowns, governments have been more heavily involved as actors in food-related conflicts. However, countries with a higher welfare and labor COVID-19 policy index are also less likely to intervene in food-related conflicts directly. Overall, our results also indicate that providing urgent welfare assistance can reduce the probability of countries experiencing riots, violence against civilians, food-related conflicts, and their associated fatalities. Although the association found is weak, the findings suggest that urgent state interventions can reduce food vulnerability and prevent major social unrest.

Appendix

Table A1
Countries analyzed with data on local food prices at sub-level until 2020

| Country                      | Number of conflict events in ACLED | Percent of conflict events in ACLED | Date of first social distancing | Date of start of local lockdown |
|------------------------------|-----------------------------------|-------------------------------------|---------------------------------|---------------------------------|
| Algeria                      | 4558                              | 10.85                               | 10 Mar 20                       | 10 Mar 20                       |
| Angola                       | 301                               | 0.72                                | 6 Feb 20                        | 20 Mar 20                       |
| Benin                        | 169                               | 0.4                                 | 3 Mar 20                        | 19 Mar 20                       |
| Burkina Faso                | 2013                              | 4.79                                | 1 Jan 20                        | 12 Mar 20                       |
| Burundi                      | 5525                              | 13.15                               | 6 Mar 20                        | 12 Mar 20                       |
| Cameroon                     | 2619                              | 6.23                                | 1 Jan 20                        | 18 Mar 20                       |
| Central African Republic     | 458                               | 1.09                                | 29 Jan 20                       | 13 Mar 20                       |
| Democratic Republic of Congo| 5630                              | 13.4                                | 20 Feb 20                       | 18 Mar 20                       |
| Ethiopia                     | 1389                              | 3.31                                | 16 Mar 20                       | 16 Mar 20                       |
| Gabon                        | 155                               | 0.37                                | 7 Feb 20                        | 13 Mar 20                       |
| Ghana                        | 715                               | 1.7                                 | 24 Jan 20                       | 16 Mar 20                       |
| Guinea                       | 886                               | 2.11                                | 29 Feb 20                       | 26 Mar 20                       |
| Kenya                        | 2528                              | 6.02                                | 20 Jan 20                       | 13 Mar 20                       |
| Lesotho                      | 39                                | 0.09                                | 6 Mar 20                        | 18 Mar 20                       |
| Liberia                      | 340                               | 0.81                                | 9 Mar 20                        | 11 Apr 20                       |
| Madagascar                  | 771                               | 1.84                                | 15 Mar 20                       | 20 Mar 20                       |
| Malawi                       | 405                               | 0.96                                | 16 Mar 20                       | 16 Mar 20                       |
| Mali                         | 1206                              | 2.87                                | 19 Mar 20                       | 19 Mar 20                       |
| Mauritania                  | 42                                | 0.1                                 | 5 Feb 20                        | 16 Mar 20                       |
| Namibia                      | 242                               | 0.58                                | 1 Mar 20                        | 17 Mar 20                       |
| Niger                        | 737                               | 1.75                                | 13 Mar 20                       | 13 Mar 20                       |
| Nigeria                     | 9824                              | 23.38                               | 1 Jan 20                        | March 29, 2020                  |
| Rwanda                       | 93                                | 0.22                                | 27 Jan 20                       | 8 Mar 20                        |
| Zimbabwe                    | 1365                              | 3.25                                | 28 Jan 20                       | 17 Mar 20                       |
| Total ACLED events          | 42,010                            | 100                                 |                                 |                                 |
Table A2
Welfare and labor COVID-19 policy response of 24 countries analyzed

