The Reach of Radio: Ending Civil Conflict through Rebel Demobilization*

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Abstract

This paper examines the role of FM radio in mitigating and ending violent conflict. We collect original data on radio broadcasts encouraging defections during the Lord's Resistance Army (LRA) insurgency, one of Africa's longest running conflicts. We provide the first quantitative evaluation of an active counter-insurgency policy. Exploiting random topography-driven variation in radio coverage along with panel variation at the grid-cell level we identify the causal effect of messaging on violence. Broadcasting defection messages reduce fatalities, violence against civilians and clashes with security forces. These reductions are propelled by an increase in defections. In response to manpower losses, the LRA resorts to increased looting for survival. Income shocks measured by exogenous movements in commodity prices have opposing effects on both the conflict and the effectiveness of messaging. Conflict-enhancing (-reducing) commodity price shocks weaken (strengthen) the pacifying effects of defection messaging. This highlights the role of economic incentives in the success of counter-insurgency policies.

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1 Introduction

In this paper, we examine how policy makers can end entrenched civil conflicts. The instability of peace agreements in the early 1990s led key policy actors to go beyond macro-level policies and address individual incentives to participate in violence. In that effort, significant resources and attention have focused on Disarmament, Demobilization, and Reintegration (DDR) programs as a means to draw combatants out of militarized structures and put them on the path to civilian life. Yet, few formal activities within such programs work to address issues that might prevent combatants from leaving conflict and entering DDR programs, particularly in the absence of a stable ceasefire.[1] Defection messaging is one such initiative that has gained support and prominence in recent years (UN-DDR, 2014).

Defection messaging aims to mitigate and end conflict by providing active combatants with information on the logistics of surrender, immunity offers and judicial processes, and the willingness of their families and communities to reintegrate them. Since print and digital media have limited reach in remote areas where armed groups often operate, several policy actors have opted for FM radios to broadcast defection messages. This strategy has taken a notable role in multiple conflicts in Africa with similar programs frequently being employed globally.[2] While the previous literature has highlighted the role of radio as a propaganda tool for inciting violence (Yanagizawa-Drott, 2014), political mobilization (Adena et al., 2015), and ethnic hatred (DellaVigna et al., 2014), little is known about its effectiveness as an instrument for peace. Focusing on the Lord's Resistance Army (LRA) insurgency in central Africa, we provide the first (known) evaluation of a defection messaging program aimed at ending an active civil conflict. In addition to examining its effectiveness in reducing violence, we provide novel insights into armed group behavior and how economic incentives to fight interact with counter-insurgency policies.

The LRA conflict started in northern Uganda in 1988 and has since devastated local populations across the region, expanding into the Democratic Republic of Congo (DRC), South Sudan, and Central African Republic (CAR) as it evolved. The insurgency was made infamous by the LRA's brutal tactics including a reliance on abducted child soldiers. Over the course of the conflict, the group has caused an estimated 100,000 deaths and displaced 2.5 million civilians (UN Security Council, 2013a). While its forces have now been reduced to 200 fighters or fewer, in its prime, the group had stable membership of as many as 3,000. Beyond its direct effect on violence, the conflict has inflicted a massive blow to the economy, society and politics of the region, the consequences of which will be felt for a long time to come (Blattman, 2009; Blattman and Annan, 2010; Rohner et al., 2013).

FM defection messaging has been employed in the LRA conflict since the early 2000s and has expanded dramatically since 2008. These programs have been largely modeled on the "*Come Home*" programs pioneered by two stations in northern Uganda in the early 2000s. Programs in-

[1] See Humphreys and Weinstein (2007) for a notable exception.

[2] See, for instance, the use of defection messaging against the FARC in Colombia (source: Time, 30/10/2009) and against Boko Haram in Nigeria (source: Public Radio International, 19/05/2017).

clude interviews with combatants who have surrendered, personal messages from family or community members, and logistical information on how to safely surrender. While we cannot directly observe combatants receiving FM radio broadcasts, a qualitative survey of ex-combatants that we undertook in northern DRC shows that more than 95% of the respondents were exposed to these messages either directly or through other LRA members.

To study the effectiveness of the program, we constructed a novel dataset combining different primary and secondary sources of data. To start with, we designed and conducted a survey of radio station operators to collate data on the annual expansion of defection messaging in the four countries affected by the conflict. Through the survey, we also collected data on radio parameters, allowing us to generate time-varying topography-corrected coverage estimates, which we exploit for our identification strategy. We combined this with the previously under-exploited LRA Crisis Tracker (LRACT) database. LRACT is a geo-coded database providing detailed information on events related to the LRA from 2008 to the present. We merged these with geographically disaggregated data on a range of variables pertinent to conflict in order to construct a grid-cell-level panel dataset.[3]

Our study focuses on the 2008–2015 period, which is when the use of FM radios became a central counter-insurgency strategy. After a sustained military offensive in 2008 drove LRA forces into remote regions of DR Congo, South Sudan, and CAR, they started operating in small groups spread across vast expanses (Lancaster et al., 2011). Under such conditions, radio represented the only means to communicate with potential defectors. The United Nations (UN) and other international NGOs began expanding capacity at small community radio stations, as well as working with communities to establish new stations (UN Security Council, 2013b). The main expansion of defection messaging began around 2010, and hence the relevant variation in the data is restricted to this period. Furthermore, the LRACT began a detailed cataloging of LRA activities in 2008. Focusing on the post-2008 period allows us to undertake an uncommonly rich analysis of the effects of radio messaging on conflict. In particular, we are able to go beyond just looking at the number of events or fatalities available from other conflict datasets and to explore the behavior (such as looting and abductions) of the LRA while suffering dwindling membership, in addition to looking at actual returnees who willingly escape from armed group enrollment or captivity.

In total, 19 radio stations with 21 antennas were actively broadcasting defection messages during our period of study spanning an area of almost 300,000 square km. The phased expansion of the messaging campaign and of radio coverage over time allows us to estimate the causal impact of messaging exploiting three sources of plausibly exogenous variation. Firstly, we measure radio coverage corrected by the topography of the affected area (see similar empirical strategies in Olken, 2009, and Yanagizawa-Drott, 2014). Secondly, we enhance the current literature by exploiting the panel dimension of our dataset and controlling for time-invariant unobservable

[3]These data collated from a myriad of sources include data on natural resources such as cash crops and minerals, weather variables such as temperature and precipitation, and alternative media such as mobile phone coverage and general FM radio coverage.

characteristics at a highly disaggregated level. Finally, we exploit the random overlapping of radio coverage from different radios to build a measure of message intensity at the grid-cell level. Instead of using administrative units which might be endogenous to conflict we use 14 km $\times$ 14 km grid cells for our analysis, chosen based on the geography of point patterns (Boots and Getis, 1988) (see Appendix B.3).

We find that defection messaging has a substantial impact on LRA-related conflict outcomes. A one standard deviation increase in the intensity of defection messaging (approximately 20 minutes of daily messaging at full cell coverage) leads to a 3% decrease in fatalities, a 1% increase in number of returnees, and a 1% decrease in the number of attacks against civilians and clashes with security forces, but no statistically significant effect on abductions. Higher intensity of defection messaging also leads to an increase in looting by the LRA, being primarily survival oriented. Allowing for non-linear effects, we find that the effect of defection messaging increases significantly with its intensity for all our main outcome variables. While low levels of intensity have a negligible effect, more than an hour of messaging per day at full cell coverage leads to an almost 15% reduction in fatalities and a 6% increase in returnees. In aggregate terms, these effects correspond to a large impact on the conflict for the period of analysis. Counterfactual estimates suggest that defection messaging led to 2,222–2,586 (33%–42%) fewer deaths, and accounted for 520 (25%) of the 2,073 returnees observed in our data.

Exploiting detailed satellite-based (cell-level) data on the presence of commodities and natural resources, we also uncover evidence of heterogeneous effects of defection messaging by income shocks. Following a burgeoning literature, we measure income shocks by exogenous changes in international prices of commodities (Berman et al., 2017; Dube and Vargas, 2013). Using LASSO (least absolute shrinkage and selection operator) regressions for covariate selection we identify cotton and groundnut oil price shocks as the two relevant shocks in the context of the LRA from a long list of commodities. In line with recent literature, we find these shocks to have opposing effects on the conflict. Exogenous positive shocks to the price of cotton reduce the conflict and increase the effectiveness of defection messaging. On the other hand, positive shocks to the price of groundnut oil have exactly the opposite effect. A one standard deviation increase in the conflict-reducing cotton price shock enhances the effect of defection messaging on fatalities by 1 pp. A similar standard deviation increase in the conflict-inducing groundnut oil price shock reduces the effect of defection messaging on fatalities by 1 pp. This suggests that both violence and the effectiveness of counter-insurgency policies such as defection messaging are closely related to economic incentives.

Finally, using an instrumental variable approach, we show that defection messaging reduces conflict intensity primarily by inducing more returnees, and we quantify the effect. A one standard deviation increase in the number of returnees reduces fatalities by 19.4%, reduces violence against civilians by 4% and increases looting by 17%. However, the number of returnees does not have any effect on abductions or clashes with security forces. The effect of a defection messaging-induced increase in the number of returnees on fatalities is robust to allowing for small violations in the exclusion restriction. However, we also find some evidence that defection messaging might have a direct ameliorating effect on violence against civilians and clashes with security forces over and above its effects through returnees.

Our results are stable across a series of robustness tests, including controlling for a wide range of potentially confounding variables such as mobile phone coverage, general FM radio coverage, and increased military activity. Results are also robust to controlling for a wide range of other time-varying controls, such as rainfall and temperature shocks, and trends in different pre-conflict economic variables, including ruggedness, GDP (proxied by nighttime light), population, and urbanization. They are also robust to using alternative data sources. Finally, we undertake a placebo test by randomly placing radio stations across space and showing that exposure to these hypothetical radio stations does not affect the conflict.

We contribute to three distinct strands of the literature. First, we contribute to the scant (quantitative) literature examining policies to end active civil wars. While the literature has concentrated on investigating the causes and consequences of such conflicts (Blattman and Miguel, 2010) or on the determinants of successful reintegration in the post-conflict phase (Humphreys and Weinstein, 2007), we know little about how to restore peace once conflicts start and become entrenched. We fill this gap by providing the first paper (known to us) on how to end conflicts by directly targeting rebels through messages encouraging defections. Furthermore, we view our paper as a starting point for new literature studying how DDR policies in general and amnesties in particular can be made to work. Rigorous quantitative evaluations of amnesties, for instance, are non-existent in the literature despite the 297 conflict amnesties granted between 1946 and 2010 (Dancy, 2018). We provide the first systematic evidence using micro-data on the effectiveness of an existing amnesty policy in bringing rebels back home.[4]

Second, we contribute to the literature studying the effects of media on social and political outcomes. Previous contributions in this field have focused on the effect of media on political accountability (Besley and Burgess, 2002; Strömberg, 2004), crime (Dahl and DellaVigna, 2009), social capital (Olken, 2009), women's agency (Jensen and Oster, 2009; La Ferrara et al., 2012), and social attitudes (Paluck and Green, 2009). More recently, the literature has highlighted the role of radio in inciting violence and hateful attitudes. For instance, Yanagizawa-Drott (2014) shows how propaganda broadcast over the radio incited violence during the Rwandan Genocide. Adena et al. (2015) show how radio was instrumental in building public support for government initiatives in Nazi Germany. Again, DellaVigna et al. (2014) show how radio was effective in shaping hateful sentiments between ethnic groups in Croatia. Building on this, we provide the first systematic analysis of how radio messaging can be used to mitigate pernicious outcomes and reduce violent conflict.[5]

Finally, we contribute to the burgeoning literature highlighting the role of economic shocks

[4]Two other policies that have been tried with limited success are sanctions on armed groups and altering production and distribution of arms through military aid and military trade (Humphreys, 2003).

[5]Several qualitative publications have spoken on this issue, most often relying on interviews with policy actors, local residents, and ex-LRA members (Lancaster and Cakaj, 2013; Ross, 2016).

in civil conflicts. Economic conditions and the availability of resources can affect an individual's willingness to participate in conflict activities by shifting their expected returns to different alternatives such as fighting or returning to civil society (Becker, 1968). Positive commodity price shocks can reduce the intensity of conflict by increasing wages and reducing the supply of labor for conflict activities (Becker, 1968; Grossman, 1991) or by improving state capacity (Fearon and Laitin, 2003; Snyder, 2006; Ross, 2012). Alternatively, they can also increase conflict by raising the returns to predation (Fearon, 2005; Dube and Vargas, 2013). While most of the literature focuses on the role of economic shocks in explaining the persistence and intensity of conflicts, this paper provides novel evidence on the effect of these shocks on the effectiveness of active policies to disincentivize conflict.

The remainder of the paper is organized as follows. In Section 2, we present background information about the LRA insurgency and the radio messaging campaign. In Section 3, we provide a conceptual framework drawing on the theoretical literature. In Section 4, we describe the data used in this paper. In Section 5, we discuss the empirical strategy. In Section 6, we present our results. Finally, in Section 7, we conclude.

2 Background

The Lord's Resistance Army was formed in 1988, when its leader Joseph Kony united remnants of several failed insurgent groups in northern Uganda. Those groups – and, by extension, the LRA – are rooted in long-standing ethnoregional divisions in Uganda. In 1986, President Yoweri Museveni successfully led a largely southern rebel force to power. While many northern elements supported change in Kampala, they violently rejected his southern rule. Despite their resolve, by 1988, most organized resistance to Museveni's presidency had either surrendered or disbanded under heavy pressure from the Ugandan Army (UPDF). The few elements that remained joined the small, but growing, LRA, which held the ostensible goal of a spiritual and democratic restoration of the nation.[6] Since then, the conflict has ravaged local communities. Occasionally, this was due to episodes of open conflict between Ugandan government forces and the LRA, but what was even more common and costly was the targeting of non-combatants by both sides, which included torturing, maiming, and killing of individuals for non-cooperation or suspected collaboration with enemy forces. Beyond these tactics, the LRA stood out for their reliance on the abduction and indoctrination of children as soldiers, which ultimately brought them international notoriety.

With the hope of bringing an end to years of relentless violent conflict, the Ugandan Amnesty Act of 2000 offered a blanket amnesty to LRA combatants willing to abandon violence. It is in this context that defection messaging has evolved from a modest innovation at two radio stations to become a central tool in reducing LRA numbers. Aware of the fear that LRA combatants and abducted individuals had of returning home despite the passing of the 2000 Amnesty Act, radios in Lira and Gulu (northern Uganda) began broadcasting programs encouraging LRA members to

[6] For deeper reading on the historical origins of the LRA, see, for instance, Allen and Vlassenroot (2010).

defect. The programs featured family members, often parents, speaking directly to LRA combatants (often abductees coerced into violence) assuring them they would be welcome and forgiven should they return. In other instances, they featured former LRA members speaking out to assure active fighters of their good health and freedom, while also emphasizing the need to return.[7] Here is an example transcript from a program featuring a former LRA member: "*I ask you [LRA soldier] to take very good care of your soldiers so that they don't commit any crimes, and lead them to the [Ugandan Army], or the UN or MONUC in Duru or Gilima. Just bring all your soldiers there. There is nothing bad they do to people here. Just take your time with all your people and come out of the bush.*"[8]

Following years of harsh conflict, the Ugandan government and the LRA signed a fragile ceasefire through the 2006 Juba peace talks. These talks permanently broke down in 2008 when, as part of the US-supported Operation Lightning Thunder, the armed forces of Uganda, DR Congo and South Sudan launched aerial attacks and raids on the LRA camps in northern DR Congo. This was soon met with brutal revenge by the LRA on local communities as it began its dispersion in north-eastern Democratic Republic of Congo, eastern CAR and western South Sudan. Following this de facto expulsion of the LRA from Uganda in 2008, the FM messaging model was soon elevated as a policy tool to diminish LRA forces in the isolated border regions. With the assistance of the American NGO Invisible Children and the United Nations Organization Stabilization Mission in the Democratic Republic of Congo (MONUSCO), new radio stations were built and other community stations were expanded. One community station in the Central African Republic (CAR), Radio Zereda, went from operating with a car battery and an umbrella skeleton to an estimated broadcast radius of almost 200 km in 2011. Today, in affected areas, FM stations cover about 300,000 square km.

While we cannot directly observe combatants receiving defection messages through the FM radio broadcasts, qualitative evidence suggests that exposure to such messages is high. For instance, Rigterink et al. (2016) find that 65% of the households in the LRA-affected counties of Ezo and Tambura in South Sudan heard messages targeting the LRA in 2013. This is despite the fact that only 33% of interviewed households owned a radio and only 27% could receive the radio signal broadcasting defection messaging, since many more had access to radios in communal spaces. Another study finds 89% of returnees citing defection messaging as "influential in their decision to escape" (Invisible Children, 2013). Results from our own independent survey of ex-combatants in northern DRC show that 73% of the respondents were listening to the radio while with the LRA. Of this 73%, 89% had heard defection messages over the radio during their stint with the LRA (65.5% of the full sample). Furthermore, 94% of respondents had heard other members discussing these broadcasts. Combining direct and indirect exposure, 95.5% of the respondents were exposed to radio messages. Finally, 67% of our respondents say that defection broadcasts influenced their

[7]More than 27,000 ex-combatants have returned home under the Amnesty Act of 2000 (Arieff et al., 2015).

[8]Additional examples are provided in Appendix D.

decision to return.[9]

Figure 1 plots the geographic distribution of LRA-related events for the period 1989–2015, divided into pre-2008 and post-2008 periods. The geographic areas affected by the conflict differ markedly across the two periods. This paper focuses on the expansion of the defection program in the border regions of Uganda, DR Congo, South Sudan and CAR in the post-2008 period, during which the conflict moved well beyond Uganda and spanned the bordering regions of four countries.

3 Conceptual framework

In this section, we draw on different strands of the theoretical literature to provide a conceptual framework for the empirical analyses we undertake in this paper. We start by looking at the literature on persuasive communication to explain why defection messaging might be effective in influencing rebels to come back (see DellaVigna and Gentzkow, 2010, for a review of the literature). Following this literature, defection messaging can be considered as an instrument of persuasive communication which can affect behavior through one or both of two models: the belief-based model and the preference-based model. In our context, we think that both these types of models could be relevant.

A belief-based model would consider combatants as rational agents relying on Bayesian updating based on new information received from the defection messages. If the information is credible and relevant for their decision-making, then combatants change their behavior by updating their perception of costs and benefits associated with the decision to leave the armed group. In our context, this is plausible for three reasons. Firstly, the most common source of news for LRA combatants is radio broadcasts (Lancaster et al., 2011). Results from our survey in northern DRC also support this finding. This suggests that, at least a priori, information channeled using radio messages could reach its target audience and potentially influence their beliefs. Secondly, credibility was directly targeted in the design of defection messages. The choice of former fighters, family or community members directly signaled credibility about the content of the information broadcast, and especially about the possibility of returning to civilian life without consequences. Lastly, secondary evidence suggests that defection messaging indeed had an impact on beliefs. By looking at civilians, Rigterink and Schomerus (2016) show that LRA-targeted defection messaging in South Sudan led civilians to show higher anxiety and fear of a potential LRA attack, hinting at individual beliefs being affected by the messages.

In a preference-based model, even if agents are not fully rational and messages are non-informative, communication can affect fighters' behaviors if two conditions are met. First, if they either implicitly value the act of going back to civilian life or being part of the LRA, and second, if defection messaging can impact these values. Given the origins of the LRA conflict, intrinsic motivation to fight for the LRA played an important role in motivating rebels. In the

[9] See Appendix Section C for more details on this survey.

early history of the group, fighters saw themselves as fighting in defense of their community, the Acholi, which had been marginalized, abused, and excluded under different regimes in independent Uganda (Schomerus, 2007). Furthermore, common Acholi religious beliefs, a unique blend of Christian and traditional practices, also played a central role in motivating the group in its early stages (Lancaster et al., 2011).

