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

Alex Armand Paul Atwell Joseph Gomes

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Abstract

We study the role of FM radio messaging in discouraging violent conflict by armed groups. Focusing on the Lord's Resistance Army (LRA), we collected unique information about defection messaging by local and international radio stations in the four countries where the LRA has operated (DR Congo, Central African Republic, South Sudan and Uganda). We exploit time and geographical variation, along with random topography-driven variation in radio coverage, to capture the causal effect of the intensity of messaging on violence, and on the LRA's strategic behavior. Higher intensity of defection messages leads to a decrease in both fatalities and the number of events involving violence against civilians and clashes. We show that this outcome is mainly explained by an increase in returnees from the armed group. In areas with higher intensity of messaging, we observe a strategic shift as the LRA tries to compensate these membership losses by engaging in higher levels of looting to reward existing members.

JEL codes: D74, N47, D89.

Keywords: Conflict, Radio, Defection, Media, LRA, Strategy, Armed Group.

*Armand: University of Navarra, Navarra Center for International Development and Institute for Fiscal Studies (e-mail: aarmand@unav.es); **Atwell**: Dept. of Political Science and Ford School of Public Policy, University of Michigan (e-mail: patwell@umich.edu); **Gomes**: University of Navarra and Navarra Center for International Development (e-mail: jgomes@unav.es). We would like to thank Pedro Carneiro, Caitriona Dowd, James Fenske, Patricia Justino, Macartan Humphreys, Luigi Minale, Marta Reynal-Querol, Andrea Tesei, Pedro Vicente, David Yanagizawa-Drott and seminar participants at the Institute for Fiscal Studies, University of Rovira i Virgili, and NEUDC 2017 for helpful comments. We are grateful to Invisible Children, who provided support in surveying stations. We wish to acknowledge financial support from the Ramon Areces Foundation (grant *Radio Messaging and Armed Group behavior*). This paper was previous circulated as "The Reach of Radio: Defection Messaging and Armed Group Behavior".

1 Introduction

Since the late 1990s, peace-building policy has made pointed efforts to go beyond macro-level political processes and address individual incentives to participate in or incite violence. A significant amount of resources and attention have focused on programs helping ex-combatants transition to civilian life, most notably Disarmament, Demobilization, and Reintegration (DDR). Yet few formal activities within such programs and evaluations of them effectively address upstream issues and draw combatants out of conflict (see Humphreys and Weinstein, 2007 for a notable exception). More recently, defection messaging initiatives have gained support and prominence at this juncture (UN-DDR, 2014). They aim to mitigate and end conflict by providing fighters information on the logistics of surrender, immunity offers and judicial processes, and the willingness of their families and communities to accept returnees.

Due to the limited reach of print and digital media in remote areas where armed groups often hold territory, several policy actors have pursued defection messaging through FM radio broadcasting. This strategy has taken a notable role in multiple conflicts in central Africa with similar programs frequently being employed across UN missions globally. Although the literature has highlighted the political salience of radio as a tool for spreading violence (Yanagizawa-Drott, 2014; Adena et al., 2015; DellaVigna et al., 2014), existing evidence on its efficacy in discouraging it remains highly limited. Exploring the effects of defection messaging on armed group behavior can also shed light on the conduct of armed conflict, recruitment strategies, and the organization of civil warfare, which remains one of the most understudied areas in the literature on conflict (Blattman and Miguel, 2010).

We target these gaps in the literature by focusing on the Lord's Resistance Army (LRA) Insurgency, in which FM defection messaging has been employed since the early 2000s. The conflict started in northern Uganda in 1987 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 and by their frequent reliance on abducted child soldiers. Over the course of the conflict, the group caused an estimated 100,000 deaths and displaced 2.5 million civilians (UN Security Council, 2013a). While today its forces have been reduced to 200 or less fighters, in its day, the group numbered as many as 3,000. Beyond its direct effect on violence, the conflict has also had persistent effects on the economy and the politics of the region.

A central goal of these programs is to communicate the credibility of Uganda's blanket LRA amnesty law (signed in 2000). The law is seen as essential in assuring combatants that they can live free and productive lives as civilians and remains in effect today. However, key incidents of violations of its conditions, internal LRA counter-narratives, and vigilante killings of LRA have been cited as causing deep scepticism on the viability of surrender and amnesty offers.[1]

[1] Rigterink and Schomerus (2016) show that LRA-targeted defection messaging was indeed influential in the region. Focusing on South Sudan only, they show that civilians facing higher exposure to these programs showed significantly higher anxiety and fear of LRA.

This conflict provides a fertile context for studying conflict dynamics. According to defection messaging proponents, mass media can be an effective tool in countering violence directly through defections, as well as indirectly through changing group composition. We approach this by constructing a novel dataset on the annual expansion of defection messaging, collected through surveys of radio station operators. Combining this information with a geo-coded database of diverse LRA-related events (including looting and defections), the LRA Crisis Tracker (LRACT), we study the effects of radio messaging on the LRA conflict during the period of 2008-2015. We focus on this period for three reasons. Firstly, the post-2008 dispersion of LRA outside of Uganda is credited with causing a shift in the strategic aims of LRA leadership; its aspirations of political legitimacy in Uganda were abandoned, while the "hunt" for Kony assured high-ranking LRA members that amnesty was unlikely for senior leadership. Secondly, after 2008, a more detailed cataloguing of information about the LRA activities began (see section 3). We are therefore able to go beyond the relationship between messaging, defections and conflict, and explore strategic behavior (such as looting and abductions) of the LRA under dwindling membership. Thirdly, the main expansion of defection messaging began around 2010 and uniquely beyond Uganda.

The use of FM radio defection programming became a central counter-insurgency strategy after the sustained military offensive in 2008 drove remaining LRA forces into remote regions of DR Congo, South Sudan, and CAR. The United Nations (UN), and other international NGOs, began expanding capacity at small community radio stations, as well as working with communities to establish a number of new stations (see, for instance, UN Security Council, 2013b). We discuss in detail the timing of this expansion and its main features (see section 5.4). In total, 18 stations (21 antennas) have partnered in these efforts, spanning an area of 400,000 square km.

The phased implementation of the messaging campaign and of the radio coverage expansion over time allows us to estimate the causal impact of messaging. We exploit three sources of plausibly exogenous variation to support this claim. Firstly, we measure the 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 characteristics at highly disaggregated level. Finally, we exploit the overlapping of radio coverage from different radios to build a measure of message intensity at the grid-cell level.

We find that increases in the intensity of defection messages translates to a higher number of returnees from the LRA and to an overall reduction in the number of fatalities. For instance, on average, a 0.25 hours increase in defection messaging (at daily frequency and full cell coverage) leads to a 3 percent decrease in fatalities, and a 1 percent increase in returnees. By allowing for non-linearities in the effect of messaging, we observe that there is a significant increase in the effect of defection messaging with its intensity. At very low levels of intensity (less than 0.5 hours per day at full cell coverage), the effect is not significant, while at 1-1.5 hours per day at full cell coverage, defection messaging can lead to reductions in fatalities of up to 7 percent. A similar non-linear relationship is present for all our main outcome variables.

Moving beyond this main result, we find a significant shift in LRA strategy. While the decrease in fatalities can be explained by a reduction in the number of attacks against civilians and of clashes with security forces, we observe an increase in looting in areas where exposure to defection messaging increased. This result is in line with Azam (2002, 2006), who shows looting can be explained as a means for an armed group to reduce the relative returns to non-military labor effort for potential recruits, while simultaneously generating spoils to reward existing recruits.[2]

We also show income shocks can affect active policies to disincentivize conflict. An individual's willingness to participate in the conflict can be related to her expected returns to different alternatives, such as fighting or returning to the civil society (often as farmers) (Becker, 1968). This in turn can be affected by economic conditions and the availability of resources. In this setting, income shocks play an important role. First, they can reduce the intensity of conflict by increasing wages and reducing the labor supply for conflict activities (Becker, 1968; Grossman, 1991). Alternatively, they can increase conflict by increasing the returns to predation (Fearon, 2005; Dube and Vargas, 2013). In the paper, we look at whether commodity price shocks, exogenously shifting the value of cash crops and natural resources at the cell-level, can impact the effectiveness of defection messaging. These shocks play an important role in explaining not only LRA activity, but also the response to defection messaging. Increases in value of conflict-enhancing commodities lead to higher levels of violence, but also weaker responses to defection messaging. On the contrary, increases in value of conflict-reducing commodities tend to have the opposite effect. This result suggests that violence and the response to defection messaging are indeed closely related to economic incentives.