| Country                  | Social Assistance | Social Insurance | Labor Markets |
|--------------------------|-------------------|-----------------|---------------|
|                          | Overall Cash-     | Public          | Reduced       |
|                          | index             | School          |               |
|                          | COVID-19          | Feeding)        |               |
|                          |                   | Support         | Labor         |
|                          |                   | Unemployment    |               |
|                          |                   | Support         |                |
|                          |                   | Benefits        |                |
|                          |                   | (waiver/subsidy)|                |
|                          |                   |                 |               |
| Algeria                  | 0.417             | 0               | 0             |
| Angola                   | 0.083             | 0               | 0             |
| Benin                    | 0.083             | 0               | 0             |
| Burkina Faso             | 0.250             | 1               | 1             |
| Burundi                  | 0.000             | 0               | 0             |
| Cameroon                 | 0.083             | 0               | 0             |
| Central African Republic | 0.000             | 0               | 0             |
| Democratic Republic of Congo | 0.000       | 0               | 0             |
| Ethiopia                 | 0.333             | 0               | 0             |
| Gabon                    | 0.000             | 0               | 0             |
| Ghana                    | 0.250             | 0               | 0             |
| Guinea                   | 0.167             | 0               | 0             |
| Kenya                    | 0.167             | 0               | 0             |
| Lesotho                  | 0.000             | 0               | 0             |
| Liberia                  | 0.167             | 0               | 0             |
| Madagascar               | 0.250             | 1               | 1             |
| Malawi                   | 0.083             | 0               | 0             |
| Mali                     | 0.167             | 1               | 1             |
| Mauritania               | 0.167             | 0               | 0             |
| Namibia                  | 0.167             | 1               | 1             |
| Niger                    | 0.083             | 0               | 0             |
| Nigeria                  | 0.250             | 1               | 1             |
| Rwanda                   | 0.333             | 1               | 1             |
| Zimbabwe                 | 0.083             | 1               | 0             |

Note. - No program implemented until May 1, 2020. Source: Gentilini et al. (2020).
| Variable | Description | Time | Boundary | Source |
|----------|-------------|------|----------|--------|
| Riots | Violent events where demonstrators or mobs engage in disruptive acts or disorganised acts of violence against property or people. | Daily events during January 1, 2015-May 2, 2020. | Georeferenced event identified with latitude and longitude. | Armed Conflict Location and Event Data Project (ACLED). |
| Violence against civilians | Violent events where an organized armed group deliberately inflicts violence upon unarmed non-combatants. | Daily events during January 1, 2015-May 2, 2020. | Georeferenced event identified with latitude and longitude. | ACLED. |
| Food-related conflict | Any violent event related to food, including livestock, agriculture, cattle. | Daily events during January 1, 2015-May 2, 2020. | Georeferenced event identified with latitude and longitude. | Own construction using violent description provided by ACLED. |
| Food looting | Any looting event related to food. | Daily events during January 1, 2015-May 2, 2020. | Georeferenced event identified with latitude and longitude. | Own construction using violent description provided by ACLED. |
| Fatalities | The total number of deaths arising from a conflict. Separate variables are provided for number of fatalities related to riots, violence against civilians, food-related conflict and food looting. | Daily events during January 1, 2015-May 2, 2020. | Georeferenced event identified with latitude and longitude. | Own construction using violent description provided by ACLED. |
| State involved as actor | The state is explicitly mentioned as an actor in the violent event in the form of the army, police, guard, or government. | Daily events during January 1, 2015-May 2, 2020. | Georeferenced event identified with latitude and longitude. | Own construction using violent description provided by ACLED. |
| Date of social distancing and lockdowns | Date of when the first social distancing measure, and first lockdown was implemented. | Exact day of implementation during January–May 2020 | Country-level | Own construction using Hale et al. (2020) and ACAPS (2020). |
| Index of welfare and labor COVID-19 response | We construct an overall welfare and labor index based on these 12 different types of interventions implemented worldwide to deal with COVID-19. These can be grouped into three broad categories. The first one, social assistance interventions include: cash-based transfers, public works, in-kind/school feeding and utility/financial support. The second, social insurance policies include: paid leave/unemployment, health insurance support, pensions and disability benefits and social security contributions. The last one, labor market interventions: include wage subsidy, training, labor regulation and reduced work time subsidy. The index ranges from 0 (no intervention) up to 1 (the country has simultaneously implemented all 12 types of interventions). | Varies according it changes during January–May 2020 | Country-level | Own construction using Gentilini et al. (2020). |
| Date of start of welfare/labor COVID-19 response | Date of when welfare and labor social welfare response were first implemented in the country. | Exact day of implementation during January–May 2020 | Country-level | Own construction using Hale et al. (2020). |
| Index local market price | Monthly local price index of the most frequent commodity in each market. | Monthly basis during January 2015-May 2, 2020. | Data available at market level, the local market price index is attached to each conflict event according to nearest geographical distance. | Own construction using the Global Food Prices Database (WFP) and for Zimbabwe only the USAID FEWS-NET. |
| Log stable nighttime (year 2015) | Average level of nighttime luminosity. | Average level for year 2015 | District level | USA Air Force Weather Agency. |
| Cultivated land | Mean level of cultivated land by district. | District level | | Rezaeedaryakenari et al. (2020). Publicly available data. They used the Global Agro-Ecological Zones (GAEZ) of Food and Agricultural Organization (FAO). |
| Size of area (district) | Geographic area in thousands of square kilometers for each district. | Time-invariant in dataset. | District level | Rezaeedaryakenari et al. (2020). Publicly available data. |
| Log mobile phone coverage | Coverage of mobile phone coverage 2G-3G at cell level. | Time-invariant in dataset. | District level | Manacorda and Tesei’s (2020) publicly available data. They used the Global System for Mobile Communications (GSM) Association. |
| % Mountains | Percentage of cell covered by mountains. | Time-invariant in dataset. | 55 × 55 km cells within country. | Manacorda and Tesei’s (2020) publicly available data. They used UNEP-WCMC. |
| % Forests | Percentage of cell covered by forests. | Time-invariant in dataset. | 55 × 55 km cells within country. | Manacorda and Tesei’s (2020) publicly available data. They used UNEP-WCMC. |
| Petroleum fields | Dummy variable indicating if in the cell there are petroleum fields. | Time-invariant in dataset. | 55 × 55 km cells within country. | Manacorda and Tesei’s (2020) publicly available data. They used GLOBCover. |
| Mines | Dummy variable indicating if in the cell there are mines. | Time-invariant in dataset. | 55 × 55 km cells within country. | Manacorda and Tesei’s (2020) publicly available data. They used PRIO. |