Later, the LRA used violence and the threat of punishment as the main instruments to coerce abducted individuals into fighting. However, indoctrination played an important role in shaping their motivation, especially in the context of child soldiers (Beber and Blattman, 2013). While ideology and spirituality provided motivation for fighters to remain in the armed group, qualitative evidence suggests that it was the *status* achieved by fighters that often drove their decision to continue fighting in the later stages of the conflict (Titeca, 2010). The choice of emotional messages during defection broadcasting specifically targeted such intrinsic motivation. The appeal to emotions and a non-confrontational approach (attempting to de-escalate the situation) could play a complementary role to the informative content of messages by influencing the intrinsic motivation among fighters. Hence, we think that the preference-based model could be as plausible as the belief-based model in explaining why defection messaging might matter.[10]

Another relevant factor in combatants' decision to defect (or to continue fighting) is economic incentives (Blattman and Miguel, 2010). If fighters are driven not only by beliefs and preferences, but also by economic incentives, then the relative trade-off between fighting or leaving the group could influence the effectiveness of messaging. The economic incentives literature has focused widely on the role of commodity price shocks as a source of economic/income shocks (Berman et al., 2017; Dube and Vargas, 2013). Commodity price shocks can generate opposing effects on conflict depending on the type of commodity under consideration. Shocks that disproportionately increase household income compared to state income are expected to reduce conflict intensity through an opportunity cost mechanism. This is the case of labor-intensive, smallholder-owned, and difficult-to-tax commodities, such as annual agricultural crops (Dal Bó and Dal Bó, 2011). In this setting, commodity price shocks can reduce the intensity of conflict by increasing wages and reducing the labor supply for conflict activities (Becker, 1968; Grossman, 1991; Hirshleifer, 1995). On the other hand, positive shocks to capital-intensive or easily appropriable commodities which accrue mainly to the state could increase conflict by increasing the returns to predation (Fearon, 2005; Dube and Vargas, 2013). Commodity price increases in this type of extractive capital-intensive sector increase resource rents, making the state a more valuable prize, and increasing incentives to seize it (Grossman, 1995; Bates et al., 2002). Alternatively, however, rising revenues can also increase *state capacity* and its ability to defend and strengthen control over the territory (Fearon and Laitin, 2003; Snyder, 2006; Ross, 2012). If any of these mechanisms are at play, then the effectiveness of defection messaging crucially depends on incentives (or disincentives) to fight generated by these income shocks.[11]

[10] Since defection messages targeted both beliefs and preferences of fighters, we cannot disentangle the relative role of each mechanism in encouraging defections in our current set-up. We leave this for future research.

[11] Apart from these, social interactions and peer effects can also influence the effects of mass media (Katz and

4 Data

Our time-varying cell-level dataset collates data from a myriad of sources. In this section, we provide a detailed description of the main variables used in the paper.

4.1 FM radio stations and coverage

Our defection messaging data are based on an original survey of an exhaustive set of radio stations that have broadcast defection messaging content aimed at the LRA at any time. To start, we generated the universe of participating radio stations by cross-referencing policy reports and through direct exchanges with international actors and radio operators. We then designed and administered a questionnaire aimed at the radio station managers of these participating radio stations. Collating the data from the survey, we constructed a panel dataset with information about each station's LRA-related messaging, including content and frequency, as well as other station characteristics, such as the normal (non-defection) programming. We also collected time-varying information on the technical characteristics of each radio station, including their exact geographic location, antenna height, and transmitter power, from which we calculated the geographical reach of each radio station.

We attempted to collect data on all 26 radio stations with 30 antennas that have broadcast defection messaging targeted at the LRA at any time. However, while we were able to identify and locate the radio stations broadcasting defection messages during the pre-2008 period (including stations in Uganda), the data on actual defection messaging during this period are fuzzy. Furthermore, due to peace talks, defection messaging had endogenously stopped in 2006. Hence, we restrict our analysis to the 21 antennas belonging to 19 radio stations that broadcast defection messaging during the 2008–2015 period. During this period, the broadcasting of defection messaging expanded over time in multiple dimensions. While some existing radio stations increased their coverage by improving their antennas, new radio stations opened in other areas. Figure 2 shows the coverage of radio stations undertaking defection messaging in the LRA-affected area across four distinct years during our study period. During this period, while most radio stations broadcast defection messaging continuously once they started, two stations ceased broadcasting by the end of 2015 due to technical failures (this includes a station that stopped due to a lightning strike).

While the expansion of radio messaging is possibly endogenous to conflict outcomes, as part of our identification strategy, we exploit the exogenous variation in the exposure to radio signals arising from the randomness of topography (explained in detail in Section 5). Following the previous literature, we construct radio coverage corrected for topography using the Longley–Rice / Irregular Terrain Model (ITM) (Enikolopov et al., 2011; Yanagizawa-Drott, 2014; Olken, 2009; Adena et al., 2015; DellaVigna et al., 2014). This model takes in station parameters and topographic characteristics to determine which areas receive a signal from the station and at what strength at

Lazarsfeld, 1955; Durlauf, 2004). For the sake of brevity, we abstain from discussing the role of social interactions here, but discuss it in the empirical section.

a maximum of 90 m resolution. Appendix Section B.1 provides further details on this procedure, including an example of radio coverage corrected for topography. Figure 2 shows the coverage of radio stations broadcasting defection messages incorporating this correction. Table 1 presents the descriptive characteristics of the radio stations using antennas as a unit of observation. Among our 30 radio antennas, 29% were based in CAR, 38% in Democratic Republic of Congo, 19% in South Sudan and 14% in Uganda. Among all radio stations that participated in the defection messaging program, 57% were broadcasting defection messages in 2015. During the period of 2008–2015, on average, radios were broadcasting broadcasting approximately 80 minutes of defection content daily. Radio signals reached approximately 101 km, on average, from the radio towers.

4.2 Conflict intensity

Our primary LRA-related conflict data are based on the LRA Crisis Tracker (LRACT) database. LRACT is an event-based data collection project that began in 2008 through the efforts of two policy NGOs: The Resolve LRA Crisis Initiative and Invisible Children. The goal of LRACT is to provide detailed and disaggregated data on LRA activities to better inform policy actors' strategies and activities. It provides geo-coded information about LRA-related events, including fatalities, defections, abductions, violence against civilians, clashes with security forces, and looting across space and time. Nearly all the events are located in the Central African Republic, Democratic Republic of Congo, South Sudan, and Uganda. LRACT reports events at the maximum spatial resolution of the population center where the event occurred and at maximum temporal resolution of the day of the event. Appendix A.2 provides additional information on the composition, definition and evolution of the conflict events over time .

We supplement the LRACT data with conflict data from the Uppsala Conflict Data Program (UCDP) and the Armed Conflict Location & Event Data Project (ACLED) databases. Each of these datasets provides event-based information, supplying precise dates and geo-coded locations of events across our area of study. The data collection methods are similar across the three datasets and these include reports from news agencies, NGOs, and governments. But beyond this, LRACT uniquely draws on a widespread network of field sources, some linked by high frequency (HF) radio. This allows LRACT verifiers to find deeper and corroborating accounts of events sourced from other channels, as well as report events that are not captured by alternative event-based datasets. While LRACT, UCDP and ACLED all aim to measure the same basic trends in conflict intensity, they use slightly different definitions. The LRACT logs any reported sighting or event plausibly involving the LRA. UCDP qualifies an event as "an incident where armed force was [used] by an organized actor against another organized actor, or against civilians, resulting in at least one direct death at a specific location and [on] a specific date" (Sundberg and Melander, 2013). ACLED collects and codes all events identified as political violence in the developing world, focusing on civil and communal conflicts, violence against civilians, rioting and protesting.

In Figure 3, we plot and compare the evolution of LRA-related violence from the three different datasets for the years 1997 to 2015 (the LRACT database is available only from the year

2008 onwards). The left panel presents the number of events and the right panel shows the number of total fatalities. While in the left panel the LRA Crisis Tracker's broader definition of events is apparent, in general, we notice that the events from the three datasets follow similar trends.

4.3 Grid-cell construction

To construct our units of observation, we superimpose a grid of equally-sized cells over the territory affected by the LRA and hold this stable over the entire period of analysis.[12] This grid-cell-based approach avoids the potential endogeneity of political boundaries to violence and allows us to control for time-invariant unobservable characteristics that are cell-specific (Harari and La Ferrara, 2013). This is particularly relevant in our context, since many conflict events are concentrated in the bordering regions of multiple countries. Nevertheless, we replicate our analysis using district-level administrative boundaries, showing that our conclusions are unaffected (see Appendix B.13).

There are no clear precedents in the literature on what the appropriate grid-cell resolution ought to be. Instead of taking a stand on the issue, we draw on the geography literature and choose grid cells of 0.125° $\times$ 0.125° resolution (approximately 14 km $\times$ 14 km at the equator) based on the geography of point patterns (Boots and Getis, 1988). However, as we will show later, our results are robust to using alternative grid resolutions. Finally, we aggregate events at the cell-year level over the period 2008–2015 to generate our final conflict database. Aggregating events reduces the possibility of measurement errors in the exact location and timing of each event. Table 1 presents descriptive statistics of violent events occurring in a given cell, as well as descriptive statistics on radio coverage and characteristics of defection messaging content. The sample includes all cells for the whole period of analysis.

4.4 Additional data

We supplement our database with additional cell-level information on a wide range of variables. Appendix A.1 provides detailed information on variables described here and on additional variables used in the paper. In Section 5, we discuss what variables are used as controls in our estimating equation.

Firstly, we exploit satellite-image-based information on economic/income shocks. Income shocks could both directly affect conflict outcomes and influence the effectiveness of defection messaging. Following a wide stream of papers, we measure income shocks by commodity price shocks (Berman et al., 2017; Dube and Vargas, 2013). We first select the main cash crops and extractive minerals for each of the four countries that form part of our study area from the CIA World Factbook (see Table B14 for a full list of included commodities). Then, as is standard in the literature, we construct commodity price shocks combining the geographical distribution of

[12] We provide a more detailed discussion about the choice of the grid extent and robustness to alternative grid extents in Appendix B.2, and about the choice of cell resolution, including its effect on our main estimates, and the modifiable areal unit problem (MAUP) in Appendix B.3. See Figure B6 for a graphical representation of the grid resolution.

commodities with yearly commodity-specific price variations in international markets. Following Bazzi and Blattman (2014), we define the price shock for any commodity as the difference in their log prices on the international markets between times t and $t-1$. Since the area under consideration is not a world-leading producer in any of the considered commodities, international prices are exogenous to the local production. Finally, to take into account the differences in the extent of crops cultivated within each cell, we multiply the price change with the percentage of the cell historically farmed with each crop (see Appendix B.11 for further details).

Existing studies focusing on the role of commodity price shocks in conflict reach seemingly different conclusions. Some find no relationship (Deaton et al., 1995), some a positive relationship (Ciccone, 2011; Savun and Cook, 2010), and others a negative relationship (Besley and Persson, 2008). These contrasting findings might be due to the selection and coverage of the commodities considered (Bazzi and Blattman, 2014; Dube and Vargas, 2013). Instead of taking a stand on which shocks ought to be considered, we rely on LASSO (least absolute shrinkage and selection operator) regressions for covariate selection.[13] The LASSO regressions provide objective criteria on which shocks are relevant in the context of the LRA conflict. Running LASSO regressions with fatalities as our main dependent variable of interest, we identify cotton and groundnut oil price shocks as relevant in our context.

Secondly, we supplement our dataset with time-varying weather data. This allows controlling for possible confounders of commodity price shocks and for additional climatic factors potentially affecting violence. These include cell-level data on rainfall, temperature, and the share of a year experiencing drought. In order to ensure comparability of the measure of rainfall on LRA activity across cells, we double standardize rainfall deviations following Hidalgo et al. (2010).[14] We compute deviations in yearly mean temperature (in degrees Celsius) using a similar procedure, but restricting the standardization to the year level.

Thirdly, to gather information on potential confounding channels of defection messaging, we collect information on mobile phone coverage and general FM radio coverage. We build cell-level mobile phone coverage using the Collins Mobile Coverage Explorer (GSMA, 2012), which provides geo-located information on yearly mobile phone coverage. Using this information, we build the percentage covered by the GSM (or 2G) network. During the period of interest, our area of interest is not covered by any of the other types of mobile phone network, such as 3G or 4G. We construct general FM radio coverage from FMLIST, an open-source worldwide radio station

[13] We implement two distinct approaches to determine the degree of penalisation: 10-fold cross-validation, which optimizes the out-of-sample prediction performance; and the corrected Akaike Information Criteria (Sugiura, 1978; Hurvich and Tsai, 1989). We keep only the commodity price shocks that are accepted by both approaches. For further reading on LASSO regressions, please refer to Tibshirani (1996), Friedman et al. (2001), and Tibshirani et al. (2015). For specific applications of LASSO in economics refer to Athey and Imbens (2017) and Varian (2014).

[14] We first account for seasonal patterns by standardizing monthly rain totals by cell and month for the period 2000–2015. For each cell, these indicators are then summed up by year and standardized over the same period. We then use the absolute value of standardized rainfall as our main measure to capture the non-monotonic relationship between rainfall and income changes. Our results remain similar using alternative functions of rainfall deviations (such as its square), linearly and non-linearly de-trended rainfall (Fujiwara et al., 2016), measures of growing-season-specific rainfall, or current and lagged year-on-year precipitation growth (Miguel et al., 2004; Ciccone, 2011).

database containing technical data of active FM radio stations from across the world.[15] As we do for the radio stations broadcasting defection messaging, we use the Longley–Rice / Irregular Terrain Model (ITM) to compute coverage corrected for topography at the cell level. Figure 4 presents GSM mobile phone network coverage in 2015 and general FM radio coverage in our study area. A total of 18% of the study area is covered by the GSM network, while 32% is covered by alternative FM coverage (corresponding to more than 500 radio stations). It is important to note that most of the area with higher intensity of LRA conflict during the period 2008–2015 is not covered by either GSM or general FM signal. In addition, GSM mobile phone coverage changes very little during this period (see Appendix Figure B3).

Finally, a number of socio-economic and geographic indicators that are mainly used for robustness checks are computed merging the grid dataset with the original source or aggregating at the cell level. Please refer to Appendix A.1 for further details.

5 Empirical strategy

To identify the causal effects of radio defection messaging on the LRA conflict, we rely on three sources of plausibly exogenous variation. First, following a burgeoning trend in the literature, we exploit local topographic variation as a random determinant of signal reception (see, for instance, Enikolopov et al., 2011; Yanagizawa-Drott, 2014; Olken, 2009; Adena et al., 2015; DellaVigna et al., 2014). The propagation of FM radio signal depends primarily on the height and power of each antenna. Without obstacles, the attenuation of the signal is proportional to the square of the distance from the antenna. In the presence of physical obstacles such as hills, mountains, or buildings, the signal can be physically blocked, creating patterns in the local coverage of the radio signal which are exogenous to local political and socio-economic conditions or conflict outcomes (see, for instance, Figure B2). Second, given the time-varying nature of our data, we are able to use cell-level fixed effects. This captures all unobserved characteristics of the cell that are invariant over time. This is particularly important in our setting, as it eliminates the possibility that at any particular point in time certain cells experience violence either due to their topography or due to other characteristics that do not change over time.

Finally, while correcting for topography and employing a cell fixed effects strategy that allows us to identify local exogenous variation in exposure to defection messages, we strengthen our identification strategy further by looking at the intensity of exposure to these messages rather than mere exposure. While exposure refers to the percentage of the cell covered by a radio signal adjusted by topography, intensity takes into account the actual number of hours of messaging reaching each cell. Exploiting the random overlap of different radio signals, we construct a measure of messaging intensity by summing up the daily exposure from each radio within each cell.

[15]These data are unfortunately available for only one point in time, corresponding to the moment in which the database is downloaded. We use data at the end of 2017. See DellaVigna et al. (2014) for a previous use of the dataset.

We define intensity of defection messaging by:

$$dm_{it} = \sum_{j=1}^{J} c_{ijt} h_{jt} \tag{1}$$

where c_{ijt} is the percentage of cell i covered by radio j at time t, and h_{jt} is the number of hours of defection messaging daily broadcast by radio j at time t.[16] Intensity is therefore set to 0 if either the cell is not covered by any defection messaging at a certain point in time or if it is covered by a radio station not broadcasting any defection messaging. Figure 5 illustrates how, in the presence of multiple radio stations, topography can generate random differences in the total number of hours of messaging to which each cell is exposed. Appendix Figure B3 plots the evolution of exposure or coverage (left panel) and the intensity (right panel) of defection messaging content over time. In Appendix B.5, we consider alternative measures of exposure to defection messaging. We consider average intensity, by dividing dm_{it} by the number of radio stations messaging in a particular cell, and the percentage of cell coverage by defection messaging, which does not consider frequency of messages. Our conclusions are robust to these alternative definitions.

Our defection messaging intensity variable has grouped different types of defection messaging content together: messaging involving sensitization content and messaging involving logistical content. Sensitization content primarily refers to programs with interviews of ex-combatants, family members and community leaders, where the interviewees talk about their experiences on returning, or make emotional appeals to their friends and kin to return home. Logistical content, on the other hand, comprises logistical information on surrendering, such as location of safe defection points. Later, we will show that our results are robust to splitting the intensity variable by the two types of content.

Our primary objective is to measure the effect of the intensity of defection messaging, dm_{it}, on LRA-related conflict outcome variables, denoted by y_{irt}, in cell i in macro-region r at time t. To this end, we estimate the following model as our main specification:

$$y_{irt} = \gamma_i + \alpha\, dm_{it} + \mathbf{X'}_{it}\beta + \delta_t M_r + u_{it} \tag{2}$$

where $\mathbf{X}_{it}$ is a vector of cell-level time-varying characteristics, γ_i are cell fixed effects and u_{it} are idiosyncratic error terms. We select controls $\mathbf{X}_{it}$ using a LASSO regression with our main outcome of interest, fatalities, as the dependent variable. The resulting list of controls includes: cotton price shock, groundnut oil price shock, rainfall and temperature deviations, and the fraction of a year characterized by drought. We include macro-region-specific time fixed effects by dividing our grid into eight macro-regions and introducing interaction terms between the time fixed effects, δ_t and macro-region indicators, M_r. In Appendix B.4, we also extend equation (2) to control for differential trends associated with potential determinants of conflict by adding interaction terms

[16]For some stations the frequency of messaging is not daily. In these cases, we computed h_{jt} by dividing the total broadcast time of defection messaging in a week by 7.

between year dummies and cell-level terrain ruggedness (Nunn and Puga, 2012), ex-ante income (proxied by nightlight), ex-ante population, urban area indicators, and country indicators. In all specifications, we normalize dm_{it} to ease the interpretation of the coefficient.

Our parameter of interest, α, captures the effect of an increase in the daily intensity of defection messaging at full cell coverage. Since we measure radio signal coverage corrected for topography, defection messaging intensity is plausibly exogenous to conflict. However, one possible threat to identification could arise if antennas have been placed endogenously to the conflict. This would be the case if antennas have been placed in locations where violence increased (or decreased) and the distance from the antennas hide unobserved determinants of violence. We rule out the possibility of endogenous location of antennas by controlling for distance from active antennas. Following Yanagizawa-Drott (2014), we control for distance from the closest active antenna and its square. In addition, since multiple antennas might cover a single cell, we also control for the median distance from all active antennas and its square. Since signal strength in a specific cell is also affected by terrain ruggedness, we also interact distances with this indicator. We allow for a flexible functional form in the way distance enters our main estimating equation, since this variable is important for our identification strategy. Our results are robust to less flexible forms, such as controlling only for the minimum distance from active antennas. Finally, in Section 6.4, we also discuss the possibility that each radio responded to an expected reduction in violence with increased radio messaging. We do not find evidence of this possibility.[17]

Since we observe events over time and space, we need to take into account that data can be correlated both spatially and temporally. As is evident from Figure 1, LRA violence appears to be highly spatially correlated. When estimating equation (2), we are therefore concerned not only about serial correlation of violence within each cell over time, but also about spatial correlation between adjacent cells. To correct for this, we estimate standard errors using the correction outlined by Conley (1999, 2008) and Hsiang (2010). We allow for correlation to be over the full time window of the dataset, and we allow for spatial correlation across cells within 100 kilometers. This cut-off is in line with other contributions in the literature, such as that of Harari and La Ferrara (2013). Our results are robust to using alternative cut-offs.

One general drawback of using conflict datasets is that events in areas where media coverage is higher may be more likely to be reported. At the same time, conflict tends to affect media coverage, as reporting from affected areas is more dangerous. Since we are directly interested in coverage, we acknowledge that our estimates might contain errors, but we expect that this would only under-estimate the importance of defection messaging. Finally, since we cannot directly observe LRA members listening to radio messages, our estimates can be interpreted as an intention-to-treat

[17] We use Demographic and Health Surveys (DHS) data for Democratic Republic of Congo and CAR to test whether, in the study area, pre-existent household characteristics correlate with the future intensity of defection messaging in a village. We do not observe any significant effect of future intensity of messaging on pre-existent wealth (unavailable for CAR), education or fertility. This supports the exogeneity of messaging intensity. However, due to the sampling strategy of the DHS and the remoteness of the study area, this analysis can be carried out only with a very small number of DHS clusters and cannot be generalized to the whole study area.

effect of defection messaging. However, available qualitative evidence suggests widespread exposure to defection messaging, with the proportion of returnees citing defection messaging as being influential in their decision to return ranging from 67% (our survey in northern DRC) to almost 90% (Invisible Children, 2013).