Our results are stable across a series of robustness tests. We build forward from the existing literature in applying a fixed effects model at a spatially disaggregated cell-level, over and above exploiting topography for identification. Our choice of grid resolution is validated by conducting our analysis at different spatial scales. Our results are also robust to controlling for a wide range of other time varying controls, including weather shocks, population, etc. Moreover, in some of our specifications we specifically control for mobile phone coverage, which has been shown to affect political mobilization and could have been a potential confounder of our results (Manacorda and Tesei, 2016). Finally, while our main source of conflict data is the LRACT, we show that our main results hold when using alternative sources for conflict data. Using these sources, we also show that our results are not driven by conventional state military pressure against the LRA, a possible confounding strategy.

We contribute to the literature studying the effect of media on social and political outcomes by providing the first systematic analysis of how radio messaging can be effectively used to encourage defections and reduce conflict. Contributions in this field focused on the effect of media on accountability for politicians (Besley and Burgess, 2002; Strömberg, 2004), on crime (Dahl and DellaVigna, 2009), on participation in social activities and trust (Olken, 2009), and on fe-

[2]We focus on economic incentives, rather than the role of socialization and social identity. The role of these factors has been largely studied in military sociology and history. See Kenny (2008) for a review.

male autonomy and fertility (Jensen and Oster, 2009; La Ferrara et al., 2012). More recently, the literature focused on the specific role of exposure to radio on political outcomes. For instance, Yanagizawa-Drott (2014) shows how propaganda broadcast via radio played an important role during the Rwandan Genocide. Adena et al. (2015) shows how radio was instrumental in ensuring support for government initiatives in Nazi Germany. Again, DellaVigna et al. (2014) shows how radio was effective in shaping hateful sentiments across different ethnic groups in Croatia. All these studies reflect how radio messaging can be manipulated to incite conflict or violence.[3] In contrast, to our knowledge, no study has focused on the capacity of messaging to disincentivize violence.[4]

Our next contribution relates to changes in armed group strategy. Recent literature has shown that rebel groups typically follow rational and targeted strategies. For example, Weinstein (2005) argues that groups rich in material resources are more prone to committing violence against civilians as they are joined by opportunistic members with little commitment to civilian populations. We show that the LRA responds to defection messaging-driven loss of membership by reducing violence against civilians and increasing looting. We interpret this increase as a way to compensate and discourage existing members from defecting. This provides novel insights into the strategic behavior of armed groups.[5]

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 describe the data used in this paper. In Section 4 we discuss the empirical strategy. In Section 5 we present our results. Finally, in Section 6 we conclude.

2 The LRA and the "Come Home" Messaging Campaign

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 the LRA by extension–are rooted in long-standing ethnoregional divisions in Uganda. In 1986, current President Yoweri Museveni successfully led a largely southern rebel force to power. While many northern elements supported change in Kampala, they violently rejected southern rule. Nevertheless, by 1988, most organized resistance to Museveni's presidency had either surrendered or disbanded. The few elements that remained joined the small, but growing LRA, which held the ostensible goal of a

[3] One exception is Paluck and Green (2009), who show how radio messaging can be used to favorably shift attitudes, behaviors and social norms in a post-conflict society.

[4] Several qualitative publications have spoken to this issue, most often relying on interviews with policy actors, local residents, and ex-LRA members (Lancaster and Cakaj, 2013; Ross, 2016). While a rich source of information on defection programs, the applicability of interview data from ex-LRA is limited by issues of self-selection.

[5] As summarized by Blattman and Miguel (2010), "[..] the most interesting directions for research include the internal organization of armed groups, rebel governance of civilians, the strategic use of violence, counterinsurgency strategy, and the roots of individual participation in violent collective action." Our paper speaks directly to the issues of the strategic use of violence, counterinsurgency strategy, and to some extent, the roots of individual participation in violent collective action.

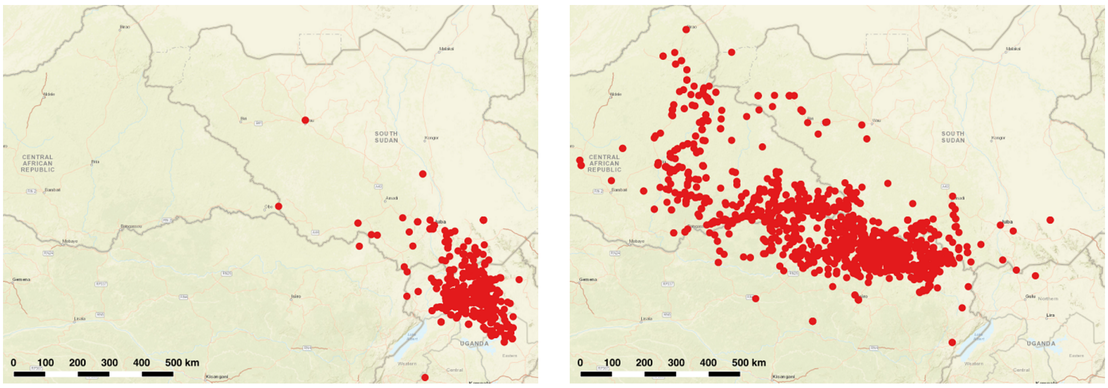
spiritual cleansing of the nation.[6]

Over the next two decades, the conflict has ravaged local communities. This was at times due to episodes of open conflict between Ugandan and LRA forces, but 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. Following years of harsh conflict, the Ugandan government and the LRA signed a fragile ceasefire via the 2006 Juba peace talks, which permanently broke down in 2008 when the armed forces of Uganda, DR Congo and South Sudan, in the US-supported Operation Lightning Thunder, 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 slow dispersion in north-eastern DR Congo, eastern CAR and western South Sudan.

Figure 1 shows the geographic distribution of LRA-related events for the period 1989-2015, divided into pre-2008 and post-2008 periods. This paper focuses on the expansion of the defection program at the border with DR Congo, South Sudan and CAR in the post 2008 period, during which we observe that the LRA is essentially inactive in Uganda.

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

1989-2007 **2008-2015**



Note. The figures show the geographical distribution of events where LRA is coded either as attacking actor or attacked actor for two periods, 1996-2007 and 2008-2015. Data source is UCDP dataset since we can observe the whole period 1989-2015.

In the context of the LRA, defection campaigns have evolved from a modest innovation at two radio stations to be a central tool in reducing LRA numbers. Aware of the fear of returning home that LRA combatants and abductees faced despite the passing of the 2000 Amnesty Act, radios in Lira and Gulu (northern Uganda) began interviewing ex-combatants, as well as community and family members, on air. The objective was to create a credible path for the fighters to leave the militarized structures and rejoin their communities. Many media accounts of the programs focus on family members, often parents, speaking directly to their children (often abductees coerced into

[6]For deeper reading on the historical origins of the LRA see Allen (2005); Beber and Blattman (2013); Allen and Vlassenroot (2010); Behrend (1999); Doom and Vlassenroot (1999); Finnström (2010); Lamwaka (2002); Omara-Otunnu (1987).

violence) assuring them they would be welcome and forgiven should they return. Others highlight the role of former-LRA members speaking out to assure others of their good health and freedom, while also emphasizing the need to return.[7] The issue of credibility was particularly salient. This is evident from an episode in Northern Uganda, where a significant number of long-term LRA members surrendered and refused the food offered by demobilization teams based on widespread rumors that Ugandan and international forces would poison them (Allen and Schomerus, 2006).