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### Table A3 (continued)

| Variable                        | Description                                                                 | Time                  | Boundary             | Source                                                                                          |
|---------------------------------|-----------------------------------------------------------------------------|-----------------------|----------------------|-------------------------------------------------------------------------------------------------|
| Diamond mines                   | Dummy variable indicating if in the cell there are diamond mines.          | Time-invariant in dataset. | $55 \times 55$ km cells within country. | Manacorda and Tesei’s (2020) publicly available data. They used USA Geological Survey. |
| Electricity                     | Km of electrical grid.                                                     | Time-invariant in dataset. | $55 \times 55$ km cells within country. | Manacorda and Tesei’s (2020) publicly available data. They used PRIO. |
| Primary roads                   | Km of primary roads by cell.                                               | Time-invariant in dataset. | $55 \times 55$ km cells within country. | Manacorda and Tesei’s (2020) publicly available data. They used the Africa Infrastructure Country diagnostic (ADB). |
| Population                      | Population size by cell.                                                   |                       | $55 \times 55$ km cells within country. | Manacorda and Tesei’s (2020) publicly available data. They used SEDAC/NASA. |
| Log infant mortality rate       | the number of children that die under one year of age in a given year, per 1000 live births. |                       |                       | Manacorda and Tesei’s (2020) publicly available data. They used PRIO. |
| Ethnic fractionalization index  | The ethnic fractionalization index corresponds to the probability that two randomly drawn individuals within a country are not from the same ethnic group in 2013. |                       | Country-level         | Altas Maradov Mira. |
| Male mortality rate             | Male mortality rate attributed to household and ambient air pollution per 100,000, based on standardized age. | Year 2016             | Country-level         | World Bank data repository. |
| Adult diabetes prevalence       | Percentage of diabetes prevalence among the adult population (aged 20-79) at the national level over the years 2010-2019. | Yearly 2015–2019      | Country-level         | World Bank data repository. |
| IMF global commodity price      | IMF all commodity price index. Value represents the benchmark prices which are representative of the global market. They are determined by the largest exporter of a given commodity. | Monthly during 2015–2020 | Global-level          | IMF data repository. |
| Colonial heritage               | Indicates whether country is a former British, French, Portuguese, German, Belgian or American Colonization Society colony. |                       | Time-invariant.       | Own estimates using historical records. |