6 Results

In this section we present our main results. We first focus on the effectiveness of defection messaging in mitigating conflict (Section 6.1) and then examine the effects of economic shocks (Section 6.2). Next, we undertake a host of robustness exercises (Section 6.3) including a placebo test (Section 6.4). Finally, using an instrumental variable specification we gauge the magnitude of returnees on the different conflict outcomes (Section 6.5).

6.1 Effectiveness of defection messaging

Fatalities

We start by examining the effects of defection messaging on violent conflict as measured by fatalities. In Table 2, we estimate equation (2) by using the log number of total fatalities, from three alternative sources, as the dependent variable.[18] While in columns 1 to 3 we use data on fatalities from the LRACT dataset, in columns 4 and 5 we use fatalities data from the ACLED and UCDP datasets. In column 1, we only control for cell- and year-specific fixed effects and for propagation controls (including controls for distance from active antennas in different forms, as explained in Section 5). In column 2, we additionally control for other time-varying controls, including commodity prices and weather shocks. Finally, in column 3, we include macro-region-specific time fixed effects in addition to the controls from the previous columns. This represents our most complete, and hence preferred, specification. In columns 4 and 5, we replicate the specification from column 3 using fatalities data from the ACLED and UCDP datasets. Table 2 shows that defection messaging significantly reduces LRA-linked fatalities. Controlling for differential trends associated with different determinants of conflict, such as cell-level terrain ruggedness, ex-ante income (proxied by nightlight), ex-ante population, urban area indicators, and country indicators, does not affect our results (see Appendix B.4).

Using data from the LRACT database, we estimate that a one standard deviation increase in messaging intensity reduces the number of fatalities by approximately 3%. This corresponds to approximately 48 minutes of daily messaging at average cell coverage (roughly 40% of the cell) or 19 minutes of daily messaging when the cell is fully covered by the radio signal. Columns 4 and 5 demonstrate that this result is robust to using data on fatalities from the ACLED and the UCDP datasets. The marginal effect is similar using the UCDP dataset, but somewhat smaller using the ACLED dataset. This is possibly a reflection of the slightly different definitions of

[18]Throughout the paper we add one to outcome variables before taking logs to accommodate 0 values.

the conflict variable across the three datasets. While ACLED and UCDP provide less detailed information about LRA activity and use different definitions of violent events, they corroborate our main results based on the LRACT data. Unless otherwise specified, in the next tables we will always use the LRACT dataset due to unavailability of data on other variables of interest apart from fatalities in the ACLED and UCDP datasets.

In Table 2, we have used the log number of fatalities as our main dependent variable. However, our results are robust to using alternative measures of fatalities, such as the number of fatalities normalized either by the population or the available land (Appendix B.5), and by restricting the sample to cells closer or further away from active antennas (Appendix B.6). Again, while our primary independent variable measures the intensity of defection messaging, many of the FM radio stations broadcasting defection messages also broadcast alternative content not related to defections. One could argue that our intensity of defection messaging variable is picking up the effects of general coverage by these specific radio stations rather than defection messaging. To rule out this possibility, we exploit information on the frequency of broadcasts of alternative content (including news broadcasts, religious preaching and entertainment programs) by our FM radio stations to build a measure of intensity of broadcast of alternative content (similar to equation [1]). Our estimates on the effect of defection messaging are not affected by the inclusion of this intensity of alternative messages variable as a control (Appendix B.7). Moreover, the broadcast of alternative content itself has no effects on the LRA conflict (see columns 1 and 2 of Appendix Table B9). Furthermore, while in our main specification we focus on the contemporaneous effect of intensity of defection messaging, using the lagged value as an alternative leads to similar conclusions (see Appendix B.5).

Our primary independent variable measures defection messaging intensity by grouping different types of messaging together. In Appendix Table B9 (columns 3–5), we show that our results are robust to splitting the intensity variable between sensitization intensity and logistical content intensity.[19] Appendix Table B9 (column 6) also shows that our results are not affected by controlling for predicted free-space *circular coverage* of the surveyed radio stations. Circular coverage does not correct signal reception for topography and hence captures the coverage of the radio signal in the absence of (random) topographic variation. This is computed using a free-space propagation model, which captures the attenuation and maximum reach of an audible signal in the absence of obstacles on flat terrain. Adding this variable as a control allows us to isolate the effects solely due to idiosyncratic variation in topography (Olken, 2009). If topography is indeed random, adding this control variable should not affect our main estimate. This result is also confirmed by the low correlation between circular coverage and intensity of messaging (0.43 in the whole study area, 0.36 if restricted to be within 100 km from an antenna). Furthermore, as already mentioned in the previous sections, our results are not dependent on the choice of cell-resolution (Appendix B.3)

[19]Since both these types of content were often broadcast together (correlation between the two measures is 0.96), we acknowledge that given our current empirical set-up, we cannot disentangle the relative effectiveness of each of these types of content. When they are added together in the specification, they are individually insignificant, but jointly significant.

and are robust to using administrative units instead of grid cells (B.13).

Composition and strategy

Next, to understand why a higher intensity of messaging leads to a reduction in fatalities, we focus on changes in both the composition and strategic behavior of the LRA in response to defection messaging. In particular, in Table 3, we examine the effects of the defection messaging campaign on five different variables available from the LRACT database: returnees (columns 1–2), abductions (columns 3–4), violence against civilians (columns 5–6), clashes with security forces (columns 7–8) and looting (columns 9–10). The odd-numbered columns 1, 3, 5, 7 and 9 represent a more parsimonious specification (as in column 1 of Table 2), while the even-numbered columns 2, 4, 6, 8 and 10 represent the more comprehensive specification (as in column 3 from Table 2).

In columns 1–2 of Table 3, we see how a higher intensity of defection messaging leads to a significant increase in the total number of returnees. A one standard deviation increase in the intensity of defection messaging leads to an increase in the number of returnees by approximately 1%. Defection messaging was thus effective in achieving its direct objective of encouraging LRA members to return to civil society. In Appendix B.8, we undertake additional analysis to understand whether the increase in the number of returnees is driven by inter-dependencies between fighters in their decision to return. We do not find evidence of such inter-dependencies. Intensity of defection messaging primarily increases defection events characterized by one or two individuals defecting at a time rather than group defections involving three or more individuals (Appendix Table B10).

In contrast to the absence of inter-dependencies in fighters' decisions to return, our survey of ex-combatants in DRC provides evidence of inter-dependencies linked to information transmission. While 65.5% of the survey respondents had heard defection messages directly themselves, more than 94% had been exposed to defection messages through other group members. Unfortunately, since we cannot observe the location and quantity of fighters and also since the armed group units tend to move very often, we cannot empirically test the role of information spillover among fighters. This suggests that while the radio messages reach the individual fighters either directly because they themselves listen to the radio or indirectly from fellow combatants who share the information they have heard on the radio, the final decision to defect is primarily an individual decision.[20]

Next, in columns 3–4 of Table 3, we examine how defection messaging affects the number of abductions by the LRA. Abduction has been a central recruitment strategy throughout the LRA's history. Estimates suggest that around 60,000 to 80,000 youths were abducted by the LRA for at least a day between 1995 and 2004. The majority of the victims were adolescents, targeted due to the ease of indoctrinating children (Annan et al., 2006; Beber and Blattman, 2013). It is possible that the LRA responds to the defection messaging-induced loss in manpower by increasing the

[20] In Appendix B.12, we also investigate the presence of spatial spillover of defection messaging, but do not find strong evidence of spatial spillover.

number of abductions. However, as can been seen from the results in columns 3–4 of Table 3, we do not find any evidence for this possibility. If anything, we see that defection messaging reduces the number of abductions by the LRA, albeit with this effect not being statistically significant.

Next, in columns 5–8 we examine the effects of defection messaging on violence against civilians and clashes with state security forces. We find that a higher intensity of defection messages reduces both these variables. A one standard deviation increase in messaging intensity decreases the number of these events by approximately 1%. This suggests that one possible mechanism in which defection messaging translates into a reduction in fatalities is through a decrease in the attacks carried out against civilians or clashes with security forces.[21]

Finally, in columns 9–10 of Table 3, we examine the effects of defection messaging on looting. We notice that while defection messaging has a benign effect on fatalities, returnees, abductions, violence against civilians and clashes, it significantly increases events characterized by looting. A one standard deviation increase in the intensity of defection messaging increases looting events by 1.6%. This is consistent with two potential mechanisms. First, looting could be used to reduce the relative returns to non-military labor efforts for potential recruits, while simultaneously generating spoils to reward existing recruits (Azam, 2002, 2006). Second, looting can be considered as a survival strategy. Groups that have been significantly reduced in strength by defections might be unable to exert the control they once had over either territory or their regular sources of finance. This might drive them to either abandon the armed struggle or engage in looting as a means of survival. We discuss this in more detail below.

Non-linearities

The marginal effects described above potentially hide non-linearities in the effect of defection messaging on the different outcome variables. To check how the effects of messaging on the different outcome variables vary with how intense the messaging was, we estimate equation (2) by allowing the coefficient to vary non-linearly. More specifically, we use four dummy variables denoting intervals of different intensities of radio messaging: 0 minutes, 0–30 minutes, 30–60 minutes and more than 60 minutes of daily messaging. Figure 6 plots the coefficients for the different outcomes against these intensity intervals. The 0-minute interval serves as the excluded category. Figure 6 shows a significant (non-linear) increase in the effect of defection messaging with intensity of messaging on all the outcome variables. While low levels of intensity have negligible impacts on the different variables, higher levels of messaging intensity lead to significant and large effects. For instance, more than 60 minutes of daily defection messaging (at full cell coverage) leads to a reduction in fatalities by 14.7% and an increase in the number of returnees by 6%. Figure 6 also demonstrates non-linear effects of defection messaging on all the other variables, including violence against civilians, clashes with security forces and looting, but no significant effects on abductions.

[21] See Kalyvas (2006) for how armed groups use violence against civilians strategically depending on their ability to control territory.

From Figure 6, we observe that defection messaging has a significant non-linear effect on looting, with 60 minutes or more of daily defection messaging (at full cell coverage) leading to a 9.7% increase in looting. As mentioned earlier, looting could be strategically motivated to reward existing LRA members (to discourage them from defecting) or it could be a manifestation of LRA's struggle for survival. In Appendix Figure B10, we probe this issue further by examining the types of goods being looted in response to more intense defection messaging. If looting is primarily a strategy to reward members, then we would expect the LRA to increase looting of all types of goods. If, on the contrary, looting is a survival strategy, we would expect higher increases in looting of food and other basic necessities (compared to other goods). Appendix Figure B10 shows that in response to more intense defection messaging, looting increases for most goods, including food, tools, clothes and medicines, weapons, and money. Therefore, we cannot rule out one mechanism over another. Nevertheless, looting of food increases substantially more compared to other commodities. This suggests that even if we cannot entirely rule out other mechanisms, it is likely that looting is used more as a survival strategy. Further, given the absence of a concomitant increase in the violence associated with the looting, it is unlikely that the increased looting represents retaliation by the LRA (see Appendix B.10).This is further corroborated by the fact that only around 0.6% of all looting events involve destruction of property.

Aggregate effects

In the previous paragraphs, we have established that defection messaging significantly reduced LRA-related conflict outcomes. In Appendix B.15, we construct simple counterfactual aggregate estimates of LRA-related conflict outcomes in the absence of defection messaging. Since we observe the conflict outcomes only in the presence of defection messaging, this lets us gauge what the outcomes would have looked like in the absence of defection messaging. Our estimates suggest that defection messaging resulted in somewhere between 33–42% fewer fatalities (or 2,222–2,586 fewer deaths), 33.5% (520 individuals) more returnees, 13.5% fewer violent events against civilians and 9.5% fewer clashes with security forces (see Table B19).

6.2 Defection messaging and economic shocks

As discussed in Section 3, economic shocks can directly affect an individual's expected returns from fighting or returning to civil society. In this section, we examine how income shocks can influence the LRA conflict and thereby the effectiveness of defection messaging. Following a wide stream of papers, we measure income shocks by shocks to the prices of commodities and natural resources (Berman et al., 2017; Dube and Vargas, 2013). Given the lack of consensus in the literature regarding which commodities ought to be used, and being cognizant of the context specificness of each conflict, we rely on LASSO regressions for covariate selection to determine the relevant commodity shocks. These LASSO regressions choose cotton and groundnut shocks as the two relevant commodities in our context from a longer list of commodities and natural resources.[22]

From the previously presented results that include these two economic shocks as controls, we already know that our results are robust to their inclusion. In Table 4, we estimate equation (2) by allowing for heterogeneity in the effects of defection messaging by the two economic shocks on each of our outcomes of interest. First, from row 1 in each column, we notice that the main effect of defection messaging on the different conflict outcomes is unaffected by the inclusion of the interaction terms. In other words, radio defection messaging continues to have a statistically significant and economically meaningful effect in reducing violent LRA conflict and encouraging defections. Next, from rows 4 and 5 in each column, we notice that cotton and groundnut oil price shocks have significant effects on the conflict and that these effects go in opposite directions. While positive shocks to the cotton price reduce conflict, positive shocks to the groundnut oil price enhance conflict. More specifically, cotton price shocks reduce fatalities, abductions (although not statistically significant), violence against civilians, and clashes with security forces, while increasing the number of returnees. In contrast, groundnut oil price shocks have exactly the opposite effect on the different outcomes.[23]

From the interaction terms in rows 2 and 3, we see that the effectiveness of defection messaging is itself a function of these income shocks. The cotton price shock, which is conflict reducing, increases the effectiveness of defection messaging, while the groundnut price shock, which is conflict enhancing, reduces the effectiveness of defection messaging. For instance, for fatalities, a one standard deviation increase in the value of the conflict-reducing cotton price shock (17.2% at full cell coverage) increases the strength of defection messaging by 1 percentage point, taking it to approximately 4%. In contrast, a one standard deviation increase in the value of the conflict-enhancing groundnut oil price shock (7% at full cell coverage) reduces the strength of defection messaging by 1 percentage point, taking it to approximately 2%. The effects of these shocks on the other conflict variables presented in Table 4 are qualitatively similar. These results suggest that economic incentives for fighting have a profound bearing on the effectiveness of defection messaging in abating violence.

Two other findings from Table 4 warrant discussion. First, as in the case of defection messaging, we do not find any statistically significant effect of economic shocks on abductions. This is in line with Blattman and Annan (2010), who argue that abductions by the LRA are close to random. Second, cotton price shocks, which reduce conflict, lead to more looting and also enhance the direct positive effect of defection messaging on looting. Groundnut oil price shocks, on the other hand, reduce both looting and the negative effects of defection messaging on looting. To summarize, shocks that reduce conflict either directly or by enhancing the effects of defection messaging lead to more looting, while shocks that increase conflict reduce looting. This again hints at the

[22] The shocks themselves are measured as a product between the % of the cell farmed with the crop and its log-price difference with the previous year on the international market. See Section 4.4 for more details.

[23] Dube and Vargas (2013) find similar opposing effects in the case of Colombia for coffee and oil price shocks. See Dal Bó and Dal Bó (2011) for a two sector general equilibrium model which can explain the existence of such opposing shocks.

LRA resorting to increased looting for survival when they suffer manpower losses and (negative) economic shocks.

6.3 Robustness checks

In this section, we conduct additional analyses and robustness tests to rule out several potentially confounding channels. We begin by focusing on alternative communication media which might be correlated with both violence and the coverage of defection messaging. In particular, in Table 5, we estimate equation (2) controlling for coverage of two types of alternative media. First, in the odd-numbered columns, we control for GSM mobile phone coverage. Mobile phone coverage can potentially affect political economy outcomes by enhancing individual access to information and coordination among individuals (see Manacorda and Tesei, 2016 for effects on political mobilization). Table 5 shows that our estimates of defection messaging intensity are unchanged by controlling for mobile phone coverage.[24] Second, one could argue that intensity of defection messaging is picking up the effects of coverage of alternative FM radio stations (broadcasting general content unrelated to defection messages) in the area. The even-numbered columns of Table 5 show that controlling for general FM radio coverage does not affect our results. Due to the potential endogeneity of these variables, we do not include these "bad" controls in our main specifications (Angrist and Pischke, 2008).

Next, we investigate the existence of spillover of LRA-targeted defection messaging on other ongoing conflicts. While positive spillover could reduce other ongoing violent conflicts in the region, negative spillover might increase activity by other armed groups as the LRA loses its strength. To investigate the presence of such spillover, we resort to the ACLED and UCDP datasets, which provide information on other armed groups operating in the area. We do not find evidence of any such spillover. While defection messaging exerts a strong negative effect on LRA-related violent events, LRA-targeted defection messaging has null effects on conflict events unrelated to the LRA (see Appendix Table B11). Furthermore, the ACLED and UCDP data allow us to determine whether the LRA is the perpetrator or on the receiving end of violence in LRA-related conflict events. Exploiting these data, we find that while defection messaging reduces both attacks perpetrated by the LRA and attacks against them, the coefficients on violence perpetrated by the LRA are much larger (see Appendix Table B11). This again suggests that defection messaging was particularly effective in reducing LRA-specific conflict activities through the LRA's actions.

Apart from allowing us to analyze the spillover of LRA-targeted defection messaging on other ongoing conflicts, the results from Appendix Table B11 also serve another purpose. One could argue that the expansion of defection messaging took place along with concomitant investments

[24]Mobile phone coverage has a negative effect on some of our conflict outcomes, such as clashes. When we interact mobile coverage with the intensity of defection messaging, we do not find any complementary effect of mobile phone coverage to intensity of messaging in reducing fatalities. Due to the potential endogeneity of mobile phone coverage, we take this result as only being suggestive. These results are available upon request.

in improving the local economy of the affected region (though we have no evidence of such investments). Hence, it is possible that the improvements in the general economic conditions of the region rather than defection messaging are driving our results. However, since our identification exploits topography-corrected intensity of messaging, it is unlikely that economic conditions also follow the same random patterns generated by topography. In addition, if the results were driven by improvements in general economic conditions, we should have seen a decrease in violence by all armed groups rather than just the LRA as the result of defection messaging. The results from Appendix Table B11 rules out this possibility.

Finally, exploiting the ACLED and UCDP datasets further also allows us to rule out confounding effects of possible increases in military action by security forces in areas with higher intensity of messaging. While it is implausible that security forces replicate (or would even want to replicate) the pattern of topography-corrected radio signals, we undertake additional analysis in Appendix B.9 to rule out this possibility. Rather than observing increased military activity, we observe a fall in events in which state forces are perpetrators of violence when the intensity of messaging is higher. Furthermore, controlling for military presence in a specific cell does not affect our estimates of the impact of defection messaging. The reduction in LRA violence as a result of increased intensity of defection messaging is therefore not associated with a contemporaneous increase in military activity (see Appendix Table B12).

6.4 Placebo test: timing of expansion versus location of antennas

In this section, we perform a placebo test by constructing a measure of hypothetical exposure to defection messages through random spatial re-allocations of the radio antennas. Comparing the effect of actual defection messaging with hypothetical exposure allows us to examine the role of antenna location in the reduction of LRA violence. Within the original area of analysis, we randomly generate new locations for the antennas in our data and calculate hypothetical intensity of messaging keeping the timing and frequency of messaging aligned with the actual data. We perform 250 simulations using this method. For each simulation, we estimate equation (2) using our main outcomes as dependent variables and computing the marginal effect of the (placebo) messaging intensity.[25] Appendix Table B18 summarizes the results. We see that the effect of defection messaging with random placebo antennas is, on average, zero for all the variables we have used in this analysis. In particular, the 5^{th}–95^{th} percentiles interval always includes zero.

6.5 IV estimates and the effect of returnees

Thus far, we have established that FM radio defection messaging encouraged combatants to give up arms and return to civil society. We have also seen that such messaging reduces fatalities, abductions (although not statistically significant), violence against civilians and clashes with security

[25] See Appendix Section B.14 for more details. The left panel of Figure B13 shows the randomly generated locations of a single antenna in all 250 iterations. The right panel shows an example of placebo coverage of the sampled antennas in a particular iteration.

forces, while increasing looting. In this section, we try to understand what part of the effect of defection messaging on the conflict outcomes, such as fatalities, is the result of messaging-induced defections, and we speculate on whether there could be other ways in which the radio messages affect the conflict outcomes. We do so by taking an instrumental variable (IV) approach.

Using an IV approach allows us to estimate how much of the change in the conflict variables is driven by returnees. In Table 6, we present the estimates of the IV model, instrumenting the number of returnees in cell i at time t with the intensity of messaging in the same cell and time period. We exploit the non-linear relationship of defection messaging on returnees and use messaging and its quadratic term as two instruments in our first stage. The number of returnees is presented in logarithms and standardized, such that the coefficients are relative to an increase of 13.7% in the number of returnees.