Following the de facto expulsion of the LRA from Uganda in 2008, attention turned to diminishing remaining forces in the isolated border regions. The FM messaging model was soon elevated as a policy tool to complement continued military efforts. With the assistance of the American NGO Invisible Children and the UN mission to the DR Congo (MONUSCO), new radio stations were built and other community stations were expanded. One community station in Central African Republic (CAR), Radio Zereda, went from operating with a car battery and umbrella skeleton to having a reported broadcast radius of 300 km in 2011. Today, in affected areas, FM stations cover about 400,000 square km. While the case of the LRA defection messaging has not been a coordinated component of an official peacekeeping mission given the ad hoc nature of efforts against the LRA, it is similar to applications in other missions' programs (notably MONUC/MONUSCO in the eastern DR Congo).[8]

Radios have been central in efforts to ensure that a lack of information is not a barrier to defection. Perhaps the best evidence of the success of the program arose from the LRA itself. Not only did they burn down a station in 2002 for broadcasting defection messages, but before the 2006 Juba Peace Talks between Uganda and LRA leadership, they demanded the cessation of messaging before meeting (Ross, 2016). After those peace talks broke down, defection messaging has grown in centrality in the international effort to provide a credible alternative to combatants.

3 Data

In this paper we make use of data from different sources. We combine an FM Radio dataset, which provides detailed information about radio stations involved in the broadcasting of defection messages, with data about violent events in the region affected by the LRA. In addition, we supplement the dataset with cell-level information about economic activity from myriad sources.

[7] Example transcript from program: "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." Additional examples are reported in Appendix E.

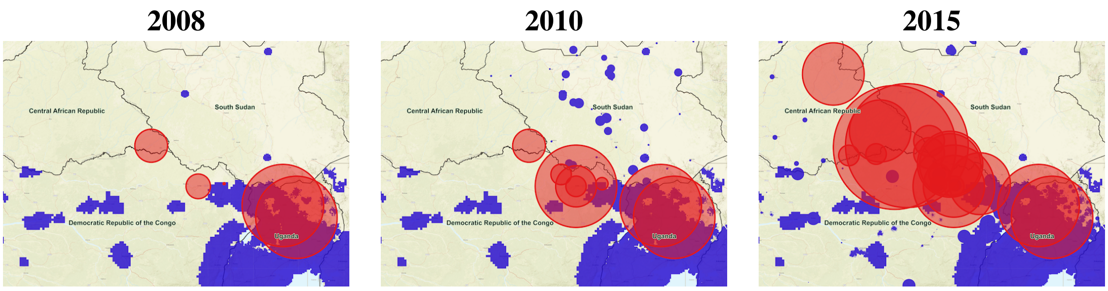
[8] Appendix C.2 presents the overall extent of the LRA conflict and the defection messaging program over the whole African continent.

3.1 FM Radio Stations and coverage

To acquire data on broadcast exposure, we designed a short questionnaire for participating stations.[9] The set of participating stations was generated by cross-referencing policy reports and through direct exchanges with international actors and radio operators to identify any station that broadcasted content targeted to LRA combatants. The questionnaire was administered to most stations with logistical support from Invisible Children. Invisible Children is an international NGO working to assist communities in LRA-affected areas of central Africa by expanding community-based early warning systems, reaching out to potential LRA defectors and affected communities through FM radio, and rehabilitating formerly-abducted children. They have intimate ties with most stations including those operated by MONUSCO (UN). Non-affiliated stations were reached through direct contacts, such as the Catholic Radio Network in South Sudan and independent stations in Uganda. Collating the data from the survey, we constructed a panel, which includes information about stations' LRA-related messaging, including content and frequency, as well as other station characteristics, such as its broadcast languages and its normal (non-defection) programming.

The broadcasting of defection messaging by radio stations 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 radio coverage in the LRA-affected area. These radios are FM stations that at least once in their history broadcasted defection messaging. Stations in the area of study that have not broadcast defection content are not included in our dataset due to data collection constraints. For the same periods, the figure also shows the extension of GSM mobile phone network, which remained relatively constant.[10]

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



Note. The figures show circular estimates of 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. Darker areas in the background map represent coverage of the GSM network (Coverage Data®Collins Bartholomew Ltd and GSMA 2017). See Figure C5 in Appendix for a comparison with defection messaging intensity.

[9] See Appendix B for a detailed description.

[10] We construct mobile coverage with use of the Collins Mobile Coverage Explorer, supplied by GSMA and Collins Bartholomew (GSMA, 2012). 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 data depends on a given Operator's submission and varies from 1 km^2 to 15-23 km^2. We present only for GSM coverage, since the area of interest is not covered by any of the other type of network during the selected years.

Similar to Yanagizawa-Drott (2014), who exploits variation in topography to capture exposure to radio signal during the Rwandan genocide, we correct our radio coverage variable for topography. This is exploited as part of our identification strategy, which is explained in detail in Section 4. Where station's technical characterists wer unavailable, we estimate topography-corrected coverage using self-reported information about the maximum circular radius at which each radio station signal is received and on the geographic coordinates of each antenna. We construct these estimates by adjusting station mast height to 150m and increasing transmitter power (kW) until a 1km ring on the reported circular radius is 15 to 20% covered with a signal of at least 50 dBμV/m.[11] This basic algorithm identifies conditions under which a signal could be plausibly received and reported at the supplied circular radius.

The topography corrections are based on the Longley-Rice/Irregular Terrain Model (ITM). This model takes in station parameters and topographic characteristics to determine which areas receive signal from the station and at what strength at a 90m resolution. Figure C5 in Appendix shows the coverage of defection messaging (in terms of intensity) using this correction.[12]

Table 1 presents descriptive characteristics about the radio stations in 2015. 18 radio stations (21 antennas in total) were identified and interviewed. Among those, 29% were based in CAR, 38% in DR Congo, 19% in South Sudan and 14% in Uganda. Broadcasting in the region regularly uses at least 13 languages, showing the large ethno-linguistic diversity of populations in the region. Among all radio stations that participated in the defection messaging program, 62% are still broadcasting in general and 43% are still broadcasting defection messages. On average, radios broadcast 1.05 hours of defection content per day.

3.2 Conflict intensity

Our main outcome of interest is LRA activity. To this end, we make use of the LRA Crisis Tracker database (LRACT). 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' strategy and activities. It provides geo-coded information about LRA-related events, including fatal attacks, looting, and abductions, and their impact on civilian populations across space and time, with nearly all events falling in Central African Republic, Democratic Republic of Congo, South Sudan, and Uganda. Events are reported at maximum spatial resolution of the population center where the event occurred and at maximum temporal resolution of the day of the event.

Many events rely on sourcing methods similar to other widely used conflict event databases, i.e. Uppsala Conflict Data Program (UCDP) (Sundberg and Melander, 2013; Croicu and Sundberg, 2016) and Armed Conflict Location & Event Data Project (ACLED) database (Raleigh et al.,

[11] We are currently collecting remaining technical parameters of stations such that topography-corrected estimates will all be based on the parameters of each station's mast and transmitter.

[12] Coverage is calculated using CloudRF (cloudrf.com), a commercial radio planning tool.

Table 1: Descriptive statistics of Radio Stations, 2015

	Mean (1)	Std.Dev. (2)	Min (3)	Max (4)	Obs. (5)
Radio characteristics					
Share of active radios	0.90	0.30	0	1	21
On Air: less than 3 hours per day or unknown	0.29	0.46	0	1	21
On Air: 3-12 hours per day	0.67	0.48	0	1	21
On Air: more than 12 hours per day	0.05	0.22	0	1	21
Average coverage radius (km)	132.86	79.87	20	300	21
Language: Pazande	0.71	0.46	0	1	21
Language: Acholi	0.67	0.48	0	1	21
Language: Lingala	0.67	0.48	0	1	21
Language: French	0.67	0.48	0	1	21
Language: Sango	0.29	0.46	0	1	21
Language: Other	0.19	0.40	0	1	21
Location of antenna					
Central African Republic	0.29	0.46	0	1	21
DR Congo	0.38	0.50	0	1	21
South Sudan	0.19	0.40	0	1	21
Uganda	0.14	0.36	0	1	21
Defection messaging broadcasting					
Broadcasting Defection content	0.48	0.51	0	1	21
Daily hours of defection messaging	1.05	1.32	0	3	21

Note. The Table presents descriptive statistics for all radio stations in the final year of our sample, 2015. *Share of active radios* indicates the share of radio stations that participated in the defection messaging effort and are still operating in 2015, independently from the content broadcast. *Language: Other* includes broadcasting in Alur, Amadi, Arabic, Bangba, Bangala, Logoti, Nemangbetu or Yogo. *Broadcasting Defection content* reports the share of radio stations that are actively broadcasting defection messages.