### Table A4

Summary statistics of countries analyzed

| Variable                                          | Total   | Mean   | Std. Dev. | Total   | Mean   | Std. Dev. | Total   | Mean   | Std. Dev. |
|----------------------------------------------------|---------|--------|-----------|---------|--------|-----------|---------|--------|-----------|
| Riots                                              | 12,572  | 0.13   | 0.33      | 524     | 0.08   | 0.28      | 346     | 0.135  | 0.342     |
| Violence against civilians                        | 24,745  | 0.28   | 0.45      | 1304    | 0.23   | 0.42      | 854     | 0.384  | 0.487     |
| Food-related incidents                             | 2871    | 0.02   | 0.16      | 174     | 0.03   | 0.17      | 160     | 0.047  | 0.211     |
| Food loafing                                       | 1798    | 0.02   | 0.12      | 110     | 0.02   | 0.13      | 107     | 0.026  | 0.160     |
| Fatalities any ACLED conflict                      | 169,454 | 1.66   | 8.59      | 6489    | 1.08   | 3.71      | 4616    | 1.894  | 6.172     |
| Fatalities to riots                                | 4552    | 0.06   | 0.89      | 272     | 0.04   | 0.36      | 134     | 0.065  | 0.415     |
| Fatalities to violence against civilians          | 50,506  | 0.69   | 6.37      | 1816    | 0.38   | 1.81      | 1236    | 0.583  | 2.360     |
| Fatalities to food-related conflict                | 6888    | 0.05   | 1.08      | 235     | 0.04   | 0.78      | 290     | 0.092  | 2.482     |
| Fatalities to food loafing                         | 4344    | 0.03   | 0.80      | 154     | 0.03   | 0.71      | 225     | 0.077  | 2.447     |
| State involved as actor in any ACLED conflict      | 40,237  | 0.32   | 0.47      | 2083    | 0.26   | 0.44      | 1548    | 0.404  | 0.491     |
| State involved as actor in riots                   | 4710    | 0.05   | 0.21      | 180     | 0.03   | 0.17      | 157     | 0.056  | 0.231     |
| State involved as actor in violence against civilians | 5309  | 0.05   | 0.22      | 225     | 0.03   | 0.17      | 279     | 0.114  | 0.318     |
| State involved as actor in food-related conflict   | 691     | 0.01   | 0.07      | 23      | 0.00   | 0.06      | 41      | 0.011  | 0.106     |
| State involved as actor in food loafing            | 396     | 0.00   | 0.05      | 10      | 0.00   | 0.04      | 26      | 0.007  | 0.082     |

**Controls and instruments**

| Variable                                          | Total   | Mean   | Std. Dev. | Total   | Mean   | Std. Dev. | Total   | Mean   | Std. Dev. |
|----------------------------------------------------|---------|--------|-----------|---------|--------|-----------|---------|--------|-----------|
| Log index local market price                       | 4.82    | 0.49   |           | 4.74    | 0.40   |           | 4.768   | 0.411  |           |
| Adult diabetes prevalence (% of population ages 20 to 79) | 4.26    | 1.73   |           | 5.01    | 1.70   |           | 4.696   | 1.739  |           |
| IMF global commodity price                         | 113.80  | 11.68  |           | 116.60  | 2.78   |           | 86.988  | 4.413  |           |
| Log stable nighttime, year 2015                     | 1.92    | 0.72   |           |         |        |           |         |        |           |
| Log mobile phone coverage 2G-3G                     | -0.52   | 0.93   |           |         |        |           |         |        |           |
| % Mountains                                        | 0.33    | 0.34   |           |         |        |           |         |        |           |
| % Forests                                          | 0.24    | 0.22   |           |         |        |           |         |        |           |
| Petroleum fields                                   | 0.06    | 0.20   |           |         |        |           |         |        |           |
| Mines                                              | 0.30    | 0.63   |           |         |        |           |         |        |           |
| Diamond mines                                      | 0.04    | 0.32   |           |         |        |           |         |        |           |
| Size of area                                       | 2989.24 | 613.91 |           |         |        |           |         |        |           |

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### Table A4 (continued)

| Variable                                                                 | Total  | Mean  | Std. Dev. | Total  | Mean  | Std. Dev. | Total  | Mean  | Std. Dev. |
|-------------------------------------------------------------------------|--------|-------|-----------|--------|-------|-----------|--------|-------|-----------|
| Electricity                                                             | 0.44   | 0.44  |           |         |       |           |         |       |           |
| Primary roads                                                           | 1.88   | 1.66  |           |         |       |           |         |       |           |
| Log population                                                         | 12.86  | 1.39  |           |         |       |           |         |       |           |
| Log infant mortality rate                                               | 2.11   | 0.43  |           |         |       |           |         |       |           |
| Log cultivated                                                         | 3.89   | 0.65  |           |         |       |           |         |       |           |
| Ethnolinguistic fractionalization index                                 | 0.61   | 0.29  |           |         |       |           |         |       |           |
| Index of welfare and labor COVID-19 response                           | 0.01   | 0.04  |           |         |       |           |         |       |           |
| Male mortality rate attributed to household and ambient air pollution, age-standardised, year 2016 | 192.60 | 79.43 |           |         |       |           |         |       |           |
| Number of observations                                                 | 42,010 |       |           | 3134   |       |           | 1330   |       |           |
| Number of countries                                                    | 24     |       |           | 24     |       |           | 24     |       |           |