From Table 6, we see that an increase in returnees has large statistically significant effects on fatalities and looting, and a smaller effect on violence against civilians (significant at 10%), but no effects on either abductions or clashes with security forces. A one standard deviation increase in the number of returnees reduces fatalities by 19.4% and violence against civilians by 4.3%, while increasing looting by 17.1%. Overall, this suggests that the intensity of the LRA conflict significantly fell due to defection messaging-induced returnees. However, while in the reduced-form regressions in Table 3 we found a statistically significant effect of defection messaging on clashes with security forces, the effect seems not to be a result of returnees. This implies that there might be other ways in which defection messaging affects the clashes with security forces, in addition to reducing violence by inducing returnees. This raises the question as to whether the exclusion restriction for these IV regressions holds.

The exclusion restriction for these IV regressions requires that defection messaging affects the different conflict outcomes under consideration only through increased returnees. Violations of the exclusion restriction do not affect the findings of our paper but might have a bearing on how we interpret the effects of defection messaging on conflict. We hence resort to recently developed methods by Conley et al. (2012), which allows us to construct bounds on our IV estimates under small violations of the exclusion restriction. In particular, we calculate 95% confidence intervals for our IV coefficients allowing for violations in the exclusion restriction following their union of confidence intervals (UCI) approach.[26] The 95% confidence intervals provided in the lower panel of Table 6 are constructed allowing for the direct effect of defection messaging on conflict, over and above its effect through returnees, to be, respectively, 1, 5, 10 and 15% of its indirect effect on conflict. These confidence intervals show that the effects of defection messaging-induced returnees on fatalities and looting are robust to violations in the exclusion restriction even if we allow the direct effect of defection messaging to be as high as 15%. However, the effects of returnees on violence against civilians or clashes with security forces are less robust.

Overall, the results from these IV regressions suggest that while defection messaging-induced

[26]The UCI approach is the most flexible approach presented by Conley et al. (2012) and does not require any distributional assumptions.

returnees directly reduce the conflict as measured by fatalities, defection messaging possibly also directly affects the strategic behavior of the LRA, which is reflected in an overall reduction in violence against civilians and clashes with security forces. We cannot, however, determine what these direct effects could be in our current set-up, and we leave it for future research.

7 Conclusion

The LRA insurgency has been a costly and bloody conflict wrecking the lives of hundreds of thousands of individuals in multiple countries across central Africa for several decades. Unfortunately, this is only the tip of the iceberg, the mass of which comprises the more than 40 active violent conflicts currently inflicting immense human and economic costs on communities across the world (IRIN, 04/04/2017). While the conflict-resolution community has been scrambling for feasible counter-insurgency policies (Humphreys, 2003), we provide evidence of a policy that actually works. Most armed groups operate in remote locations spanning large areas where conventional military operations are infeasible. We show that in such settings, FM radio messaging can effectively encourage defections among rebels and reduce overall violence.

Apart from establishing the effectiveness of defection messaging as a low-cost, non-violent counter-insurgency policy, our findings provide two additional policy lessons. First, we found that economic incentives measured by commodity price shocks directly affect LRA activity and also the effectiveness of defection messaging. This suggests that counter-insurgency policies should not only focus on the pathway to leave the conflict, but also on the economic incentives that keep fighters in the armed groups. Second, more attention and consideration should be directed to the effects of defections on remaining members. While fatalities can be considered the main indicator of conflict intensity and violence, other actions of armed groups, such as looting, can also be costly for affected communities. We saw that a higher intensity of defection messaging caused increases in looting in the same areas where it reduced fatalities and other forms of violence. This suggests that defection messaging operations should be complemented by interventions that disincentivize fighters from looting.

Our paper also opens up several avenues for further research. While we have shown the effectiveness of defection messaging in general, more work is required to disentangle the effects of emotional appeals by friends and kin from purely logistical information about how to leave the armed groups. Finally, more research is warranted on how defection messaging influences rebels beyond directly encouraging them to return.

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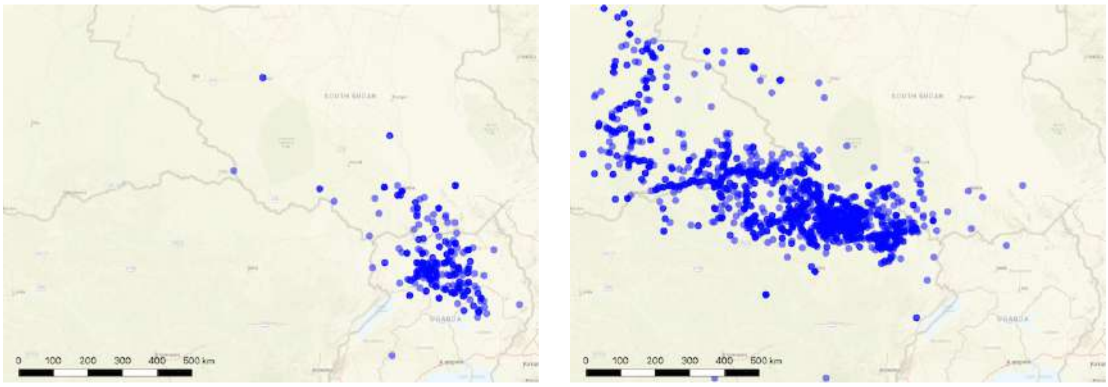
Figure 1: Extent of LRA-related violent events, 1989–2015

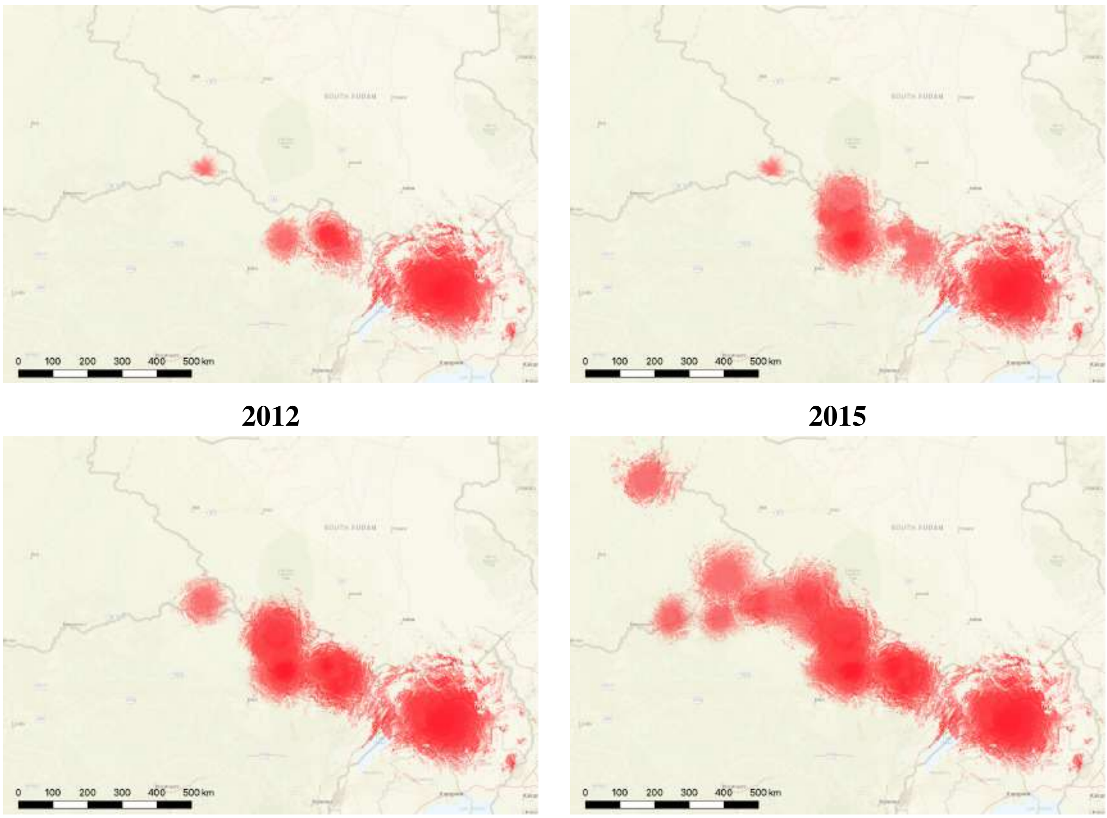
1989-2007 **2008-2015**



Notes. The geographical distribution of LRA-related violent events in the two periods: 1996–2007 (left panel) and 2008–2015 (right panel). The geographic extent of the figure is restricted to the study area. Data source: UCDP dataset (which provides data for the whole period of 1989–2015). Basemap source: ESRI.

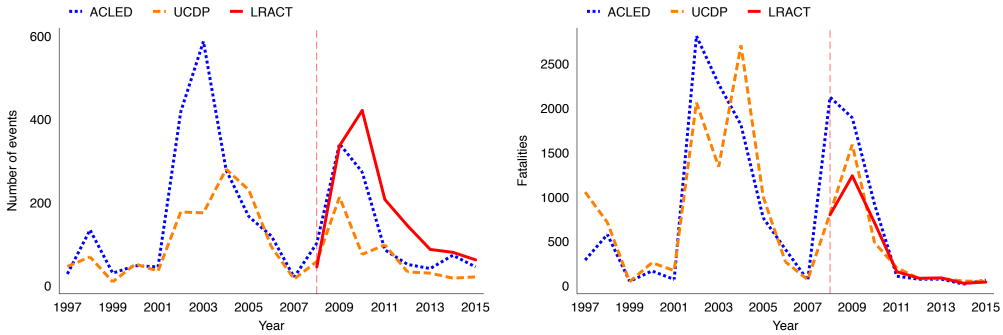
Figure 2: The expansion of radio stations broadcasting defection messaging in LRA-affected areas

2008 **2010**



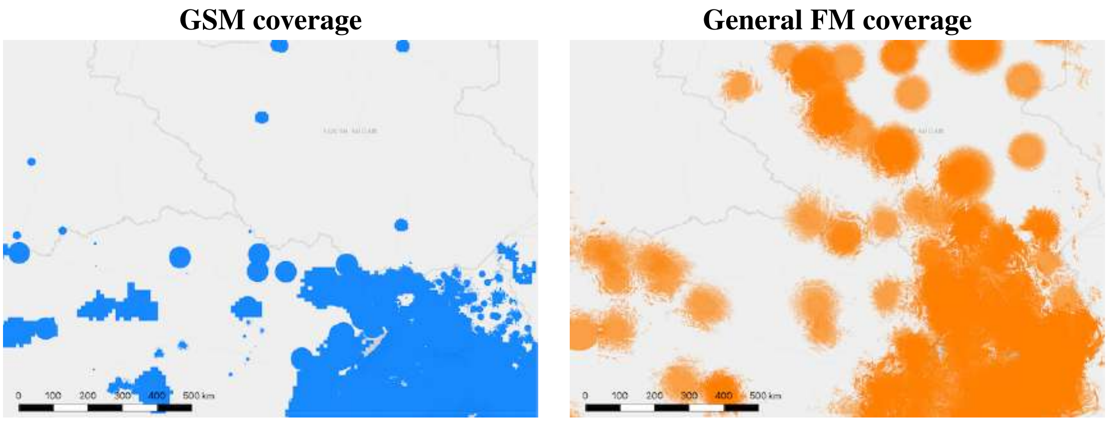
Notes. Coverage of active radio stations in different years. We select all radio stations that broadcast defection messages for at least one year, including the pre-2008 period. Coverage is corrected for topography using technical specifications of the radio stations and applying the Longley–Rice / Irregular Terrain Model (ITM). See Appendix Figure 5 for a comparison with defection messaging intensity. The geographic extent of the figures is restricted to the study area. Basemap source: ESRI.

Figure 3: The intensity of LRA-related conflict, 1997–2015



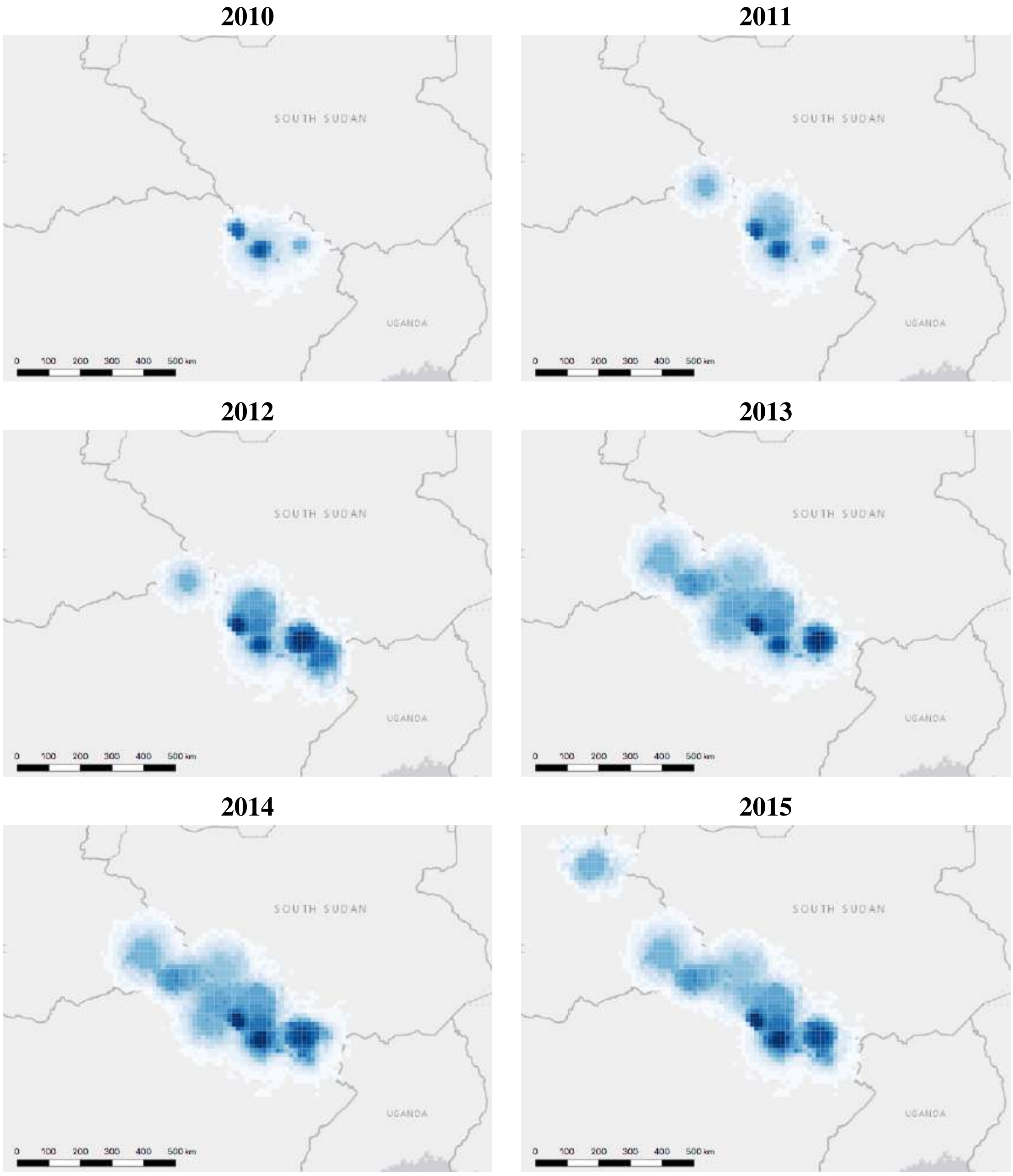
Notes. The time series of conflict intensity from the ACLED, UCDP and LRACT databases. The left panel presents the number of events, while the right panel focuses on the number of total fatalities. Dotted vertical lines represent the year in which LRACT data became available.

Figure 4: Mobile phone and alternative radio FM coverage



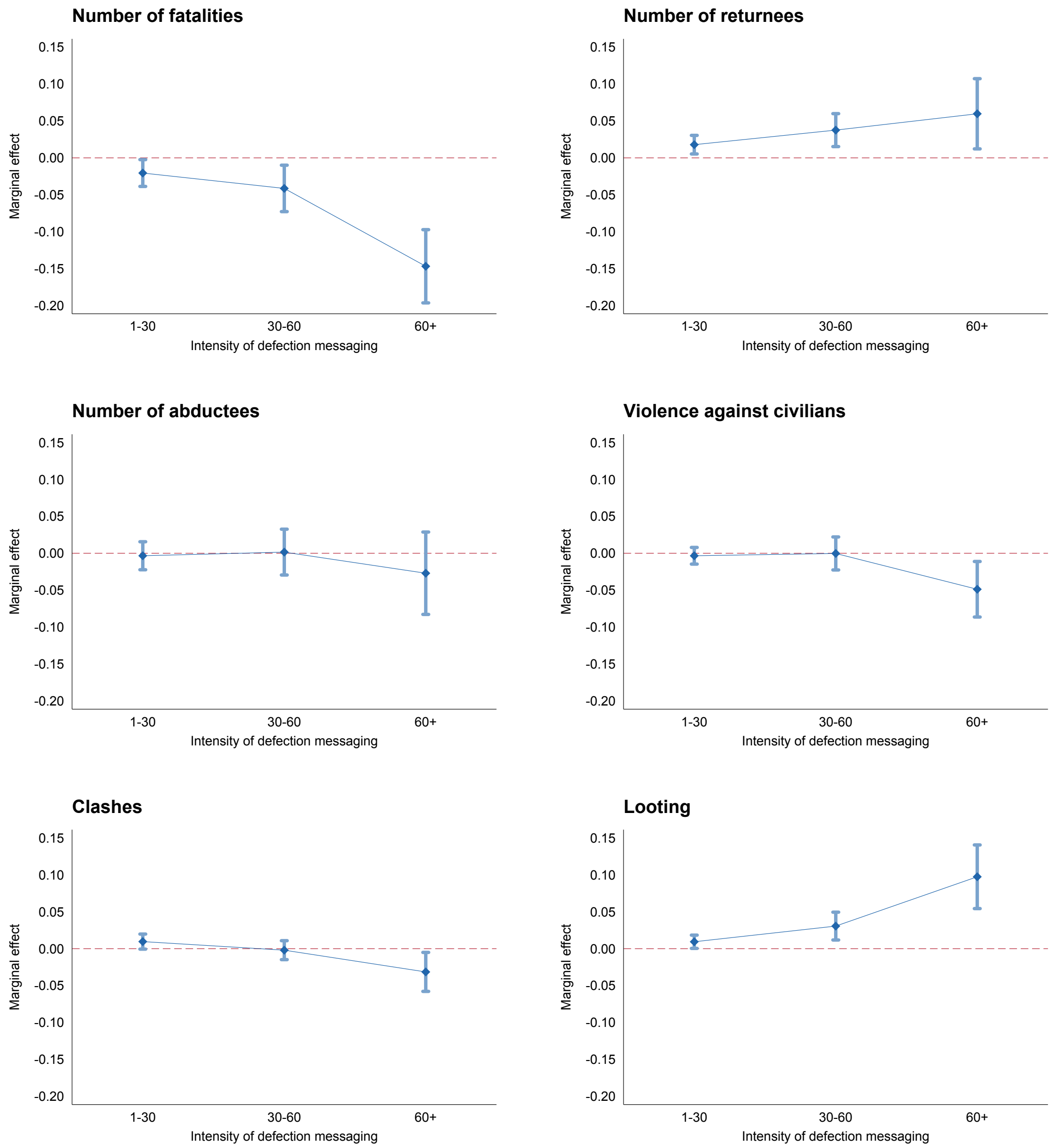
Notes. The left panel plots coverage of GSM mobile phone network. The right panel plots coverage of general FM radio stations which broadcast general content unrelated to defection messaging. GSM network coverage is computed for the year 2015 from Coverage Data®Collins Bartholomew Ltd and GSMA 2017. FM coverage is computed for the year 2017 from the FMLIST database. FM coverage is corrected for topography using technical specifications of the radio stations and applying the Longley–Rice / Irregular Terrain Model (ITM). The geographic area is restricted to the study area. Basemap source: ESRI.

Figure 5: Geographic distribution of messaging intensity



Notes. The geographic distribution of defection messaging intensity (total number of hours of daily broadcast) across years. Darker colors represent higher intensity, while lighter colors represent lower intensity (with transparent cells showing zero coverage). Cell resolution is 0.125° × 0.125° (see Figure B7 for the grid extent).