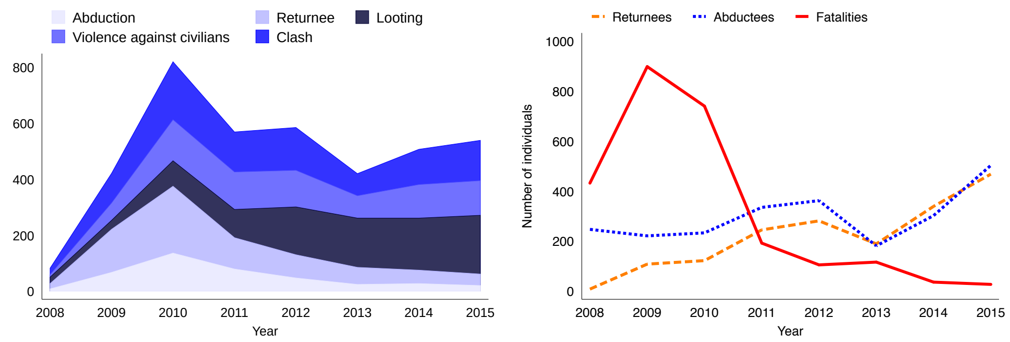
2010). These include reports from news agencies, NGOs, and governments, but beyond this, LRACT uniquely draws on a widespread network of field sources, some linked by High Frequency (HF) radios. This allows LRACT verifiers to find deeper and corroborating accounts of events sourced from other channels, as well as report events that are not captured by alternative event-based datasets.

We measure conflict intensity using conflict-related event-level information from this dataset. We draw data on specific incidents and locations, to group events into several categories such as conflict between government forces and the LRA, violence against civilians, abductions, looting, etc. The left panel in Figure 3 presents the series of total events associated with the LRA and its decomposition by type of incident. The right panel shows instead the series of the number of returnees, abductees and fatalities over the period of analysis.

In the literature, obtaining accurate information about the location and the frequency of events is recognized as including some measurement error. To address this limitation, we repeat our main estimations using both data from UCDP and ACLED.[13] Each is comprised of event-based information, supplying precise dates and geo-coded locations for events across our area of study. While LRACT, UCDP and ACLED all aim to measure the same basic trends, i.e. conflict intensity, they use slightly different definitions (Eck, 2012). The LRACT logs any reported sighting or event which plausibly involves the LRA. UCDP qualifies an event as “an incident where armed force

[13] *Uppsala Conflict Data Program* and *Armed Conflict Location and Event Data*

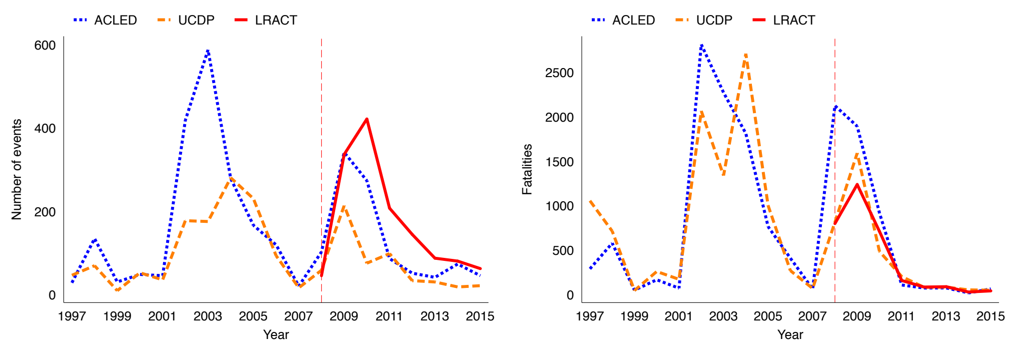
Figure 3: Composition of LRA-related events and number of involved individuals



Note. The figures show the time series of conflict events and involved individuals as measured by the LRACT database. The left panel presents the composition of total events per year, while the right panel focuses on the number of returnees, abductees and fatalities.

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 a specific date." ACLED instead collects and codes all events identified as political violence in the developing world, focusing on civil and communal conflicts, violence against civilians, remote violence, rioting and protesting. Figure 4 shows the evolution of LRA-related violence from 1997 to 2015, comparing events across the three datasets. 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 the events from the three datasets follow similar trends.

Figure 4: The intensity of LRA-related conflict, 1997-2015



Note. The figures show the time series of conflict intensity as measured by 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 years when LRACT data became available. Since we are focusing on violent behavior only, we exclude from the analysis all events that are coded as "non-violent" events.

To construct a unit of observation, we superimpose a grid of equally-sized cells over territory affected by the LRA and hold this stable over the period of analysis. This approach for studying political relationships over space has been frequently employed in the literature (see for instance Michalopoulos, 2012; Harari and La Ferrara, 2013; Montalvo and Reynal-Querol, 2016). This grid-cell based approach also avoids the potential of political boundaries to be endogenous to violence.[14] For our baseline specifications, we construct cross-sectional units of observation as cells of 0.125 degrees of latitude by 0.125 degrees of longitude, or roughly 14 km by 14km at the equator. Sides are placed in correspondence of integer values of latitude and longitude. Our results are robust to grids with lower resolution. In Appendix C.1, we provide a detailed discussion about the choice of cell resolution, including its effect on our main estimates, i.e. the Modifiable Areal Unit Problem (MAUP). See Figure C4 for a graphical representation of the grid resolution.

In addition to the MAUP, defining the grid extent is also a discretionary process with no clear precedent in the literature. In our case, we select all events where LRA is an actor and we look at the distribution of their latitude and longitude. To compute this distribution, we consider the period 1997-2015 in order to be more conservative and gain further dispersion in the geographical distribution of events. We then select a geographical area that is defined by the 1st and 99th percentiles of both latitude and longitude of events minus and plus 0.5 degrees respectively. Our results are robust to expanding our study area further (see Appendix C.2).

While similar studies have relied on administrative divisions as a unit of analysis (see, for example, Yanagizawa-Drott, 2014), a grid precludes potential endogeneity of unobserved determinants of violence to those boundaries, which are outcomes of political processes. Administrative boundaries might be also capture variation in geography and political history that can be related to time variation in conflict intensity. While using administrative units could enable us to obtain time variation in demographics and other characteristics, we do not have consistent data on such variation, particularly given the international extent of events. Furthermore, by using a grid cell based approach, we can observe the outcome by cell over time and can control for time-invariant unobservable characteristics that are cell-specific. This also captures fixed effects of cross-border cells, which would be otherwise divided by administrative boundaries. This is particularly important as many events center around the border regions.

Events are aggregated at the cell-year level over the period 2008-2015. Aggregating events smoothes the possibility of measurement errors in the exact location and timing of each event. Table 2 presents descriptive statistics on 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.

The left panel in Figure 5 shows coverage of defection messaging content over time in the selected geographical area. The percentage refers to the share of cells receiving the signal from at least one station broadcasting this content.

3.3 Additional data

We supplement cell-level observations with information from satellite imagery on income shocks, weather shocks and demographics. See Appendix A for a summary of these variables and data sources.

[14] While argue this approach is superior in the context of our study, our results are also robust to the use of district-level administrative boundaries rather than gridded cells. See Appendix C.5.