### Table A5
First-stage IV regression of Tables 1–3

|                          | (1)         | (2)         | (3)         |
|--------------------------|-------------|-------------|-------------|
|                          | First social distancing | Strict lock down | Index welfare/labor |
| Male mortality rate attributed to household and ambient air pollution male | −0.120*** | 0.000** | −0.000*** |
|                          | (0.001)     | (0.000)     | (0.000)     |
| Diabetes prevalence (% of population ages 20 to 79) | −3.189*** | 0.005*** | −0.003*** |
|                          | (0.054)     | (0.001)     | (0.000)     |
| Former colony (never colonised reference group):                       |            |             |             |
| British                  | −43.649***  | 0.037***    | 0.009***    |
|                          | (0.480)     | (0.006)     | (0.001)     |
| French                   | −14.998***  | 0.060***    | 0.020***    |
|                          | (0.476)     | (0.006)     | (0.001)     |
| Portuguese               | −36.827***  | 0.037***    | 0.013***    |
|                          | (0.892)     | (0.011)     | (0.002)     |
| German                   | −45.109***  | 0.063***    | 0.007***    |
|                          | (0.554)     | (0.007)     | (0.002)     |
| Belgian                  | −16.255***  | 0.049***    | 0.012***    |
|                          | (0.458)     | (0.006)     | (0.001)     |
| American Colonization Society | 12.062*** | 0.023**    | 0.020***    |
|                          | (0.876)     | (0.011)     | (0.002)     |
| IMF all commodity price    | −0.021***   | −0.006***   | −0.001***   |
|                          | (0.006)     | (0.000)     | (0.000)     |
| Log index local market price | 1.497***   | 0.017***    | 0.001***    |
|                          | (0.160)     | (0.002)     | (0.000)     |
| Log stable nightlight (year 2015) | 4.162***   | −0.011***   | −0.000***   |
|                          | (0.139)     | (0.002)     | (0.000)     |
| Log mobile phone coverage 2G-3G | −2.230*** | 0.002      | −0.000***   |
|                          | (0.084)     | (0.001)     | (0.000)     |
| % Mountains               | 6.402***    | 0.006**     | 0.000**     |
|                          | (0.294)     | (0.004)     | (0.001)     |
| % Forests                | −7.042***   | −0.003      | −0.004***   |
|                          | (0.356)     | (0.004)     | (0.001)     |
| Petroleum fields          | 6.402***    | −0.011**    | 0.001      |
|                          | (0.361)     | (0.004)     | (0.001)     |
| Mines                    | 1.129***    | 0.006**     | 0.001**     |
|                          | (0.118)     | (0.001)     | (0.000)     |
| Diamond mines            | 2.604***    | −0.001      | 0.001**     |
|                          | (0.207)     | (0.002)     | (0.001)     |
| Size of area              | −0.000      | −0.000      | −0.000      |
|                          | (0.000)     | (0.000)     | (0.000)     |
| Electricity              | −3.413***   | −0.002      | −0.002***   |
|                          | (0.202)     | (0.002)     | (0.001)     |
| Primary roads             | 1.498***    | −0.003***   | −0.001***   |
|                          | (0.075)     | (0.001)     | (0.000)     |
| Log population            | −2.710***   | 0.002**     | 0.001**     |
|                          | (0.074)     | (0.001)     | (0.000)     |
| Log infant mortality rate | −0.279      | 0.012***    | −0.015***   |
|                          | (0.282)     | (0.003)     | (0.001)     |
| Log cultivated           | 3.223***    | 0.004**     | 0.003**     |
|                          | (0.137)     | (0.002)     | (0.000)     |
| Ethnolinguistic fractionalization index                               | −19.392*** | 0.036***    | 0.011***    |
|                          | (0.499)     | (0.006)     | (0.001)     |
| Observations             | 42,010      | 42,010      | 42,010      |
| R-squared                | 0.817       | 0.186       | 0.113       |
| F-statistic of excluded instruments                                   | 1039.23     | 4211.99     | 520.55      |

Note. Significant at the ***p < 0.01, **p < 0.05 and * p < 0.1 levels.