Figure 6: Non-linear effect of defection messaging



Notes. This figure plots the coefficients of equation (2) against the intensity of defection messaging decomposed into four dummy variables denoting different intervals of radio messaging intensity: 0 minutes, 0–30 minutes, 30–60 minutes and more than 60 minutes of daily messaging. The dummy for "0 minutes" serves as the excluded category. The dependent variables are the number of fatalities (upper left panel), the number of returnees (upper right panel), the number of abductees (middle left panel), the number of events characterized by violence against civilians (middle right panel), clashes with security forces (bottom left panel), and looting (bottom right panel). All outcome variables are measured in logs. For comparison, we allow the vertical axis to vary at the same scale for all outcome variables. Confidence intervals are computed at 95% of confidence, standard errors are allowed to be correlated over time and space (see Conley, 1999, 2008; Hsiang, 2010).

Table 1: Descriptive statistics

	Mean (1)	Std.Dev. (2)	Min (3)	Max (4)	Obs. (5)
ANTENNA-LEVEL CHARACTERISTICS					
Situation in 2015					
Share of active antennas	0.93	0.25	0	1	30
Share broadcasting defection content	0.57	0.50	0	1	30
Location: Central African Republic	0.20	0.41	0	1	30
Location: DR Congo	0.53	0.51	0	1	30
Location: South Sudan	0.13	0.35	0	1	30
Location: Uganda	0.13	0.35	0	1	30
Average 2008-2015					
Hours on-air (when active)	12.61	6.08	2	24	30
Daily minutes of defection messaging	80.19	48.17	9	225	30
Daily minutes of sensitization content	66.33	42.16	6	178	30
Daily minutes of logistical content	13.86	12.47	0	48	30
Distance reached by signal (km)	100.66	32.83	48	192	30
CELL-LEVEL CHARACTERISTICS (2008-15)					
Radio Coverage					
Cell covered by defection messaging	0.09	0.29	0	1	60600
Intensity of messaging	3.46	18.91	0	371	60600
Distance to closest antenna (km)	325.23	169.40	2	848	60600
Median distance from active antennas (km)	489.14	184.38	6	1012	60600
Cell covered (circular coverage)	0.33	0.47	0	1	60600
Conflict (LRACT Database)					
Total fatalities	0.05	1.74	0	184	60600
Number of returnees	0.03	0.62	0	39	60600
Number of abductees	0.11	2.16	0	207	60600
Events: violence against civilians	0.01	0.10	0	3	60600
Events: clashes	0.00	0.07	0	2	60600
Events: looting	0.02	0.27	0	23	60600
Conflict (ACLED Database)					
Number of events (LRA)	0.02	0.39	0	30	60600
Number of events (LRA attacking)	0.01	0.35	0	29	60600
Number of events (LRA attacked)	0.00	0.08	0	10	60600
Total fatalities (LRA)	0.09	3.88	0	515	60600
Number of events (non-LRA)	0.07	1.05	0	85	60600
Total fatalities (non-LRA)	0.37	13.14	0	1707	60600
Conflict (UCDP Database)					
Number of events (LRA)	0.01	0.17	0	16	60600
Number of events (LRA attacking)	0.01	0.13	0	10	60600
Number of events (LRA attacked)	0.00	0.06	0	6	60600
Total fatalities (LRA)	0.06	1.94	0	241	60600
Number of events (non-LRA)	0.01	0.27	0	28	60600
Total fatalities (non-LRA)	0.21	8.27	0	1012	60600
Other indicators					
FM coverage (% cell)	0.32	0.40	0	1	60600
GSM coverage (% cell)	0.18	0.37	0	1	60600
Mean precipitation (mm/day)	3.69	1.00	1	7	60600
Average temperature (°C)	26.29	2.79	19	37	60600
Population (log)	7.56	1.59	3	12	60600

Notes. This table presents descriptive statistics for all radio stations in the final year of our sample, 2015; the average for the years 2008–2015; and cell-level descriptive statistics for cells at the 0.125° × 0.125° resolution (approximately 14 km × 14 km at the equator). *Share of active antennas* indicates the share of antennas that participated in the defection messaging effort and are still operating in 2015, independently from the content broadcast. *Share broadcasting defection content* reports the share of radio stations that are actively broadcasting defection messages. *Distance reached by signal* is computed as the 75th percentile of the distance reached by an antenna. *Distance to closest antenna* is computed as minimum distance of the cell's centroid to an active antenna. *Population* is the log of the population living within a cell. *Intensity of messaging* is the total number of minutes of daily defection messaging broadcast in a cell, corrected by the share of the cell covered by radio signal (see equation 1). See Appendix Table A1 for further information about the variables.

Table 2: Effect of defection messaging on fatalities

Dependent variable:	**Number of fatalities linked to LRA activity**				
Event Dataset:	LRACT	LRACT	LRACT	ACLED	UCDP
	(1)	(2)	(3)	(4)	(5)
Intensity of messaging	-0.029***	-0.028***	-0.027***	-0.016***	-0.025***
	(0.005)	(0.005)	(0.005)	(0.002)	(0.004)
Observations	60600	60600	60600	60600	60600
Number of Years	8	8	8	8	8
Number of Cells	7575	7575	7575	7575	7575
Additional controls	No	Yes	Yes	Yes	Yes
Year $\times$ Macro-Region FE	No	No	Yes	Yes	Yes

Notes. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors in parenthesis are allowed to be correlated over time and space (see Conley, 1999, 2008; Hsiang, 2010). Coefficients are estimated with a Fixed Effects model. All specifications include cell and year fixed effects, and propagation controls. Additional controls include commodity price and weather shocks (see section 4). The dependent variable is the total number of LRA-related fatalities (in logs) in each cell at time t. In columns 1–3, fatalities are computed from the LRACT dataset, while in columns 4 and 5 from the ACLED and UCDP datasets, respectively. Columns 3–5 include interaction terms between year and macro-region indicators. The time period is restricted to 2008–2015.

Table 3: Effect of defection messaging on additional outcomes related to LRA violence

Dependent variable:	**Number of individuals...**				**Number of events involving...**					
	Returning		Being Abducted		Violence against civilians		Clashes		Looting	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Intensity of messaging	0.010**	0.009**	-0.006	-0.005	-0.010**	-0.010**	-0.006**	-0.006**	0.017***	0.016***
	(0.004)	(0.004)	(0.005)	(0.005)	(0.004)	(0.004)	(0.003)	(0.003)	(0.004)	(0.004)
Observations	60600	60600	60600	60600	60600	60600	60600	60600	60600	60600
Number of Years	8	8	8	8	8	8	8	8	8	8
Number of Cells	7575	7575	7575	7575	7575	7575	7575	7575	7575	7575
Additional controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Year × Macro-Region FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes

Notes. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors in parenthesis are allowed to be correlated over time and space (see Conley, 1999, 2008; Hsiang, 2010). Coefficients are estimated with a Fixed Effects model. All specifications include cell and year fixed effects, and propagation controls. Additional controls include commodity price and weather shocks (see section 4). The dependent variables are the number of individuals returning from the LRA (columns 1–2), the number of individuals abducted (columns 3–4), the number of events involving violence against civilians (columns 5–6), the number of events involving clashes between the LRA and other actors (columns 7–8), and the number of events involving looting by the LRA (columns 9–10). All outcomes are computed from the LRACT dataset. The time period is restricted to 2008–2015.

Table 4: Defection messaging and commodity price shocks

Dependent variable:	**Number of fatalities linked to LRA**	**Number of individuals...**		**Number of events involving...**		
		Returning	Being abducted	Violence against civilians	Clashes	Looting
	(1)	(2)	(3)	(4)	(5)	(6)
Intensity of messaging	-0.028***	0.010**	-0.005	-0.010**	-0.006**	0.016***
	(0.005)	(0.004)	(0.005)	(0.004)	(0.003)	(0.004)
* Cotton price shock	-0.074***	0.011	-0.016	-0.018	-0.016	0.052***
	(0.022)	(0.017)	(0.019)	(0.014)	(0.010)	(0.016)
* Groundnut oil price shock	0.139***	-0.102***	0.029	0.047**	0.035**	-0.088***
	(0.035)	(0.038)	(0.037)	(0.024)	(0.016)	(0.026)
Cotton price shock	-0.022***	0.012**	0.003	-0.007	-0.005	0.013***
	(0.007)	(0.005)	(0.007)	(0.005)	(0.003)	(0.004)
Groundnut oil price shock	0.045**	-0.038**	0.009	0.013	0.001	-0.012
	(0.019)	(0.015)	(0.019)	(0.013)	(0.009)	(0.009)
Observations	60600	60600	60600	60600	60600	60600
Number of Years	8	8	8	8	8	8
Number of Cells	7575	7575	7575	7575	7575	7575
Additional controls	Yes	Yes	Yes	Yes	Yes	Yes
Year $\times$ Macro-Region FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors in parenthesis are allowed to be correlated over time and space (see Conley, 1999, 2008; Hsiang, 2010). Coefficients are estimated with a Fixed Effects model. All specifications include cell and year fixed effects, and propagation controls. Additional controls include commodity price and weather shocks (see section 4). The dependent variables are the number of fatalities linked to LRA (columns 1 and 2) and the number of violent events involving different LRA activities (columns 3–10). The time period is restricted to 2008–2015.

Table 5: Defection messaging and alternative coverage

Dependent variable:	**Number of fatalities**		**Number of individuals...**				**Number of events involving...**					
			Returning		Being abducted		Violence against civilians		Clashes		Looting	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Intensity of messaging	-0.027***	-0.028***	0.009**	0.009**	-0.005	-0.006	-0.010**	-0.010**	-0.006**	-0.006**	0.016***	0.016***
	(0.005)	(0.005)	(0.004)	(0.004)	(0.005)	(0.005)	(0.004)	(0.004)	(0.003)	(0.003)	(0.004)	(0.004)
GSM coverage (% cell)	-0.018		-0.003		-0.006		-0.017		-0.020**		0.001	
	(0.015)		(0.011)		(0.018)		(0.012)		(0.008)		(0.017)	
Radio Coverage (% cell, FMLIST) x Year		-0.001		-0.002***		-0.002**		-0.001		-0.000		-0.002***
		(0.001)		(0.001)		(0.001)		(0.001)		(0.000)		(0.000)
Observations	60600	60600	60600	60600	60600	60600	60600	60600	60600	60600	60600	60600
Number of Years	8	8	8	8	8	8	8	8	8	8	8	8
Number of Cells	7575	7575	7575	7575	7575	7575	7575	7575	7575	7575	7575	7575
Additional controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year × Macro-Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors in parenthesis are allowed to be correlated over time and space (see Conley, 1999, 2008; Hsiang, 2010). Coefficients are estimated with a Fixed Effects model. All specifications include cell and year fixed effects, and propagation controls. Additional controls include commodity price and weather shocks (see section 4). The dependent variables are the number of fatalities linked to LRA (columns 1 and 2) and the number of violent events involving different LRA activities (columns 3–10). The time period is restricted to 2008–2015.

Table 6: Effect of returnees on conflict intensity and LRA activity

Dependent variable:	**Number of fatalities**	**Number of individuals being abducted**	**Number of events involving...** Violence against civilians	Clashes	Looting
	(1)	(2)	(3)	(4)	(5)
Panel A. IV					
Number of returnees	-0.194***	0.004	-0.043**	-0.026	0.171***
	(0.047)	(0.039)	(0.022)	(0.019)	(0.028)
Panel B. Confidence intervals assuming intensity of messaging is plausibly exogenous					
Direct effect: $\alpha \cdot \pm 1\%$	[-0.287; -0.101]	[-0.066; 0.074]	[-0.085; -0.001]	[-0.059; 0.007]	[0.117; 0.226]
Direct effect: $\alpha \cdot \pm 5\%$	[-0.297; -0.096]	[-0.072; 0.078]	[-0.087; 0.000]	[-0.061; 0.008]	[0.111; 0.237]
Direct effect: $\alpha \cdot \pm 10\%$	[-0.309; -0.089]	[-0.078; 0.083]	[-0.090; 0.002]	[-0.062; 0.009]	[0.103; 0.251]
Direct effect: $\alpha \cdot \pm 15\%$	[-0.322; -0.081]	[-0.085; 0.089]	[-0.093; 0.004]	[-0.064; 0.010]	[0.094; 0.265]
Observations	60600	60600	60600	60600	60600
Number of Years	8	8	8	8	8
Number of Cells	7575	7575	7575	7575	7575
F-test excluded instruments	11.28	11.28	11.28	11.28	11.28

Notes. Panel A: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Coefficients are estimated with an Instrumental Variable Fixed Effects model. Number of returnees is reported in logarithm and standardized (one standard deviation corresponds to an increase in returnees of 13.7%), and is instrumented using intensity of messaging and its square. All specifications include cell and year fixed effects, and propagation controls. Additional controls include commodity price and weather shocks (see section 4). The dependent variables are the number of fatalities linked to LRA (column 1), the number of individuals being abducted (column 2) and the number of violent events involving different LRA activities (columns 4–5). The time period is restricted to 2008–2015. *Panel B*: the confidence intervals are computed at 95% allowing for a violation in the exclusion restriction following the union of confidence intervals approach (Conley et al., 2012). "Direct effect: $\alpha \cdot \pm x\%$" indicates that we allow the direct effect of the instrument on the outcome variable to range from -x% to x% of the direct effect (α) estimated in tables 2 and 3. In the main estimates x is assumed to be 0 (valid exclusion restriction). We allow the direct effect to be both positive and negative in order to provide more conservative estimates.

ONLINE APPENDIX for "The Reach of Radio"

A Summary of data and variable definition

A.1 Definition of main variables

Table A1: Cell-level variables

Variable (Source)	Description
Conflict intensity (LRACT, ACLED and UCDP)	Number of violent events (and fatalities) in each cell for a specific year. Data are obtained from three distinct databases providing detailed information on events and their geo-location: the LRA Crisis Tracker (LRACT) database, the Uppsala Conflict Data Program (UCDP) database (Sundberg and Melander, 2013) and the Armed Conflict Location & Event Data Project (ACLED) database (Raleigh et al., 2010). See Section A.2 for further details.
Mobile phone coverage (GSMA, 2012)	Dummy variable equal to 1 if at time t the cell is covered by the 2G (GSM) network. Data come from the Collins Mobile Coverage Explorer, supplied by GSMA and Collins Bartholomew. The dataset provides geo-located information on yearly mobile phone coverage for 2G (GSM), 3G and 4G (LTE) networks on a global basis. It is built using submissions from Mobile Network Operators and is then aggregated. The resolution of coverage varies from 1 km^2 to 15–23 km^2.
Crop coverage (Monfreda et al., 2008)	Share of the cell covered by a crop. M3-Crops Data offers a raster dataset at the $5' \times 5'$ latitude/longitude grid for 175 crops in the period 1997–2003.
Commodity prices (GEM and USGS)	Commodity prices on international markets are obtained from two sources: the World Bank's Global Economic Monitor (GEM) Commodities dataset, and the U.S. Geological Survey's Historical Statistics for Mineral and Material Commodities in the United States (USGS, 2016).
Precipitation (CHIRPS, Funk et al., 2015)	Average amount of daily precipitations (in mm) in the cell, based on daily precipitations data provided by the Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS) database. CHIRPS provides $0.05° \times 0.05°$ resolution satellite imagery supplemented with in-situ monitoring station data.
Temperature (PRIO-GRID)	Yearly mean temperature (in degrees Celsius) in the cell, based on monthly meteorological statistics from GHCN/CAMS, developed by NOAA/National Weather Service. Data are available for the period 1948–2014. For 2015, we impute cell-level temperature using a linear extrapolation.
Share of year experiencing drought (PRIO-GRID)	Proportion of months out of 12 months that are part of the longest streak of consecutive months ending in the given year with SPI1 values below -1.5. Data are built using SPI data from the International Research Institute for Climate and Society.
Population (CIESIN-CIAT, 2005)	Population size in each cell over time. Population estimates are available for 1990, 1995, 2000, and 2005.
Terrain Ruggedness (Nunn and Puga, 2012)	Terrain ruggedness calculated at the level of 30 arc-second cells on a regular geographic grid covering the Earth.
Nightlight (PRIO-GRID)	Average nighttime light emission from the DMSP-OLS Nighttime Lights Time Series v.4. Image and data processing by NOAA's National Geophysical Data Center. DMSP data are collected by US Air Force Weather Agency.
Urban cover (PRIO-GRID)	Share of the cell covered by urban areas in 2009. Data extracted from the Globcover 2009 dataset v.2.3. It follows the FAO land cover classification system used by Globcover - category "Artificial areas".
Mineral presence (MRDS-USGS)	Dummy variable indicating whether mineral is present in the cell. The database provides geo-located extraction sites by type of mineral and the magnitude of production.
General FM radio coverage (fmlist.org)	Percentage of cell covered by topography-corrected FM radio signals from any FM radio station (excluding defection messaging broadcasting stations) in the region. Since technical parameters are not available for all radio stations, we impute the missing parameters by an iterative imputation using the median value of the missing parameter, when at least 10 observations are available. We start at the smallest level (region), and we increase the level if the minimum number of observations is not available. The largest level is the full study area.

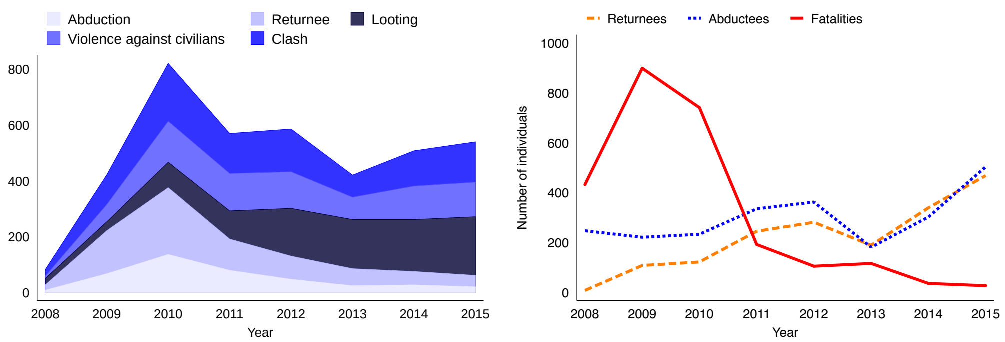
A.2 Definition of LRA events

The LRACT variables used in the paper are defined in Table A3. Figure A1 presents the series of total events associated with the LRA by type of incident (left panel), and the series of the number of fatalities, returnees, and abductees over the period of analysis (right panel). See The Resolve (2015) for further details about the dataset.

Table A3: Definition of variables from the LRACT dataset

Variable	Description
Returnees	Sum of adult and child returnees. These are defined as adult and child escapees, who return from armed group captivity or enrollment willingly. This category excludes armed group members captured and civilians released.
Abductees	Number of people "taken captive against their will by the LRA for any period of time, including short-term abductions".
Violence against civilians	Number of events characterized by "any physical violence committed against civilians which resulted in death or injury, including sexual or gender based violence".
Clash	Number of events in which "an armed group violently engage with one or more armed groups or security forces (any organized, armed, non-rebel or terrorist group)".
Looting	Number of events in which "LRA members commit robbery, extortion, or destruction of property".

Figure A1: Composition of LRA-related events and number of involved individuals



Notes. The figures plot the time series of different conflict events. The left panel presents the composition of total events per year, while the right panel focuses on the number of returnees, abductees and fatalities. Data source: LRACT.

B Additional analysis

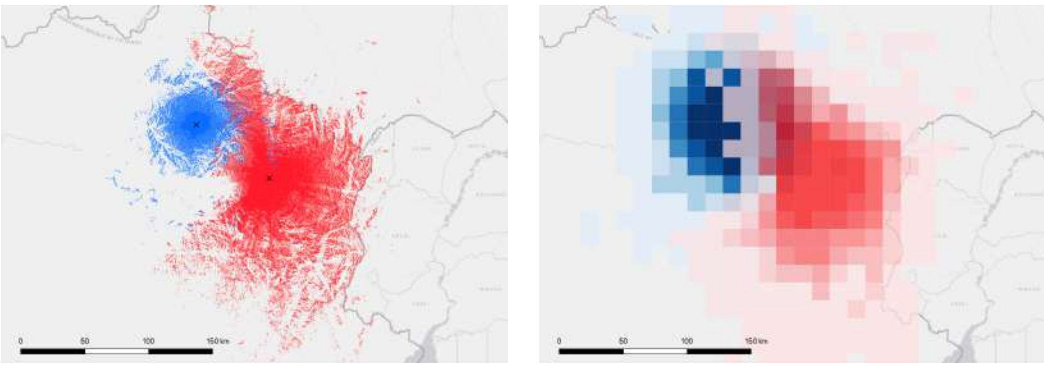
B.1 Radio coverage

To compute radio coverage for each radio station involved in the program we apply the field standard radio propagation model i.e., the Longley–Rice or Irregular Terrain Model. The model uses the geographic coordinates and technical parameters as inputs to generate coverage of each radio station over space. The technical parameters primarily include the mast/tower height and the transmitter power which we collected from our radio survey. We partnered with a radio engineer to finalize all other parameters needed to adapt the model to our setting. Coverage is calculated using

CloudRF (cloudrf.com), a commercial radio planning tool. Figure B2 presents an example output from the model for two different radio stations. Radio coverage is first computed at the finest resolution of 90 meters (left panel). It is then merged to the grid in the study area in order to build percent coverage of each radio at the cell level (right panel). Conditional on distance from each antenna, variation in topography generates not only plausibly random coverage of the signal, but also plausibly random overlap of different radio signals. These features, together with different frequencies of messaging from different radio stations, are exploited when building our main source of variation, the intensity of messaging (see equation 1). Figure B3 plots the evolution of exposure or coverage (left panel) and the intensity (right panel) of defection messaging content over time.