Table 2: Cell-level descriptive statistics, 2008-2015

	Mean (1)	Std.Dev. (2)	Min (3)	Max (4)	Obs. (5)
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: clash / violence against civilians	0.02	0.30	0	20	60600
Events: looting	0.02	0.27	0	23	60600
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
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
Radio Coverage					
Cell covered by radio	0.32	0.47	0	1	60600
Cell covered by defection messaging	0.19	0.39	0	1	60600
Intensity of messaging	0.16	0.41	0	3	60600
Min distance from active antennas (km)	291.74	167.92	2	777	60600
Other indicators					
GSM coverage (% cell)	0.18	0.37	0	1	60600
Violence-reducing shock	2.38	1.37	-1	9	60600
Violence-enhancing shock	1.16	2.70	0	11	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

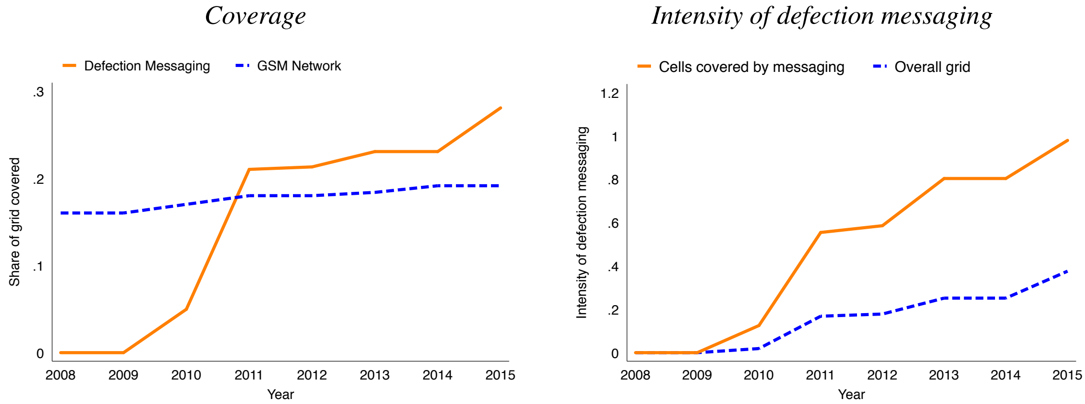
Note. The table reports cell-level discriptive statistics for cells measuring approximately 14km by 14km at the equator (0.125 by 0.125 degrees). See Appendix C.1 for a discussion about the choice of cell resolution. *Min distance from active antennas* is computed as minimum distance of the cell's centroid to an active antenna. *Population* is reported as log of the cell's population. *Intensity of messaging* is defined as the number of hours of daily defection messaging broadcast in a cell, corrected by the share of the cell that is covered by radio signal (see equation 3). Table A1 in Appendix presents further descriptions of data sources and calculations.

3.3.1 Commodities and income shocks

We are interested in understanding whether income shocks driving LRA activity impact the effectiveness of messaging. To disentangle the role of radio messaging from the role of productive rents, we look specifically at the relationship between the value of local productive or extractive activities and conflict intensity (see for instance, Dube and Vargas, 2013). To capture exogeneous variation in the value, we combine the geographical distribution of commodities with yearly commodity-specific price variation in international markets, which we assume to be exogeneous to local production.

We focus specifically on two types of commodities: cash-crops and natural resources. Data on the geographical distribution of agricultural crops is obtained from M3-Crops Data by Monfreda

Figure 5: Coverage and intensity of defection messaging, by year



Note. The left figure shows the share of cells that are covered by the radio signal from defection messaging stations and by the GSM cell-phone network. The right figure presents instead the average intensity of defection messaging, as defined by equation (3). Source: own elaboration.

et al. (2008). It offers a raster dataset at the 5 minute by 5 minute latitude/longitude grid and information about harvested area in hectares for 175 crops in the year 2000. It provides highly spatially disaggregated information by combining national-, state-, and county-level census statistics with satellite imagery for land cover, which provides an improvement from just using survey data. In addition, while most global land cover data sets group croplands into just a few categories, this dataset allows for significantly increasing the variation that is observed in each cell by providing crop-level information for all major crops in the area. For the geographical distribution of natural resources, we instead rely on the Mineral Resource Data System (MRDS) provided by the United States Geological Survey (USGS). We supplement this with information from PRIO/Uppsala datasets (Tollefsen et al., 2012) on natural resource distribution, each of which is summarized in the Appendix.

We supplement information about intensity of crops and of natural resources at the cell level with international commodity prices. These series are obtained from two sources: the Global Economic Monitor (GEM) Commodities dataset, provided by the World Bank, and the Historical Statistics for Mineral and Material Commodities in the United States (USGS, 2016). The first is a collection of monthly prices in international markets from 1960 to present. The second provides information about the current use and flow of minerals and materials in the United States economy and their price. Appendix C.8 presents a detailed discussion about commodity prices and the source used for each commodity.

To build income shocks at cell level, we first selected the main cash crops and natural resources for each country covered by the study area (see Table C9 in Appendix). It is important to note that for none of these commodities the area of analysis is a world leader in exports, supporting the assumption that international prices are exogeneous to local production.

Given the heterogeneity of the area, we do not rely on individual commodity income shocks, but we build two indices depending on the role of income shocks associated with each commodity on the level of violence in the LRA conflict, proxied as standard in the literature with the number of fatalities. To this purpose, we first build individual-commodity income shocks at the cell-level by multiplying a dummy variable indicating the presence of the commodity in the cell with the (log) price of the commodity in the international market. We then jointly estimate the effect of individual-commodity income shocks on total LRA fatalities. We split commodities into two categories depending on the direction of this effect: *conflict-enhancing* commodities and *conflict-reducing* commodities. We present the detalied results in Appendix C.8.

We build the conflict-enhancing (CE) and the conflict-reducing (CR) income shocks by summing individual-commodity income shocks in each category for each cell. We define the CE and CR income shock by:

$$CE_{it} = \sum_{k=1}^{K} E_k \times \omega_{ik} \times p_{kt} \tag{1}$$

$$CR_{it} = \sum_{k=1}^{K} (1 - E_k) \times \omega_{ik} \times p_{kt} \tag{2}$$

where E_k is an indicator variable equal to one if crop k is conflict-enhancing and 0 if conflict-reducing, ω_{ik} is an indicator variable equal to one if the crop k is farmed or extracted in cell i. p_{kt} is the natural log of the price of crop k in the international market.

3.3.2 Weather and demographics

To control for possible confounders of commodity price shocks presented in section 3.3.1, we supplement our dataset with time-varying controls for climatic characteristics that could affect both conflict and the value of cells producing agricultural commodities. Specifically, we build controls for rainfall and temperature.

We measure rainfall variation using daily precipitations at cell-level using the Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS) database. CHIRPS is an improvement over information from weather stations as it combines in-situ monitoring station data with 0.05 degree resolution satellite imagery (Funk et al., 2015). Given the large heterogeneity of the study area, we do not focus on raw rainfall totals as a control variable. Variation in rainfall might have fundamentally different effects depending on local climate and on land characteristics. In order to measure comparably the effect of rainfall on LRA activity, we therefore build rainfall deviations following the procedure used by Hidalgo et al. (2010). 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 by year and standardized over the same period. We then use the absolute value of standardized rainfall as our main measure since the relationship between rainfall and income changes is non-monotonic.[15]

[15] Similar results are obtained when 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

We compute temperature deviations using a similar procedure, but restricting the standardization process to year-level. Average temperature is obtained from the PRIO-GRID database, which provides yearly mean temperature (in degrees Celsius) in each cell, based on monthly meteorological statistics from GHCN/CAMS (NOAA/National Weather Service). In addition, we control for total population in each cell. The first source provides population size in each cell over time and is provided by the Center for International Earth Science Information Network and the International Center for Tropical Agriculture (CIESIN-CIAT, 2005). While this variable only picks up long-run changes in population, it might still suffer from endogeneity. Our main estimates are unaffected by its presence in our main specification.

4 Empirical Strategy

Putting together the data from the different sources above, we construct a cell-level dataset on LRA and Non-LRA related conflict variables, radio coverage and messaging, and a wide range of time varying cell level variables which have been found to be relevant for conflict. Our dataset spans across the four countries of DR Congo, South Sudan, CAR and Uganda.[16] In this section we show results using a cell resolution of 0.125x0.125 degrees, or around 14 km by 14 km near the equator. Our results are not dependent on the cell size selected. In Appendix C.1, we show that our results hold under alternative cell sizes.

We exploit time and space varying exposure to radio messaging over the period 2008-2015. For identification, we rely on three sources of plausibly exogenous variation: the topography of the affected area, changes in the reach of radio signals, and areas where stations' signals overlap. This allows us to give a causal interpretation to our results.

Firstly, we make use of local topographic variation as a random determinant of signal reception. The assumption that topography makes radio signal reception random is inspired by Yanagizawa-Drott (2014), who exploits topographic variation to capture exposure to radio signal during the Rwandan genocide. The propagation of FM radio signal depends on the height and power of each antenna and, without obstacles, the attenuation of the signal is proportional to the square of the distance from the antenna. However, in the presence of physical obstacles, such as hills, mountains, or buildings, the signal can be physically blocked, creating patterns in local coverage of the radio signal exogenous to local political and economic factors.

Next, 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 time t, certain cells could be affected by violence due to their topographic characteristics or other time-invariant characteristics. This strategy is in line with Olken (2009), who uses a similar type of variation, in addition

and lagged year-on-year precipitation growth (Miguel et al., 2004; Ciccone, 2011).

[16]Since Uganda played a central role in the pre-2008 period and only marginal one in the period under analysis, we test the robustness of our estimates to the inclusion or exclusion of Uganda from the analysis. Results are unaffected.

to topographic variation, when looking at the impact of television and radio on social capital in Indonesia.

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

$$dm_{it} = \sum_{j=1}^{J} c_{itj} h_{jt} \tag{3}$$

where c_{itj} is the percentage coverage in cell i of radio j at time t and h_{jt} is the number of hours of defection messaging daily broadcast by radio j at time t. Intensity is therefore set to 0 if the cell is not covered by any defection message at a certain point in time, or if it is covered by a radio station not broadcasting any defection messaging. The right panel in Figure 5 shows the evolution of the (average) intensity of defection messaging over time.

By looking at intensity, we not only add another level of randomness to our main independent variable, but we also improve the measurement. In fact, intensity is a superior measure of exposure to messaging compared to pure radio coverage of the area. In Section 5.4, we discuss the possibility that each radio responded to expected reduction in violence with increased radio frequency. We do not find evidence of this possibility.[17]

It is plausible to assume that this is exogenous to conflict, especially once we measure the signal coverage corrected for topography. To further capture the possibility that antennas might have been placed in locations where violence increased (or decreased), or that distance from the antenna would also capture unobserved determinants of violence, we control for distance from active antennas. Since the signal strength of each radio signal decreases in the square of distance from the transmitter, we include a polynomial of second degree in the minimum distance from an active antenna and in the mean distance from all active antennas. Figure D11 in Appendix presents the distribution of these two variables. We allow for a more 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.

Our primary objective is to measure the effect of the intensity of defection messaging on an

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

outcome variable y_{it}, which captures violence intensity (or LRA activity) in cell i at time t. To this end, we estimate the following model as our main specification:

$$y_{it} = \alpha_0 + \alpha_1 dm_{it} + \mathbf{X}'_{it}\beta + \sum_{t=2}^{T} \gamma_t d_t + \sum_{t=2}^{T} \sum_{r=2}^{R} \psi_{tr} d_t m_r + c_i + u_{it} \quad (4)$$

where $\mathbf{X}_{it}$ is a vector of cell-level time-varying characteristics, d_t are year-specific dummy variables, c_i are cell fixed effects and u_{it} are idiosyncratic error terms. We include macro-region time fixed effects by dividing our grid into 8 macro-regions and introducing interaction terms between d_t and macro-region indicators, m_r. In all specifications, we normalize dm_{it} to ease the interpretation of the coefficient. In our main specification, we focus on the contemporaneous effect of intensity of defection messaging. Using the lagged value leads to similar conclusions (see Appendix C.6).

Our parameter of interest is α_1, which captures the effect of an increase in the daily intensity of defection messaging at full-cell coverage. Since we cannot control for LRA members receiving the radio message, our estimates can be interpreted as an Intent-to-Treat effect of defection messaging. Qualitative evidence supports the conclusion that exposure to defection messaging is widespread, particularly including second-hand exposure: 89% of returnees have cited defection messaging as "influential in their decision to escape" (Invisible Children, 2013). Furthermore, focusing on the access of civilians to messaging which can serve as a simple proxy for regional access to messaging, we observe that even where radio ownership tends to be low, exposure to messaging could be high through radios available in communal spaces. For instance, Rigterink et al. (2016) show that in South Sudan (in the LRA-affected counties of Ezo and Tambura) in the year 2013, while only 33% of interviewed households owned a radio and only 27% could receive the radio signal broadcasting defection messaging, 65% had heard messages targeting the LRA.

Since we observe events over time and space, we need to take into account that data can be correlated both spatially and temporally. As evident from Figure 2, LRA violence appears to be highly spatially correlated. When estimating equation (4) 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 Conley (1999, 2008) and Hsiang (2010) correction. We allow for correlation to be over the full time window of the dataset and we allow for spatial correlation across cells within 100 kilometres.[18]

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 error, but expect that this would only under-estimate the importance of defection messaging.

[18]This cut-off is in line with other contributions in the literature, such as Harari and La Ferrara (2013), and our results are robust to using alternative cut-offs.

5 Results

In this section we present the estimates for the effect of defection messaging on different indicators of conflict. We firstly focus on the effectiveness of defection messaging in reducing violence (section 5.1) and we then analyze the effects of messaging on the strategic behavior of the LRA (section 5.2).

5.1 Effectiveness of defection messaging

Encouraging defections among rebels is ultimately motivated by the desire to reduce violence, either by directly altering combatant behavior, or changing the overall group dynamic through changes in membership. Fatalities arising from such violence represents a major social cost of the LRA conflict and hence we begin by focusing on how defection messaging has affected the number of fatalities. To do so, we estimate equation 4 by using the log number of total fatalities as the dependent variable and we present the estimates in Table 3.[19] In column 1, we only control for cell and year-specific fixed effects, and distance polynomials, while in columns (2)-(5), we also control for other time-varying controls and macro-region specific time fixed effects. In columns (3) and (5), we also interact the intensity of messaging with different types of commodity price shocks.

An increase of one standard deviation in intensity leads to a reduction in the number of fatalities by around 3 percent. The effectiveness of defection messaging is closely related to commodity price shocks, especially for confict-enhancing commodities. When intensity of messaging increases by one standard deviation, a one standard deviation increase in the value of conflict-enhancing commodities leads to a 1 percent reduction in the effectiveness of defection messaging in reducing fatalities. This suggests that, while overall fatalities are affected by exogeneous variation in commodity prices, the effectiveness of defection messaging is also dependent on the economic incentives driving the level of violence in a cell.

To understand why a higher intensity of messaging leads to a reduction in fatalities associated with a reduction in violence against civilians and in clashes against security forces, we focus on changes in LRA composition induced by defection messaging. Specifically, we focus on whether the defection messaging campaign was effective in achieving its direct objective of increasing returns from the armed group to civil society. The LRACT defines a *returnee* an "abducted civilian that was released, rescued, able to escape, or an LRA member willfully defected or captured within the incident reported."[20] In Table 4, we show how defection messaging impacted the total number of returnees.

[19] We focus on log of the overall number of fatalities in each cell (we add one to this variable before taking logs to accommodate 0 values). Using the number of fatalities normalized by the population in the cell as dependent variable lead to the same conclusions. See Appendix Table C8.

[20] In the LRACT dataset, it is not possible to distinguish between forced recruits and actual believers that are returning or defecting from the LRA. We therefore focus on the number of individuals as dependent variable to capture the intensity of returnees. When analyzing the number of events involving at least one individual returning, we reach the same conclusions.