Figure B2: Radio coverage: an illustration

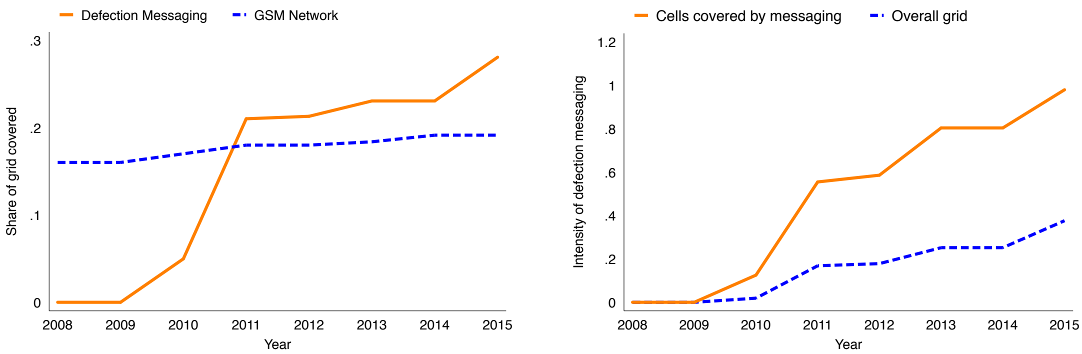
90-meter resolution | **0.125° × 0.125° resolution**



Notes. Example of topography-corrected radio coverage (computed with the Longley–Rice or Irregular Terrain Model) in the study area for two antennas (“X” indicates the location of an antenna). The left panel shows radio coverage at a 90-meter resolution, while the right panel shows radio coverage using grid cells of 0.125° × 0.125° resolution. Each cell is assigned with the value of the share of the cell covered by the signal, with darker colors representing larger shares. Transparent cells indicate no coverage. Basemap source: ESRI.

Figure B3: Coverage and intensity of defection messaging, by year

Coverage | Intensity of defection messaging

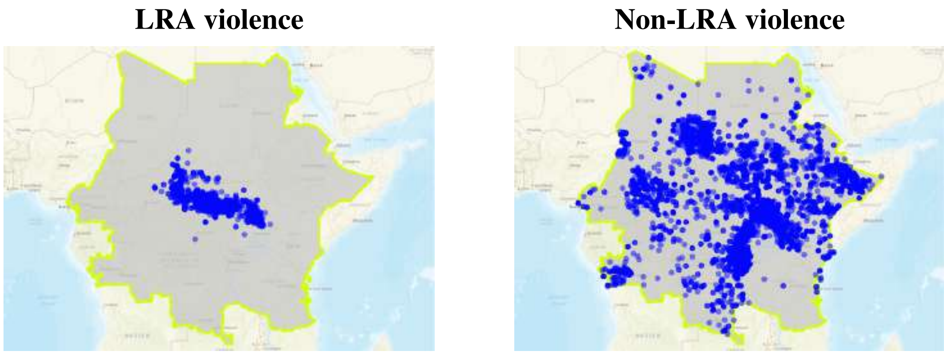


Notes. The left figure shows the share of cells that are covered by radio signals from defection messaging stations and by the GSM mobile-phone network. The right figure presents the intensity (averaged at the grid-cell level) of defection messaging, as defined by equation (1). Source: own elaboration.

B.2 Geographical extent of study

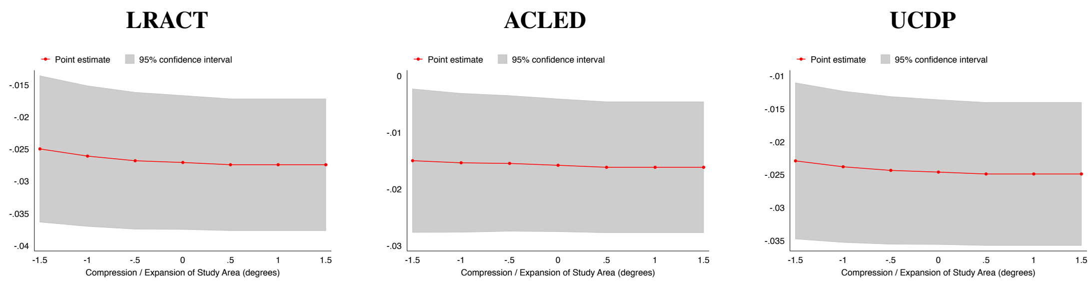
Figure B4 presents the geographical extent of violence in the region of our study. As no clear precedent exists in the literature, we select the geographic extent of our analysis using a rule based on the geographic distribution of LRA-related events during 1997–2015. While our study focuses on the 2008–2015 period, we use a longer period for determining the geographic extent, to take into account the entire area in which the LRA has historically operated.We then select a geographical area that is defined by the 1^{st} percentile minus 0.5° and 99^{th} percentile plus 0.5° of both latitude and longitude of the events. The parameter 0.5 is chosen to allow a buffer around the events that fall on the edge of the grid. Estimates of the effect of defection messaging on the number of fatalities are robust to variation in this parameter (Figure B5).

Figure B4: Extent of violence in the region (1989–2015)



Notes. Geographical distribution of violent events in the countries of our study region highlighted in yellow. Each dot represents an event as defined in the UCDP dataset. In the left figure, dots are LRA violent events, while in the right figure, dots are non-LRA events.

Figure B5: Size of study area and sensitivity of estimates

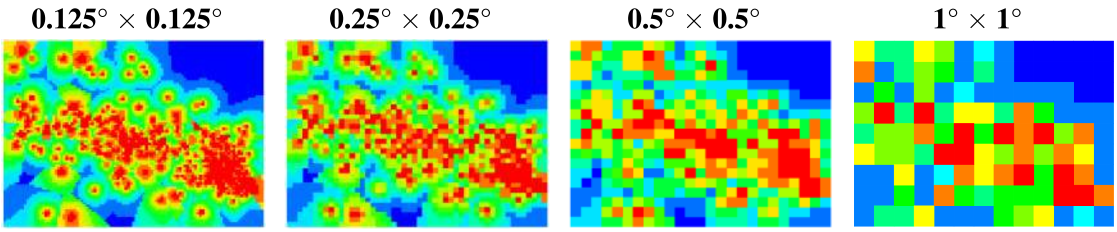


Notes. Variation of estimates (and standard errors) of equation (2) when the size of the study area changes. The dependent variables are the number of fatalities (in logs) using the LRACT, ACLED and UCDP datasets. The expansion and compression of the area is reported on the horizontal axis in degrees.

B.3 Cell size analysis and the Modifiable Areal Unit Problem

The objective of this section is to determine the correct grid to be used for our analysis.[2] Figure B6 presents the geographic distribution of the probability of observing an LRA event in a specific cell in the study area for four alternative resolutions: 0.125° $\times$ 0.125° (high resolution), 0.25° $\times$ 0.25°, 0.5° $\times$ 0.5°, and 1° $\times$ 1° (low resolution). Given the clustering of events and the full extent of the events observed, a finer resolution allows capturing a much larger variation compared to lower resolutions. Aggregating cells affects the overall information contained by the grid.

Figure B6: Probability of observing a violent event per cell, by cell resolution



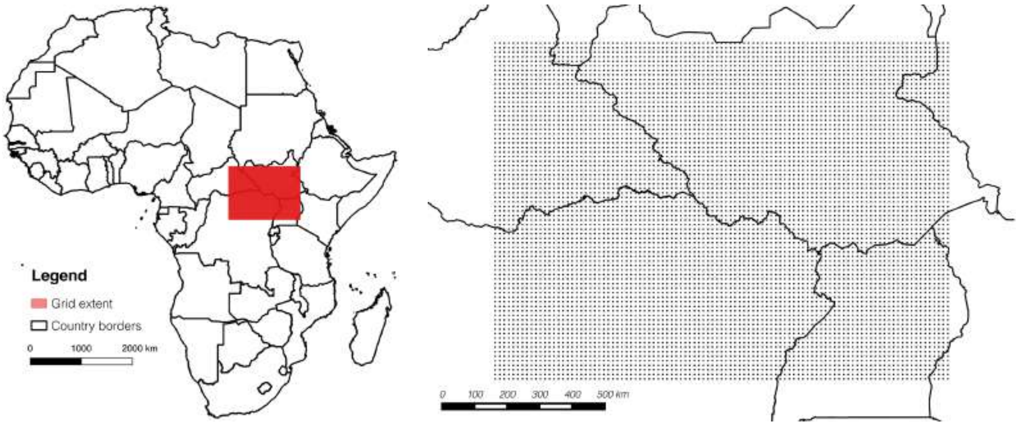
Notes. The distribution of the probability of observing an LRA-related event in a specific cell for four alternative resolutions. The probability density function is estimated using a Kernel estimator assuming a quartic distribution where the bandwidth is determined using the minimum number of data points method (k = 1). Cell resolution is expressed in degrees per side. Results are produced using Stata command *spkde*. We use the ACLED database for the period 1996-2015 to compute these statistics, since it allows observing events in the period before 2008 and it provides higher geographical dispersion of events with respect to UCDP (see Section B.2). Results are similar using the LRACT for the post-2008 period only.

While no ideal resolution exists, grid resolution can be related to the geometry of point patterns (Hengl, 2006). According to Boots and Getis (1988), the grid resolution should be at most half the average of the mean/median shortest distance, i.e. the mean spacing between the closest point pairs. When we include (exclude) events taking place in the same location, the corresponding median is approximately 22 km (25 km). We therefore select a cell resolution of 0.125° $\times$ 0.125° (approximately 14 km $\times$ 14 km at the equator). Figure B7 plots the area covered by the grid and illustrates its resolution.

The Modifiable Areal Unit Problem (MAUP) occurs when cell sizes are chosen in order to provide a pre-selected type of result. We construct cells of 0.125° $\times$ 0.125°, 0.25° $\times$ 0.25°, and 0.5° $\times$ 0.5°, and we estimate our main specification for each of these grids. Figure B8 shows how intensity of messaging and our main estimates for the effect of intensity of defection messaging on fatalities and returnees change with the grid resolution. While the mean intensity of defection messaging is relatively unchanged across resolutions (hovering around the value 3.45), the standard deviation decreases from around 19 when the cell size is 0.125° $\times$ 0.125° to 17 when the cell size is 0.5° $\times$ 0.5° (upper panel of Figure B8). As evident from the lower panel of Figure B8, estimates of the marginal effect of intensity of messaging (using equation (2)) varies, when the resolution of the grid changes, for both fatalities and returnees. The direction of the effect is

[2] In our study, we are analyzing a two-dimensional spatial point pattern S, defined as a set of points s_i ($i = 1, ..., n$) and located in a two-dimensional region R. Each point represents the location in R of a violent event where the LRA is an actor and has coordinates (s_{i1}, s_{i2}). In this setting, a grid is a regular tessellation of the study region R that divides it into a set of contiguous cells. We discuss issues related to the selection of the region R in Section B.2.

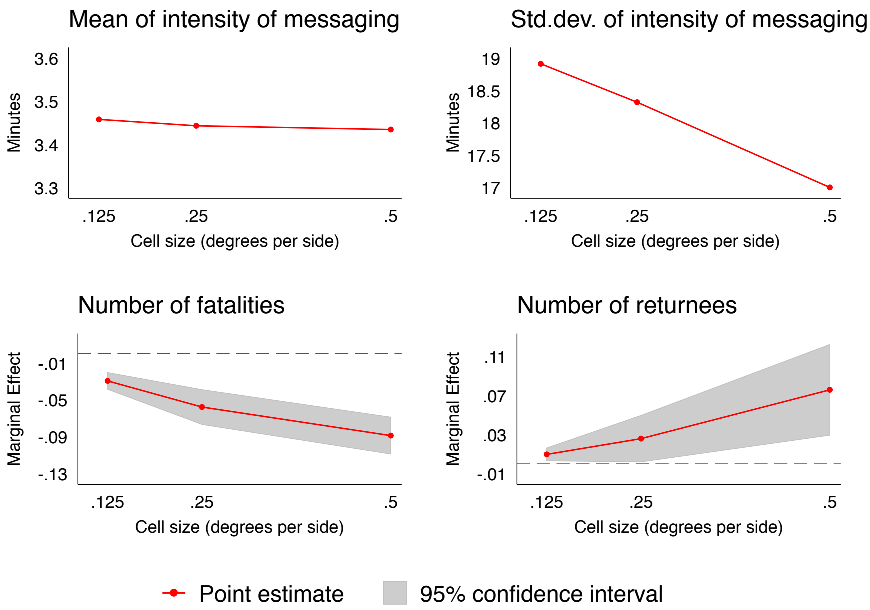
Figure B7: Geographical coverage and grid resolution



Notes. The left panel shows the area covered by the grid. The right panel shows its resolution. Each dot represents the centroid of a 0.125° × 0.125° cell.

not affected by the cell size. However, the coefficients increase with the cell size. In line with Fotheringham and Wong (1991), the increase in the coefficient following aggregation is explained by the reduction in the variation of the variables under consideration because of averaging across cells. The correlation between two variables is expected to increase when the variance is reduced and the covariance is stable.

Figure B8: Cell size, intensity of messaging and estimates of the effect



Notes. The upper panel shows how the mean and standard deviation of intensity of messaging, defined by equation (1), varies with the cell size (resolution is reported on the horizontal axis). The lower panel shows how estimates of equation (2) varies when the resolution of the grid changes. We consider as outcomes the number of fatalities (bottom left) and the number of returnees (bottom right). Both outcomes are reported in logs.

B.4 Variable-specific trends

To control for differential trends associated with determinants of conflict, we add interaction terms between the year of observation and cell-level terrain ruggedness, ex-ante income proxied by nightlight, ex-ante log-population, and country indicator dummies. Table B5 presents the results. Similar results are obtained with interactions with year dummies to allow for non-linear time effects. In both cases, results are unaffected.

Table B5: Robustness to adding variable-specific trends

Dependent variable:	Number of fatalities linked to LRA activity					
	(1)	(2)	(3)	(4)	(5)	(6)
Intensity of messaging	-0.028***	-0.028***	-0.028***	-0.028***	-0.028***	-0.028***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Ruggedness × Year		0.001				0.001
		(0.001)				(0.001)
Nightlight (2007) × Year			0.000			-0.000
			(0.000)			(0.001)
Population (2005) × Year				-0.000		0.000*
				(0.000)		(0.000)
Urban cover (2009) × Year				0.000		-0.000
				(0.000)		(0.002)
CAR × Year					0.003**	0.004**
					(0.001)	(0.002)
DRC × Year					0.000	-0.001
					(0.001)	(0.001)
Uganda × Year					0.002**	-0.000
					(0.001)	(0.001)
South Sudan × Year					0.001	0.001*
					(0.001)	(0.001)
Observations	60600	60600	60600	60600	60600	60600
Number of Years	8	8	8	8	8	8
Number of Cells	7575	7575	7575	7575	7575	7575

Notes. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors in parenthesis are allowed to be correlated over time and space (see Conley, 1999, 2008; Hsiang, 2010). The dependent variable is the number of fatalities linked to LRA. All specifications include cell and year FE, propagation controls, and additional controls. Additional controls include commodity price and weather shocks (see section 4). See Table A1 for variable definitions. The time period is restricted to 2008–2015.

B.5 Robustness to alternative definitions of intensity and fatalities

Firstly, when considering the number of fatalities, we present results by normalizing fatalities by the population living in the cell (in thousands of inhabitants). Table B6 presents the results in columns 2, 4 and 6.[3] Secondly, our measure of radio intensity is constructed by summing up the proportion of cell coverage times the hours of messaging for each cell as defined by equation (1). One alternative would be to consider the cell level intensity averaged over the number of radio stations messaging in a particular cell (columns 3–4). Again, another alternative could be to use the percent cell coverage by defection messaging rather than intensity (columns 5–6). Our results are robust to using these alternative definitions.

In the main text we focused on the contemporaneous effect of defection messaging on different indicators of violence and of LRA strategic behavior. In Table B7 we show that our results are

[3]In results not provided, we have also experimented by normalizing the number of fatalities by the amount of available land in the cell, defined as the amount of land (in square kilometers) that is not covered by forest. Results are robust.

Table B6: Robustness to alternative definitions of fatalities and intensity of messaging

Dependent variable:	**Number of fatalities linked to LRA activity**					
Normalization by:	**-**	**Population**	**-**	**Population**	**-**	**Population**
	(1)	(2)	(3)	(4)	(5)	(6)
Intensity of messaging	-0.027***	-0.026***				
	(0.005)	(0.005)				
Average intensity of messaging			-0.012**	-0.014***		
			(0.004)	(0.005)		
% cell covered by defection messaging					-0.102***	-0.117***
					(0.020)	(0.022)
Observations	60600	60600	60600	60600	60600	60600
Number of Years	8	8	8	8	8	8
Number of Cells	7575	7575	7575	7575	7575	7575

Notes. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors in parenthesis are allowed to be correlated over time and space (see Conley, 1999, 2008; Hsiang, 2010). Average intensity of defection messaging is defined as the intensity of defection messaging (see equation 1) divided by the number of radio stations covering the cell. The variable is then standardized for ease of interpretation. The dependent variable is the number of fatalities linked to LRA computed from the LRACT dataset. Normalization by "*Population*" refers to number of fatalities per thousand inhabitants. See Table A1 for variable definitions. All specifications include cell and year FE, propagation controls, additional controls and interactions between year dummies and macro-region dummies. Additional controls include commodity price and weather shocks (see section 4). The time period is restricted to 2008–2015.

robust to using lagged intensity of messaging.

Table B7: Defection messaging and lagged intensity of messaging

Dependent variable:	**Number of fatalities**	**Number of individuals...**		**Number of events involving...**		
		Returning	Being abducted	Violence against civilians	Clashes	Looting
	(1)	(2)	(3)	(4)	(5)	(6)
Intensity of messaging (t - 1)	-0.035***	0.005	-0.011**	-0.020***	-0.011***	0.012***
	(0.006)	(0.004)	(0.006)	(0.005)	(0.003)	(0.004)
Observations	60600	60600	60600	60600	60600	60600
Number of Years	8	8	8	8	8	8
Number of Cells	7575	7575	7575	7575	7575	7575

Notes. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors in parenthesis are allowed to be correlated over time and space (see Conley, 1999, 2008; Hsiang, 2010). The dependent variables are the number of fatalities linked to LRA (column 1), the number of individuals returning or being abducted (columns 2–3) and the number of violent events involving different LRA activities (columns 4–6). All specifications include cell and year FE, propagation controls, additional controls and interactions between year dummies and macro-region dummies. Additional controls include commodity price and weather shocks (see section 4). The time period is restricted to 2008–2015.

B.6 Robustness to sample selection

Table B8 presents estimates of the effect of intensity of messaging on the number of fatalities by restricting the sample to different subsets of cells. Firstly, in columns 1–3, we consider the whole study area, while in columns 4–6, we restrict the sample to cells ever covered by messaging. In addition, in columns 2 and 5, we exclude cells in the surroundings of antennas (within 50 km), while in columns 3 and 6 we consider only cells closer to antennas (within 250 km, roughly equal to the median distance from an antenna in the whole study area).

B.7 Alternative content and targeted coverage

In order to control for the potentially confounding effects of alternative content broadcast by radios that participated in the defection messaging effort, we collected information on number of minutes of news, entertainment and religious preaching broadcast by these radios. Exploiting these data

Table B8: Effect of defection messaging on fatalities, robustness to sample selection

Dependent variable:	Number of fatalities linked to LRA activity					
Selected Area	All cells in study area			Only cells ever covered by messaging		
Sub-sample (km from nearest antenna):	0-max	50-max	0-250	0-max	50-max	0-250
	(1)	(2)	(3)	(4)	(5)	(6)
Intensity of messaging	-0.027***	-0.028***	-0.025***	-0.022***	-0.021**	-0.022***
	(0.005)	(0.007)	(0.006)	(0.006)	(0.008)	(0.006)
Observations	60600	58072	21357	12168	9694	10560
Number of Years	8	8	8	8	8	8
Number of Cells	7575	7492	3911	1521	1438	1521

Notes. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors in parenthesis are allowed to be correlated over time and space (see Conley, 1999, 2008; Hsiang, 2010). The dependent variable is the total number of fatalities (in logs) in each cell at time t. All specifications include cell and year FE, propagation controls, additional controls and interactions between year dummies and macro-region dummies. Additional controls include commodity price and weather shocks (see section 4). The time period is restricted to 2008–2015.

we construct measures of coverage and intensity of broadcast of alternative content (similar to equation 1). Table B9 controls for the intensity of alternative content (column 1) and the % of the cell covered by alternative content (column 2).[4] As an additional robustness test, we also control for (potentially endogenous) targeted circular coverage of defection messaging (column 3 of Table B9). Circular coverage does not correct signal reception for topography and is computed using a free-space propagation model, which captures the attenuation and maximum reach of an audible signal in the absence of obstacles in a flat terrain.[5] Our estimates are robust to these controls.