Table 3: Effect of defection messaging on fatalities

Dependent variable:	Number of fatalities (log)				
	(1) FE	(2) FE	(3) FE	(4) FE	(5) FE
Intensity of messaging	-0.036***	-0.033***	-0.032***	-0.030***	-0.031***
	(0.004)	(0.004)	(0.005)	(0.004)	(0.004)
* Conflict-reducing shock			-0.002		0.001
			(0.003)		(0.004)
* Conflict-enhancing shock				0.010***	0.010***
				(0.001)	(0.001)
Conflict-reducing shock		-0.044***	-0.047***	-0.045***	-0.044***
		(0.007)	(0.007)	(0.007)	(0.007)
Conflict-enhancing shock		0.039***	0.039***	0.042***	0.042***
		(0.008)	(0.008)	(0.008)	(0.008)
Absolute Rainfall deviation		-0.004***	-0.004***	-0.003***	-0.003***
		(0.001)	(0.001)	(0.001)	(0.001)
Absolute Temperature deviation		-0.000	-0.000	0.000	0.000
		(0.002)	(0.002)	(0.002)	(0.002)
Observations	60600	60600	60600	60600	60600
Number of Years	8	8	8	8	8
Number of Cells	7575	7575	7575	7575	7575
Cell and Year FE	Yes	Yes	Yes	Yes	Yes
Distance polynomial	Yes	Yes	Yes	Yes	Yes
Additional controls	No	Yes	Yes	Yes	Yes
Year x Macro-Region FE	No	Yes	Yes	Yes	Yes

Note. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. 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. Cell-level population is built using data from the Center for International Earth Science Information Network and the International Center for Tropical Agriculture (CIESIN-CIAT, 2005). Distance polynomial is a polynomial of second degree in the minimum distance from an active antenna and in the mean distance from all active antennas. Additional controls include income and weather shocks, and demographic characteristics (see section 3 for a detailed description). The time period is restricted to 2008-2015. See Appendix C.1 for a discussion about the choice of cell resolution.

A higher intensity of defection messaging leads to a statistically significant increase in the total number of returnees. A one standard deviation increase in defection messaging intensity leads to an increase of returnees by 1 percent. These results suggest that defection messaging was indeed effective in increasing defections in our period of study. Similarly to fatalities, increases in the value of conflict-enhancing commodities leads to reduced effectiveness of defection messaging.

To check how the effects of messaging on fatalities vary with how intense the messaging was, we estimate equation (4) by allowing the coefficient to vary non-linearly. Specifically we use seven dummy variables for different intensities of radio messaging (we exclude the dummy variable for intensity equal to zero). Figure 6 plots the coefficients for different outcomes. It is evident that there is a significant (non-linear) increase in the effect of defection messaging with intensity of messaging. Very low levels of intensity have no impact on both variables, while daily messaging of the duration of 1-1.5 hours (at full cell coverage) can lead to a reduction in fatalities of up to 7 percent and 2 percent in returnees.

5.2 Armed group behavior

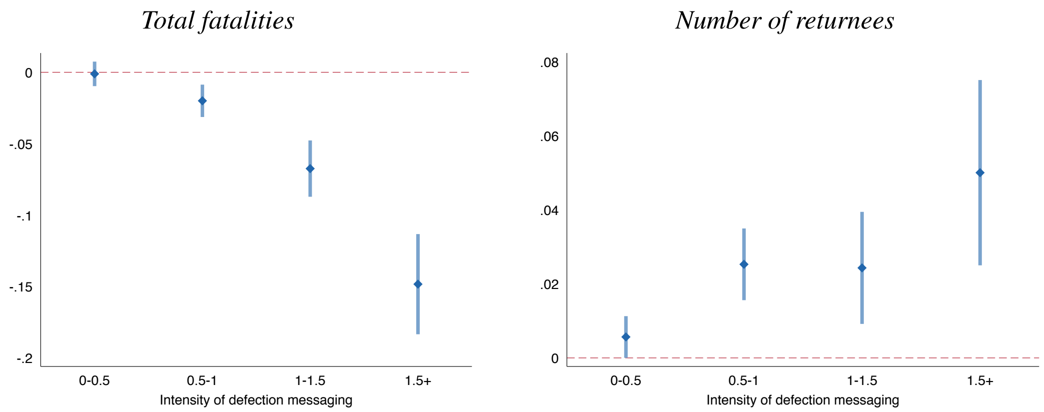
In the previous section, we observed that a higher intensity of defection messaging is leading to reductions in the number of fatalities associated with the LRA and to an increase in the number of people returning from the armed group. In this section, we shift our focus to the strategic

Table 4: Effect of defection messaging on the number of returnees

Dependent variable:	Number of individuals returning from the LRA (log)				
	(1)	(2)	(3)	(4)	(5)
	FE	FE	FE	FE	FE
Intensity of messaging	0.011***	0.010***	0.009***	0.009***	0.009***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
* Conflict-reducing shock			0.002		0.000
			(0.003)		(0.003)
* Conflict-enhancing shock				-0.004***	-0.004***
				(0.001)	(0.001)
Conflict-reducing shock		-0.000	0.002	-0.000	0.000
		(0.007)	(0.007)	(0.007)	(0.007)
Conflict-enhancing shock		-0.001	-0.001	-0.002	-0.002
		(0.006)	(0.006)	(0.005)	(0.005)
Absolute Rainfall deviation		-0.001	-0.001	-0.001	-0.001
		(0.001)	(0.001)	(0.001)	(0.001)
Absolute Temperature deviation		0.002*	0.002*	0.002	0.002
		(0.001)	(0.001)	(0.001)	(0.001)
Observations	60600	60600	60600	60600	60600
Number of Years	8	8	8	8	8
Number of Cells	7575	7575	7575	7575	7575
Cell and Year FE	Yes	Yes	Yes	Yes	Yes
Distance polynomial	Yes	Yes	Yes	Yes	Yes
Additional controls	No	Yes	Yes	Yes	Yes
Year x Macro-Region FE	No	Yes	Yes	Yes	Yes

Note. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. 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 individuals defecting. Distance polynomial is a polynomial of second degree in the minimum distance from an active antenna and in the mean distance from all active antennas. Additional controls include income and weather shocks, and demographic characteristics (see section 3 for a detailed description). The time period is restricted to 2008-2015. See Appendix C.1 for a discussion about the choice of cell resolution.

Figure 6: Non-linear effect of defection messaging on fatalities and returnees



Note. This figure plots the coefficients of equation (4) where intensity of defection messaging is decomposed into five dummy variables for each group of intensity reported in the horizontal axis. The excluded variable is the dummy variable for zero-intensity. The dependent variables are the number of fatalities (left panel) and the number of returnees (right panel), both reported in logarithm.

behavior of the LRA and its members to understand the mechanism behind the impact of defection messaging. In guerrilla conflict, evidence shows that armed groups prefer selective and strategic violence rather than indiscriminate violence (Kalyvas, 2006). Exploiting the detailed information provided by the LRACT database, we focus on three different types of variables related to LRA strategy: intensity of violence against civilians committed by the LRA and clashes against security forces, changes in group composition (driven by returnees and new abductees), and finally looting by the LRA. This analysis is particularly important in the post-2008 period since the LRA still possessed a significant number of members, but had less control of stable territories.

5.2.1 Violence against civilians and clashes with security forces

The LRA is notorious for its use of violence against civilians. We therefore begin by focusing on whether the reduction in fatalities observed when intensity of messaging increases is also linked to a shift in the number of attacks that the LRA is carrying out. We focus on the number of events defined either as "LRA violence" or "clash" in the database.[21] These are events characterized by direct violence either against civilians or another group. Specifically, the LRACT defines *LRA violence* as "any physical violence committed against civilians which resulted in death or injury", and a *clash* as an incident where "at least one Armed Group and one state security force are violently engaged." Table 5 presents the estimates of equation (4) where the dependent variable is the number of events that are either defined as LRA violence or clash.

Table 5: Effect of defection messaging on violence against civilians and clashes

Dependent variable:	**Number of events involving clashes or violence against civilians**				
	(1)	(2)	(3)	(4)	(5)
	FE	FE	FE	FE	FE
Intensity of messaging	-0.061***	-0.055***	-0.056***	-0.051***	-0.054***
	(0.009)	(0.009)	(0.011)	(0.009)	(0.011)
* Conflict-reducing shock			0.002		0.007
			(0.006)		(0.007)
* Conflict-enhancing shock				0.015***	0.017***
				(0.002)	(0.003)
Conflict-reducing shock		-0.068***	-0.066***	-0.069***	-0.060***
		(0.013)	(0.011)	(0.013)	(0.011)
Conflict-enhancing shock		0.061***	0.060***	0.065***	0.065***
		(0.014)	(0.013)	(0.014)	(0.014)
Absolute Rainfall deviation		-0.008***	-0.008***	-0.007***	-0.007***
		(0.002)	(0.002)	(0.002)	(0.002)
Absolute Temperature deviation		0.000	0.001	0.001	0.001
		(0.003)	(0.003)	(0.003)	(0.003)
Observations	60600	60600	60600	60600	60600
Number of Years	8	8	8	8	8
Number of Cells	7575	7575	7575	7575	7575
Cell and Year FE	Yes	Yes	Yes	Yes	Yes
Distance polynomial	Yes	Yes	Yes	Yes	Yes
Additional controls	No	Yes	Yes	Yes	Yes
Year x Macro-Region FE	No	Yes	Yes	Yes	Yes

Note. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. 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 where the actor is the LRA. Violent events include clashes between the LRA and other actors and violence against civilians. Distance polynomial is a polynomial of second degree in the minimum distance from an active antenna and in the mean distance from all active antennas. Additional controls include income and weather shocks, and demographic characteristics (see section 3 for a detailed description). The time period is restricted to 2008-2015. See Appendix C.1 for a discussion about the choice of cell resolution.