Table B9: Defection messaging and additional content

Dependent variable:	Number of fatalities linked to LRA activity					
	(1)	(2)	(3)	(4)	(5)	(6)
Intensity of messaging	-0.030***	-0.027***	-0.027***			
	(0.007)	(0.006)	(0.005)			
Intensity of alternative content	0.009					
	(0.016)					
% cell covered by alternative content		-0.001				
		(0.008)				
Circular coverage of messaging			-0.008			
			(0.005)			
Intensity of messaging: sensitization content				-0.027***		-0.020
				(0.005)		(0.012)
Intensity of messaging: logistical content					-0.026***	-0.008
					(0.005)	(0.011)
Observations	60600	60600	60600	60600	60600	60600
Number of Years	8	8	8	8	8	8
Number of Cells	7575	7575	7575	7575	7575	7575

Notes. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors in parenthesis are allowed to be correlated over time and space (see Conley, 1999, 2008; Hsiang, 2010). The dependent variable is the number of fatalities linked to LRA. The dependent variable is the number of fatalities linked to LRA. Alternative content includes news, entertainment and religious preaching. Circular coverage of defection messaging is a dummy variable equal to 1 if a cell is covered by messaging assuming a flat terrain. All specifications include cell and year FE, propagation controls, and additional controls. Additional controls include commodity price and weather shocks (see section 4). The time period is restricted to 2008–2015.

In columns 4–6 of Table B9, we analyze the effects of two distinct types of defection messaging content: sensitization content and logistical content. Sensitization content primarily refers

[4] Both variables are standardized. The correlation of these variables with intensity of messaging is low (0.27 with alternative content intensity and 0.35 with % cell covered).

[5] Correlation between intensity of messaging and circular coverage is equal to 0.43 in the whole study area, 0.36 if restricted to be within 100 km from an antenna.

to programs with interviews of ex-combatants, family members and community leaders, where the interviewees talk about their experiences on returning, and/or make emotional appeals to their friends and kin to return home. Logistical content, on the other hand, comprises logistical information on surrendering. From columns 4–6, we notice that both types of content are effective in reducing fatalities and the marginal effects are comparable. However, since both these types of content were often broadcast together (correlation between the two measures is 0.96), we acknowledge that given our current empirical set-up we cannot fully disentangle the relative effectiveness of each of these types of contents.[6]

B.8 Spillovers across fighters

Table B10 presents estimates of the effect of intensity of messaging on the number of events characterized by returnees, distinguishing by the number of returnees in each event. We consider the events in which one or two individuals return as being motivated by individual behavior (individual returnees). We consider events characterized by a larger number of returnees as being motivated by a social interaction effect (group returnees). Figure B9 plots the non-linear effects.

Table B10: Effect of defection messaging on the type of returnee event

Dependent variable:	**Number of events characterized by...**					
	Any number of returnees		Individual returnees		Group returnees	
	(1)	(2)	(3)	(4)	(5)	(6)
Intensity of messaging	0.006**	0.006**	0.005*	0.005*	0.001	0.001
	(0.003)	(0.003)	(0.003)	(0.003)	(0.001)	(0.001)
Population (2005) x Year		-0.000		-0.000		-0.000
		(0.000)		(0.000)		(0.000)
Urban cover (2009) x Year		-0.000		-0.000		-0.000
		(0.000)		(0.000)		(0.000)
Observations	60600	60600	60600	60600	60600	60600
Number of Years	8	8	8	8	8	8
Number of Cells	7575	7575	7575	7575	7575	7575

Notes. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors in parenthesis are allowed to be correlated over time and space (see Conley, 1999, 2008; Hsiang, 2010). The dependent variable is the number of events characterized by returnees, distinguishing by the number of returnees per event. Individual returnees are events characterized by 1 or 2 returnees. Group returnees are events characterized by 3 or more returnees. All specifications include cell and year FE, propagation controls, additional controls and interactions between year dummies and macro-region dummies. Additional controls include commodity price and weather shocks (see section 4). The time period is restricted to 2008–2015.

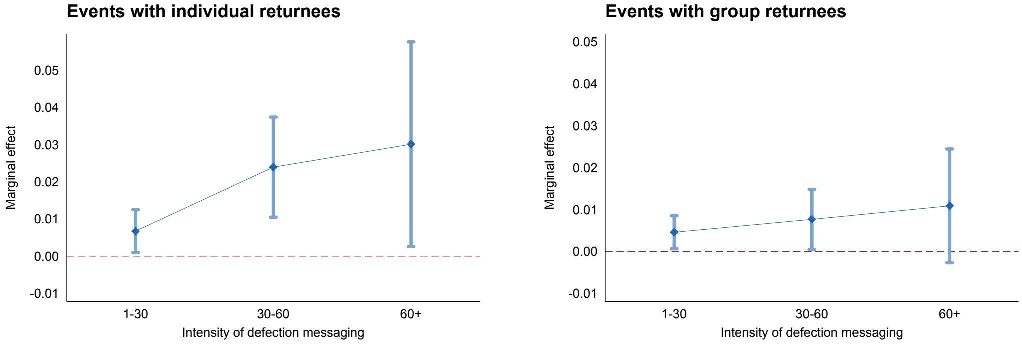
B.9 Spillovers on other violent events

We first look at whether defection messaging intensity affects other violent events (unrelated to the LRA) in the region. Table B11 presents estimates of the effect of intensity of messaging on the number of violent events separated by whether the LRA was involved or not (columns 1–4) and by whether the LRA is the perpetrator or in the receiving end of the violence (columns 5–8).

Next, we investigate whether intensity of defection messaging is capturing military presence. Since military operations are not directly observable to us, we rely on event-based data from

[6]We asked our radio survey respondents to report the number of minutes in each category of defection messaging. When this information is not available, we split the total amount of defection messaging equally among the categories that have been reported as being part of the defection content for the radio station.

Figure B9: Non-linear effect of defection messaging on type of returnee event



Notes. Coefficients of equation (2) where intensity of defection messaging is decomposed into four dummy variables for each group of intensity reported in the horizontal axis. The excluded variable is the dummy variable for zero-intensity. The dependent variable is the number of events characterized by returnees, distinguishing by the number of returnees per event. Individual returnees are events characterized by 1 or 2 returnees. Group returnees are events characterized by 3 or more returnees. For comparison, we allow the vertical axis to vary with the same scale for all outcome variables.

Table B11: Effect of defection messaging on LRA versus non-LRA activity

Dependent variable:	**Number of violent events by ...**							
	Actor involved in the violent event				**LRA role in the violent event**			
	LRA was involved		*LRA was not involved*		*LRA attacked*		*LRA was attacked*	
Event dataset:	ACLED	UCDP	ACLED	UCDP	ACLED	UCDP	ACLED	UCDP
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Intensity of messaging	-0.007***	-0.011***	-0.001	-0.001**	-0.007***	-0.010***	-0.003***	-0.003***
	(0.002)	(0.002)	(0.001)	(0.000)	(0.002)	(0.001)	(0.001)	(0.001)
Observations	60600	60600	60600	60600	60600	60600	60600	60600
Number of Years	8	8	8	8	8	8	8	8
Number of Cells	7575	7575	7575	7575	7575	7575	7575	7575

Notes. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors in parenthesis are allowed to be correlated over time and space (see Conley, 1999, 2008; Hsiang, 2010). The dependent variable is the number of violent events in which at least one actor is the LRA, in columns 1–2, in which none of the actors is the LRA, in columns 3–4, in which LRA is attacking, in columns 5–6 and in which LRA is being attacked, in columns 7–8. All specifications include cell and year FE, propagation controls, additional controls and interactions between year dummies and macro-region dummies. Additional controls include commodity price and weather shocks (see section 4). The time period is restricted to 2008–2015.

ACLED and UCDP identifying events in which the security forces are involved (including non-violent events) to construct a proxy for military presence. Columns 1 and 2 in Table B12 provide estimates of equation (2) where the dependent variable is the number of events in which a security force is the perpetrator of the action. In columns 3–6, we estimate equation (2) controlling for (potentially endogenous) military presence at cell level. We define army presence using a dummy variable equal to 1 if at time t in a cell at least one event is recorded in either ACLED or UCDP in which a security force is involved and 0 otherwise.

B.10 Analysis of looting

Table B13 shows the effect of intensity of messaging on the number of events that are characterized by either zero killings or at least one killing (columns 1–2), and on the number of looting events associated to other violent events (columns 3–6). We then look at the effect of intensity of messaging on type of goods looted by estimating equation (2) using the number of events charac-

Table B12: Effect of defection messaging and army presence

Dependent variable:	N. of violent events in which the army is the perpetrator		Number of fatalities linked to LRA activity			
Event database:	UCDP	ACLED	LRACT	LRACT	LRACT	LRACT
	(1)	(2)	(3)	(4)	(5)	(6)
Intensity of messaging	-0.003***	-0.003***	-0.027***	-0.027***	-0.027***	-0.026***
	(0.001)	(0.001)	(0.005)	(0.005)	(0.005)	(0.005)
Army presence (ACLED)			0.061***	0.197***		
			(0.014)	(0.050)		
* Minimum distance				-0.000***		
				(0.000)		
Army presence (UCDP)					0.178***	0.453***
					(0.042)	(0.110)
* Minimum distance						-0.001***
						(0.000)
Observations	60600	60600	60600	60600	60600	60600
Number of Years	8	8	8	8	8	8
Number of Cells	7575	7575	7575	7575	7575	7575

Notes. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors in parenthesis are allowed to be correlated over time and space (see Conley, 1999, 2008; Hsiang, 2010). The dependent variables are the number of violent events where the perpetrator is the army (columns 1 and 2) and the number of LRA-associated fatalities reported in logarithm (columns 3-6). All specifications include cell and year FE, propagation controls, additional controls and interactions between year dummies and macro-region dummies. Additional controls include commodity price and weather shocks (see section 4). The time period is restricted to 2008–2015.

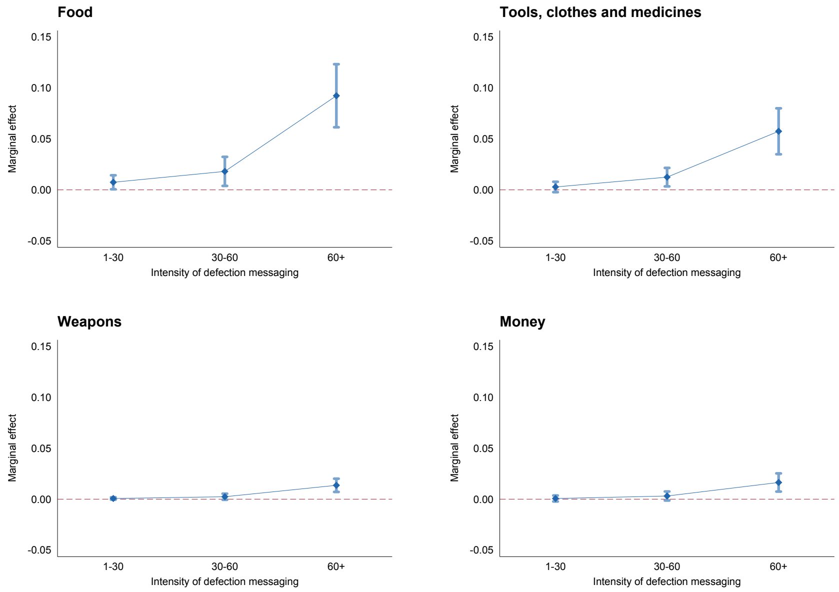
terized by looting of a specific good as dependent variable and allowing the effect of intensity of messaging to be non-linear. We distinguish between food, tools, clothes and medicines, weapons, and money. Figure B10 plots the coefficients.

Table B13: Effect of defection messaging on violent looting

Dependent variable:	Number of LRA events...		Number of events characterized by looting and...			
	without death	with death	no death	at least one death	at least one injury	at least one abduction
	(1)	(2)	(3)	(4)	(5)	(6)
Intensity of messaging	0.009*	-0.013***	0.017***	-0.001	0.002**	0.008***
	(0.005)	(0.004)	(0.004)	(0.001)	(0.001)	(0.002)
Observations	60600	60600	60600	60600	60600	60600
Number of Years	8	8	8	8	8	8
Number of Cells	7575	7575	7575	7575	7575	7575

Notes. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors in parenthesis are allowed to be correlated over time and space (see Conley, 1999, 2008; Hsiang, 2010). The dependent variables are the number of events where LRA is the perpetrator, depending on the number of fatalities associated with the event, in columns 1–2, and the number of events where looting occurs concurrently (or not) with other violent events, in columns 3–6. All specifications include cell and year FE, propagation controls, additional controls and interactions between year dummies and macro-region dummies. Additional controls include commodity price and weather shocks (see section 4). The time period is restricted to 2008–2015.

Figure B10: Non-linear effect of defection messaging on goods looted



Notes. Coefficients of equation (2) where intensity of defection messaging is decomposed into four dummy variables for each group of intensity reported in the horizontal axis. The excluded category is the dummy variable for zero-intensity. The dependent variables are the number of events characterized by looting, by looted good. All outcome variables are reported in logs. For comparison, we allow the vertical axis to vary with the same scale for all outcome variables. Confidence intervals are computed at 95% of confidence, standard errors are allowed to be correlated over time and space (see Conley, 1999, 2008; Hsiang, 2010).

B.11 Commodities and price shocks

Table B14 presents the list of the main cash crops and natural resources in the four countries affected by LRA violence based on the CIA World Factbook. To build commodity price shocks, we combine information about the geographical distribution of commodities with their prices on the international market. Our data on the geographical distribution of agricultural crops are based on the M3-Crops database (Monfreda et al., 2008), which offers a raster dataset at the $5' \times 5'$ latitude/longitude grid and information about harvested area for 175 crops in the 1997–2003 period. This highly spatially disaggregated information combining national-, state-, and county-level census statistics with satellite imagery for land cover provides an improvement from just using survey data. While most global land cover datasets group croplands into just a few categories, this dataset allows for significantly increasing the variation observed in each cell by providing crop-level information for all major crops in the area. Our price-series data are based on the World Bank's Global Economic Monitor (GEM) Commodities dataset. We also consider extractive resources using information about the geographical distribution of minerals (Mineral Resource Data System-USGS, and the PRIO/Uppsala datasets) and their prices (Historical Statistics for Mineral and Material Commodities in the United States, USGS, 2016).[7]

Commodity price shocks are computed as the product of the share of a cell cropped with a

[7]However, minerals are either not widespread in our study area or the LASSO procedure rejects shocks to mineral prices as relevant. See Section 5.

Table B14: Main exported crops and natural resources present in LRA-affected countries

Type	Commodity	Price (Source)	Geo-location
Cash Crops	Coffee	Coffee, Robusta, \$/kg, real 2010\$ (GEM)	M3-Crops
	Cotton	Cotton, A Index, \$/kg, real 2010\$ (GEM)	M3-Crops
	Oil palm	Palm oil, \$/mt, real 2010\$ (GEM)	M3-Crops
	Groundnuts	Groundnut oil, \$/mt, real 2010\$ (GEM)	M3-Crops
	Rubber	Rubber, Singapore, \$/kg, real 2010\$ (GEM)	M3-Crops
	Sesame	Grains, 2010=100, real 2010\$ (GEM)	M3-Crops
	Sugar	Sugar, world, \$/kg, real 2010\$ (GEM)	M3-Crops
	Tea	Tea average, \$/kg, real 2010\$ (GEM)	M3-Crops
	Tobacco	Tobacco, \$/mt, real 2010\$ (GEM)	M3-Crops
Extractive resources	Cobalt	Cobalt, \$/mt, real 1998\$ (USGS)	MRDS
	Copper	Copper, \$/mt, real 2010\$ (GEM)	MRDS
	Gold	Gold, \$/toz, real 2010\$ (GEM)	PRIO Goldata

Notes. Commodities are listed in order of relative importance. South Sudan includes the information for Sudan. Source: CIA World Factbook. We exclude diamonds and crude oil from our analysis, since they are not present in the area of analysis, and wood since no information is available on the type of forest cover that could be exploited for the international market.

commodity and the log-price difference between time t and time $t-1$. Figure B11 shows the geographic distribution of areas farmed with cotton and groundnuts, the main crops selected for analysis in the main text, and the times series of their prices on the international market. Prices are normalized using the year 2010 with the base value equal to 100. The dashed line is a moving average of the time series using a plus/minus 5 year window. Table B15 presents the descriptive statistics of commodity price shocks, conditional on cells where the commodity is either produced or extracted.

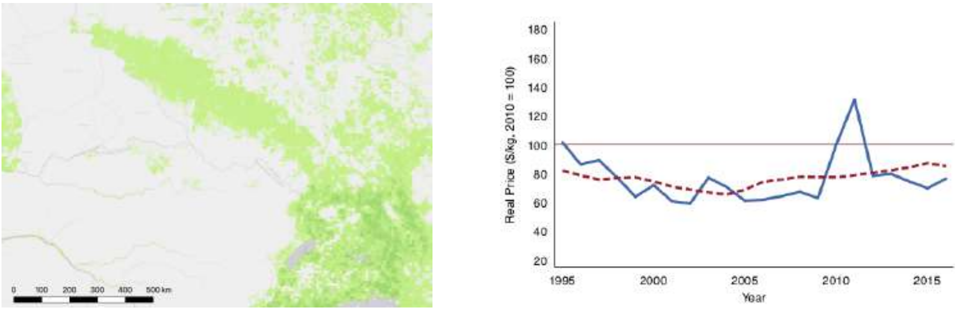
Table B15: Descriptive statistics on cash-crops price shocks

	Mean (1)	Std.Dev. (2)	Min (3)	Max (4)	Obs. (5)
Cobalt price shock	-0.107	0.274	-0.689	0.189	8
Coffee price shock	-0.001	0.087	-0.281	0.223	3824
Copper price shock	-0.035	0.167	-0.237	0.345	16
Cotton price shock	0.006	0.172	-0.519	0.466	3272
Gold price shock	0.061	0.125	-0.164	0.194	40
Groundnut oil price shock	-0.001	0.070	-0.524	0.380	9232
Palm oil price shock	-0.027	0.143	-0.265	0.241	40
Sesame price shock	-0.000	0.026	-0.214	0.310	8176
Sugar price shock	0.027	0.158	-0.193	0.413	1216
Tea price shock	0.021	0.056	-0.092	0.182	104

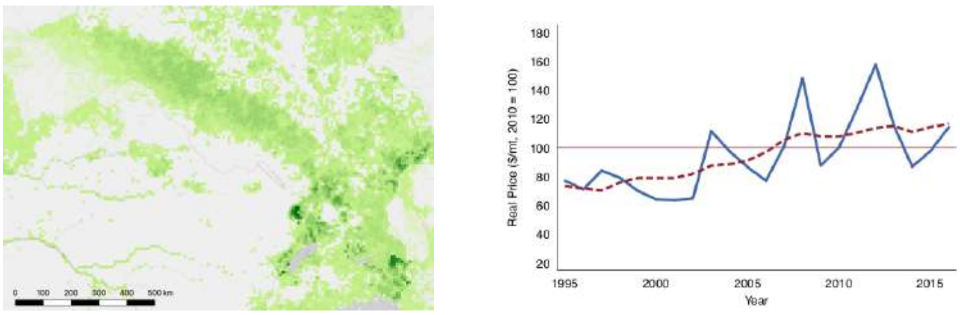
Notes. Descriptive statistics for all commodity price shocks, conditional on cells where the crop is produced or extracted. A shock is defined as the product between the share of cell farmed with the commodity (ranging 0–100) and the log-price difference between t and $t-1$.

Figure B11: Geographic distribution and price series of main cash-crops

Panel A. Cotton



Panel B. Groundnuts



Notes. The geographic distribution (left panels) and the price series (right panels) for cotton and groundnut oil. The geographic extent of the figure is restricted to the study area. Prices are reported in real values using US$ per corresponding unit. Prices are normalized using the year 2010 as base. The horizontal line shows the base value of 100. The dashed line is a moving average of the time series using a plus/minus 5 year window. Source: M3-Crops Data (Monfreda et al., 2008), World Bank's GEM Commodities dataset.

B.12 Spatial spillover

In this section, we investigate the presence of spatial spillovers using a spatial Durbin model (Anselin, 2013). In this model, the violence in each cell depends on the observable characteristics of the cell and on the same characteristics of the neighboring cells. We estimate the following model:

$$y_{it} \quad = \quad \gamma_i + \alpha\, dm_{it} + \alpha_2 W \mathbf{dm}_t + \mathbf{X'}_{it}\beta_1 + W\mathbf{X}_{it}\beta_2 + \alpha_t M_r + u_{it} \tag{3}$$

where the structure of spatial dependence between observations is defined through a symmetric weighting matrix W. Our benchmark weighting matrix is a binary contiguity matrix in which a weight of $1/m$ is assigned to cells surrounding the cell of interest within a 0.5° distance cutoff, and a weight of 0 to other cells.[8] m corresponds to the number of cells considered in the spillover area surrounding the cell. In practice, we are controlling for the average value of the control variable in the surrounding cells. We are aware that while the model aims at measuring spatial spillovers, in our setting, averaging across multiple cells leads to reduced variation, which could invalidate our assumption of exogeneity of topography-corrected signal. Table B16 presents estimates for equation (3). We include an F-test of joint-significance of the main and spillover effect of intensity of messaging.

Table B16: Defection messaging, treatment spillover and commodity price shocks

Dependent variable:	**Number of fatalities**	**Number of individuals...** Returning	Being abducted	**Number of events involving...** Violence against civilians	Clashes	Looting
	(1)	(2)	(3)	(4)	(5)	(6)
Intensity of messaging	-0.027**	0.000	-0.016	-0.012	-0.000	0.010
	(0.011)	(0.008)	(0.010)	(0.009)	(0.004)	(0.007)
Avg intensity of messaging (surrounding cells)	-0.001	0.012*	0.012	0.003	-0.007**	0.008
	(0.009)	(0.007)	(0.010)	(0.007)	(0.003)	(0.007)
Observations	60600	60600	60600	60600	60600	60600
Number of Years	8	8	8	8	8	8
Number of Cells	7575	7575	7575	7575	7575	7575
Joint-significance F-test (p-value)	0.000	0.003	0.315	0.052	0.001	0.000

Notes. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors in parenthesis are allowed to be correlated over time and space (see Conley, 1999, 2008; Hsiang, 2010). Coefficients are estimated using a spatial Durbin model (see equation (3)). All specifications include cell and year fixed effects, propagation controls, additional controls and interactions between year dummies and macro-region dummies. Additional controls include commodity price and weather shocks (see section 4). Controls are included both at the level of the cell and, as average, at the level of the surrounding cells. The dependent variables are the number of fatalities linked to LRA (column 1), the number of individuals returning (columns 2), the number of abductees (columns 3) and the number of other LRA-related violent events (columns 4–6). The joint-significance F-test includes the main effect and the spillover effect. The time period is restricted to 2008–2015.

The effect of intensity of messaging on fatalities is mainly accounted by the intensity in the same cell, with no significant spatial spillover (column 1). For returnees, on the other hand, the main effect of intensity of messaging is captured as a spillover effect (column 2). This suggests

[8] Due to the resolution of analysis, intensity of messaging tends to present a high degree of spatial correlation. We therefore extend the area we consider to compute the spillover effect up to the point in which the correlation between intensity of messaging in the main cell and the average in the surrounding cells is lower than 0.85. This corresponds to 0.5° distance from the cell.

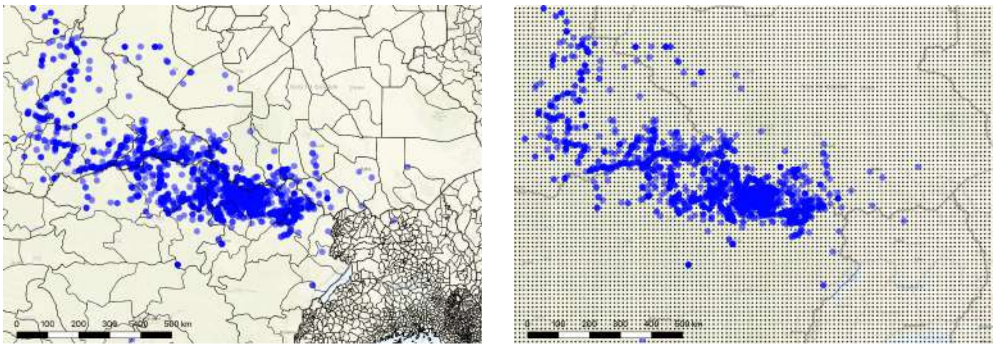
that returnees might return in the main cell, but they might be operating in the surrounding cells when they are exposed to the message. A similar effect is observed for clashes (columns 5). For abductees, in line with the results in the main text, we do not observe any effect (column 3). Finally, for looting the effect is more dispersed between main cell and surrounding cells (column 6).

B.13 Administrative-unit-level analysis

In this section, we use third-level administrative units (corresponding to districts) from the GADM database for our analysis. Figure B12 plots the distribution of LRA events in the period 2008–2015 for the 458 administrative units in our study area (left panel) and for the grid used for the main analysis (right panel). Table B17 estimates the effect of intensity of messaging on LRA fatalities using administrative boundaries.[9]

Figure B12: Comparison between administrative boundaries and gridded dataset

Administrative boundaries | **0.125° × 0.125° grid**



Notes. The geographic distribution of LRA events in the period 2008–2015 for the 458 administrative units in our study area (left panel) and for the grid used for the main analysis (right panel).

Table B17: Effect of defection messaging using administrative divisions as unit of observation

Dependent variable:	**Number of fatalities linked to LRA activity (per 1000 inhabitants)**			
	(1)	(2)	(3)	(4)
Intensity of messaging	-0.008***	-0.008***	-0.008***	-0.008***
	(0.002)	(0.002)	(0.002)	(0.002)
Observations	3664	3664	3664	3664
Number of Years	8	8	8	8
Number of Administrative Areas	458	458	458	458
Additional controls	No	Yes	Yes	Yes
Year × Country FE	No	No	Yes	No
Year × Macro-Region FE	No	No	No	Yes

Notes. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors in parenthesis are allowed to be correlated over time and space (see Conley, 1999, 2008; Hsiang, 2010). The dependent variable is the number of LRA-associated fatalities per 1000 inhabitants, reported in logarithm. All specifications include cell and year FE, and propagation controls. Distances are computed as average of cell-level distances within a defined administrative area. Administrative units are computed from the GADM database. Additional controls include commodity price and weather shocks (see section 4). The time period is restricted to 2008–2015.

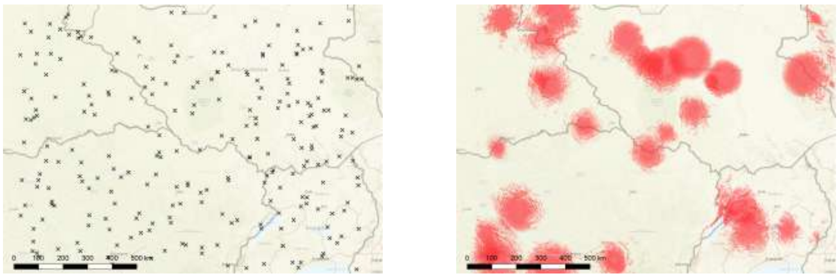
[9] Since the use of administrative boundaries leads to units of unequal size, we use per capita fatalities as our main outcome variable, though general findings are similar using other outcome variables. At this level of analysis, one standard deviation in intensity of messaging corresponds to roughly 5.45 minutes of messaging at full district coverage.

B.14 Placebo test

The left panel in Figure B13 shows the random position of an antenna in each of the 250 iterations used, while the right panel shows the radio coverage in one specific iteration. Table B18 presents descriptive statistics of placebo test estimates of the effect of intensity of messaging on outcome variables. Figure B14 shows the distribution of the coefficient of intensity of messaging on fatalities in the placebo samples.

Figure B13: Allocation of antennas and example of placebo coverage

Random allocation of antenna **Placebo coverage**



Notes. The left panel shows the random position of a single antenna in all 250 iterations. The right panel shows an example of placebo coverage of the sampled antennas for one specific iteration (for the year 2015 and the iteration number 143).

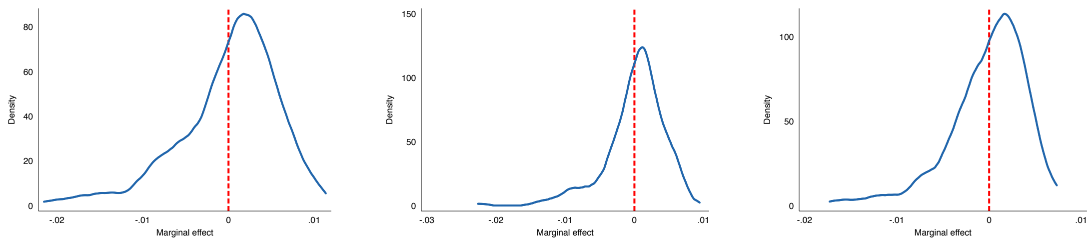
Table B18: Placebo test descriptive statistics

	Coefficient on intensity of defection messaging				
	Mean	St.dev.	5^{th} pct.	Median	95^{th} pct.
	(1)	(2)	(3)	(4)	(5)
Number of fatalities	0.000	0.003	-0.005	0.001	0.003
Number of returnees	-0.000	0.001	-0.002	-0.000	0.003
Number of abductees	-0.000	0.002	-0.003	-0.000	0.003
Number of events with violence against civilians	0.000	0.001	-0.002	0.000	0.002
Number of events with clashes	-0.000	0.001	-0.001	0.000	0.001
Number of events with looting	-0.000	0.002	-0.002	-0.000	0.003
Number of fatalities (ACLED)	0.000	0.002	-0.003	0.000	0.002
Number of fatalities (UCDP)	-0.000	0.002	-0.005	0.000	0.003

Notes. Descriptive statistics of the coefficient on intensity of defection messaging in the placebo test (250 simulations). Each observation is an estimated coefficient in equation (2) where radio coverage is generated by randomly allocating antennas in the original grid.

Figure B14: Distribution of marginal effects of intensity of messaging on violent events

LRACT ACLED UCDP



Notes. The distribution of the coefficient on intensity of defection messaging on fatalities in the placebo samples using the LRACT, ACLED and UCDP datasets. We perform 250 simulations. The dotted red line indicates zero.

B.15 Aggregate effect of defection messaging on the LRA insurgency (2008–2015)

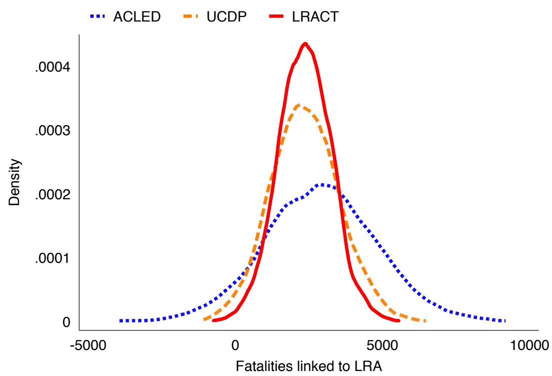
The aggregate impact of defection messaging is given by the difference between the actual estimate (provided by event-based datasets) and the counterfactual estimate imposing absence of defection messaging. This is computed using estimates from equation (2) and by predicting the dependent variable assuming zero intensity, and holding all other control variables constant. To avoid the re-transformation problem, we estimate the effect in levels, rather than in logs. Following results on non-linear effects of defection messaging, we estimate equation (2) including intensity of messaging and its square. To account for estimation uncertainty, we iterate the procedure 2000 times by assuming estimates are distributed normally with mean equal to the point estimate and standard deviation equal to the standard error. In each iteration, coefficients are drawn from these distributions. Table B19 presents the results. Figure B15 shows the distribution of actual minus counterfactual estimates for fatalities.

Table B19: Aggregate effects of defection messaging on the LRA insurgency during 2008–2015

	Actual estimate	**Counterfactual estimate (zero intensity of messaging)**			
		Mean	Standard deviation	Impact of defection messaging Difference	% change
	(1)	(2)	(3)	(4)	(5)
Number of fatalities	3137	5376	898	-2238.756	-41.65%
Number of fatalities (UCDP)	3348	5570	1117	-2221.894	-39.89%
Number of fatalities (ACLED)	5263	7849	1848	-2585.693	-32.94%
Number of returnees	2073	1553	273	520.0514	33.49%
Events: violence against civilians	989	1139	184	-149.655	-13.14%
Events: clashes	501	554	89	-52.5365	-9.49%
Events: looting	1158	627	174	531.1233	84.73%

Notes. Actual estimate corresponds to estimates computed using the LRACT (if not otherwise indicated), UCDP and ACLED datasets. The counterfactual estimate is computed imposing zero intensity of messaging and predicting the outcome variables using estimates from equation (2). To account for estimation uncertainty, we iterate the procedure by assuming estimates are distributed normally with mean equal to the point estimate and standard deviation equal to the standard error. In each iteration, coefficients are drawn from these distributions. We use 2000 iterations. The time period is restricted to 2008–2015.

Figure B15: Reduction in fatalities attributed to defection messaging

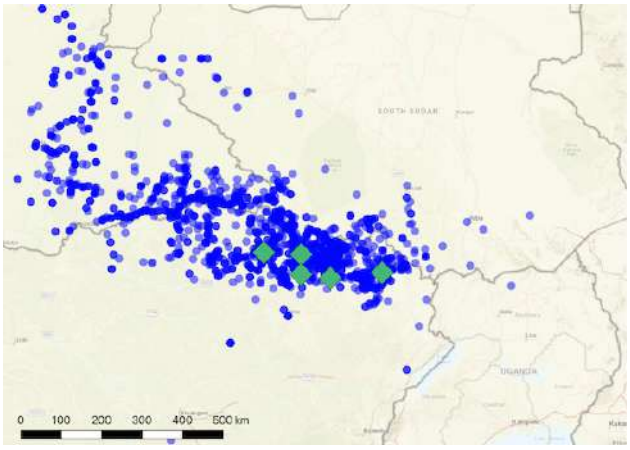


Notes. Distribution of the reduction in fatalities attributed to defection messaging using ACLED, UCDP and LRACT datasets. This is computed as difference between the actual estimate of fatalities, as reported in the datasets, and the counterfactual estimate, computed imposing zero intensity of messaging and predicting the outcomes using estimates from equation (2).

C Survey of returnees

In this section we provide a brief overview of our individual-level survey of returnees who had spent at least one month with the LRA.[10] We located and identified returnees based on lists in each community made available by civil society organizations and local associations (APRUs). Since the lists were numbered, respondents were randomly selected on the basis of these numbers. If the person corresponding to one of the numbers drawn was not available for the survey (either because they could not be located or because they refused to take the interview), the number was replaced by the next number on the list (non-response rate was 18%). Our final sample comprises 89 returnees drawn from the four northern DRC provinces of Ango, Dungu, Faradje and Niangara. For security reasons, we did not extend the survey to South Sudan and CAR. In total, we interviewed returnees in more than 15 villages, organized in five clusters (see Figure C16). Our sample size allows identifying (under unknown population and unknown standard deviation of outcome variables) a standardized effect of 0.3 in a one-sample mean comparison (assuming 80% of power and 5% of confidence).

Figure C16: Location of Respondents



Notes. The distribution of respondents from the returnees survey. To avoid the possibility of identification of respondents, each rhombus represents a cluster of respondents. Each dot represents an LRA-related violent event in the period 2008–2015. The geographic extent of the figure is restricted to the study area. Basemap source: ESRI.

Table C20 provides the summary statistics of the main variables. 58% (52) of our 89 respondents were male and 42% (37) were female. The average age of the respondents was approximately 27 years (25 for women and 29 for men). The main purpose of our survey was to understand whether in practice LRA members had access to radios and had heard defection messaging during their stint with the LRA. From Table C20 we see that 73% of our respondents listened to the radio while with the LRA and 65.5% of the respondents had heard defection messages during their stint at the LRA. Furthermore, 94% of the respondents had heard other group members discussing the broadcasts asking rebels to return. Combining direct and indirect exposure, 95.5% of our sample

[10] The survey was conducted by Innovative Hub for Research in Africa / Marakuja Research Kivu, a research organization based in DRC.

was exposed to defection messaging.

Finally, we see that more than 67% of the respondents say that the broadcasts had influenced their decision to return. Hence, our returnees survey shows that while the LRA were highly mobile and operated across vast expanses, the combatants were still exposed to radio defection messages either directly or indirectly quite frequently. And such broadcasts had a direct influence on their decision to lay down arms and return home.

Table C20: Summary Statistics for Returnees Survey

Variable	Mean	Std. Dev.	Min.	Max.	N
Male	0.584	0.496	0	1	89
Age	27.045	9.060	17	53	89
Birth Year	1990.865	9.099	1965	2001	89
Year joined LRA	2010.101	2.927	2007	2018	89
Age when joined the LRA	19.247	9.645	6	49	89
Approximate length of stay with the LRA (months)	27.066	28.387	1	111.6	89
Listened to radio while with LRA	0.73	0.446	0	1	89
Heard defection messaging while with LRA	0.655	0.478	0	1	87
Heard members discuss def. broadcasts while in the LRA	0.944	0.232	0	1	89
Exposure to radio messages	0.955	0.208	0	1	89
Broadcasts influenced decision to return	0.674	0.471	0	1	89
Nights spent in same place while with LRA	1.553	1.139	1	5	85

Notes. For "Heard defection messaging while with LRA" and "Nights spent in same place while with LRA", the answer "I don't know" has been set to missing.

Table C21 tabulates the frequency of messaging exposure. The left panel shows the frequency of direct exposure and the right panel shows the frequency of indirect exposure. Approximately 72% of the 57 respondents who had heard defection messages on the radio were exposed to the messages at least once a week and among the 84 respondents who had heard other group members discuss messages 44% did so at least once a week. This is despite the fact that on average they spent less than 2 nights in the same place.

Table C21: Frequency of hearing messages

	Defection broadcasts		Group members discussing broadcasts	
	Frequency	Percent	Frequency	Percent
Once a month	3	5.26	32	38.1
Every two weeks	13	22.81	15	17.86
Every week	33	57.89	30	35.71
Everyday	8	14.04	7	8.33
Total	57	100	84	100

D Examples of defection messages

In this section, we present some examples of messages broadcast during the defection messaging campaign. The following examples are drawn from a repository of broadcasts containing both audio files and transcripts hosted on The Voice Project. The first example is a message recorded by the chairperson of a village and addressed to children in LRA and to Joseph Kony:

> *My name is Pauline Achan; chairperson LCI of Akoyo village. As a mother, I will not talk much but I do appeal to you my children who are still in the bush that today if you hear my voice, you should not have any doubt. Some people used to say the people whose voices are played on radio are all dead, but today I am speaking from home in Odek and for you, who are still alive, you should hear me. Moses the son of Jackson stayed in the bush for eight years, but he is now farming together with us here at home without any problem. Now Lucore, I used to call you Lucore, if you are still alive please come home. Joseph Kony, you know me very well, I am the daughter of Obonyo Sione and I am your cousin. If you can hear me now please come back home because home is very good, girls have become tailors, others are builders and others are doing different useful work. Come back home because I am sure even you were abducted against your will. Thank you.*

The second example is a message recorded by a former LRA combatant:

> *My name is Opio but most of you from the bush know me by the name Aditi from Copil, I want to appeal to you my brothers to come out of the bush because whatever takes place there are not proper. For instance forcing people to kill is something I never wanted to do but I was forced into doing it. It is really not prober (sic) to be beaten like I was beaten while I was still there. So I appeal to everybody in the bush to come out. I still remember people like Owila we lived together with in Gilber battalion. I request you to come home because life at home is very good, there is now total peace. For me when I came back home, I was first taken to [Gulu Support the Children Organization] and later I was handed over to my parents who welcomed me with maximum happiness.*
>
> *You know very well that in the bush there is no proper medication should you get wounded but at home you have access to health services whenever you are sick and you can be treated. Human beings are not supposed to be treated like animals where your wounds are tied with banana leaves instead of receiving proper medication. So make up your mind and come out now.*
>
> *I have stayed with you people like Atingo nyim, Oyoo and Olwere and all other people. My primary interest is that you should come back home and live a good life instead of suffering in the bush. Come and stay with us the rest of people who returned. For us we are enjoying peace and we meet with returnees from other places from time to time. Thank you.*