Higher intensity of defection messages reduces violence against civilians and clashes against security forces. A one standard deviation increase in messaging intensity decreases the number of these events by around 0.05. This suggests that one possible mechanism in which defection

[21] We consider the sum of the two categories. We reach similar conclusions considering them separately.

messaging translates into a reduction in fatalities is through a decrease in the attacks carried out against civilians and against security forces. This result is not driven by increases in military activity in areas where the intensity of messaging is higher (see Appendix C.4).

We are also interested in understanding whether defection messaging is more or less effective in the presence of income shocks. In columns (3)-(5), we allow for heterogeneity in the effects of defection messaging under conflict-enhancing and conflict-reducing commodity price shocks. Firstly, we observe that increases in fatalities induced by conflict-enhancing shocks are mainly explained by increases in clashes with security forces and in attacks against civilians. The opposite is true for conflict-reducing commodity price shocks. Secondly, similarly to the result for total fatalities, increases in message intensity in areas characterized by income shocks associated with conflict-enhancing commodities lead to smaller reductions in violence against civilians and in clashes. Together with the result on total fatalities, this suggest that incentives for fighting are strongly associated with higher levels of violence against humans, and that stronger incentives makes defection messaging less effective in reducing violence.

5.2.2 Abductions

Abduction has been a central recruitment strategy throughout the LRA's history. It is estimated that from 1995 to 2004 around 60,000 to 80,000 youth were taken by the LRA for at least a day, the majority of these being adolescents (Annan et al., 2006). In this section, we study whether the LRA responds to the increase in the number of returnees induced by defection messaging, with an increase in the number of abductees. The LRACT defines any incident as an *abduction* event if the incident "involves one or more persons taken captive against their will by the LRA for any period of time, including short-term abductions."

In Table 6, we focus specifically on this outcome, by looking at the total number of abductees. We do not observe any significant effect on abductions performed by the LRA.[22]

Not surprisingly, abduction is a strategy used by the LRA to support its activities when incentives for fighting are higher. In fact, abductions expand in response to increases in the value of conflict-enhancing commodities and drop in response to increases in the value of conflict-reducing commodities. However, we do not observe any significant interaction with defection messaging. This suggest that defection messaging is effective in reducing the level of violence through an increased number of returnees, but does not have a direct effect in the way the LRA recruits new soldiers. We also cannot identify any non-linear effect (see Figure 7).

5.2.3 Looting

A third strategy we study is looting. LRACT classifies an event as looting when "LRA members commit robbery, extortion, or destruction of property." Table 7 presents estimates for equation (4)

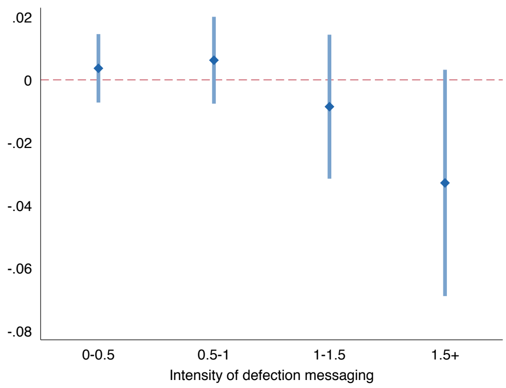
[22] Information about returnees and abductions dis-aggregated by age and gender is not always available in the dataset (around 50 percent of observations have this information). Due to the high sample selection of dis-aggregated data, we rely on total numbers as our main outcome variable.

Table 6: Effect of defection messaging on the number of abductees

Dependent variable:	Number of abductees (log)				
	(1)	(2)	(3)	(4)	(5)
	FE	FE	FE	FE	FE
Intensity of messaging	-0.009**	-0.006	-0.005	-0.005	-0.005
	(0.004)	(0.004)	(0.005)	(0.004)	(0.005)
* Conflict-reducing shock			-0.002		-0.001
			(0.004)		(0.004)
* Conflict-enhancing shock				0.002	0.002
				(0.002)	(0.002)
Conflict-reducing shock		-0.038***	-0.041***	-0.039***	-0.040***
		(0.012)	(0.012)	(0.012)	(0.012)
Conflict-enhancing shock		0.030***	0.030***	0.031***	0.031***
		(0.010)	(0.010)	(0.010)	(0.010)
Absolute Rainfall deviation		-0.002	-0.002	-0.002	-0.002
		(0.002)	(0.002)	(0.002)	(0.002)
Absolute Temperature deviation		0.005**	0.005**	0.005**	0.005**
		(0.002)	(0.002)	(0.002)	(0.002)
Observations	60600	60600	60600	60600	60600
Number of Years	8	8	8	8	8
Number of Cells	7575	7575	7575	7575	7575
Cell and Year FE	Yes	Yes	Yes	Yes	Yes
Distance polynomial	Yes	Yes	Yes	Yes	Yes
Additional controls	No	Yes	Yes	Yes	Yes
Year x Macro-Region FE	No	Yes	Yes	Yes	Yes

Note. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. 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 individuals abducted. Distance polynomial is a polynomial of second degree in the minimum distance from an active antenna and in the mean distance from all active antennas. Additional controls include income and weather shocks, and demographic characteristics (see section 3 for a detailed description). The time period is restricted to 2008-2015. See Appendix C.1 for a discussion about the choice of cell resolution.

Figure 7: Non-linear effect of defection messaging on the number of abductees



Note. This figure plots the coefficients of equation (4) where intensity of defection messaging is decomposed into five dummy variables for each group of intensity reported in the horizontal axis. The excluded variable is the dummy variable for zero-intensity. The dependent variables are the number of returnees (left panel) and the number of abductees (right panel), both reported in logarithm.

where the dependent variable is the number of events characterized by looting. Similar to previous tables, while in columns (1) and (2), we focus on the main effect, in columns (3)-(5) we focus on the interaction of messaging intensity with commodity price shocks.

While defection messaging is effective in decreasing fatalities and increasing returnees, we observe an increase in looting associated with increases in the intensity of messaging. A one

Table 7: Effect of defection messaging on looting

Dependent variable:	Number of events involving looting by LRA				
	(1) FE	(2) FE	(3) FE	(4) FE	(5) FE
Intensity of messaging	0.045***	0.045***	0.046***	0.042***	0.045***
	(0.010)	(0.010)	(0.011)	(0.010)	(0.011)
* Conflict-reducing shock			-0.002		-0.007
			(0.005)		(0.005)
* Conflict-enhancing shock				-0.013***	-0.014***
				(0.002)	(0.003)
Conflict-reducing shock		0.006	0.003	0.007	-0.002
		(0.010)	(0.008)	(0.010)	(0.008)
Conflict-enhancing shock		-0.021*	-0.021*	-0.025**	-0.025**
		(0.011)	(0.011)	(0.011)	(0.011)
Absolute Rainfall deviation		0.004**	0.004**	0.004**	0.004**
		(0.002)	(0.002)	(0.002)	(0.002)
Absolute Temperature deviation		0.011***	0.011***	0.011***	0.011***
		(0.003)	(0.003)	(0.003)	(0.003)
Observations	60600	60600	60600	60600	60600
Number of Years	8	8	8	8	8
Number of Cells	7575	7575	7575	7575	7575
Cell and Year FE	Yes	Yes	Yes	Yes	Yes
Distance polynomial	Yes	Yes	Yes	Yes	Yes
Additional controls	No	Yes	Yes	Yes	Yes
Year x Macro-Region FE	No	Yes	Yes	Yes	Yes

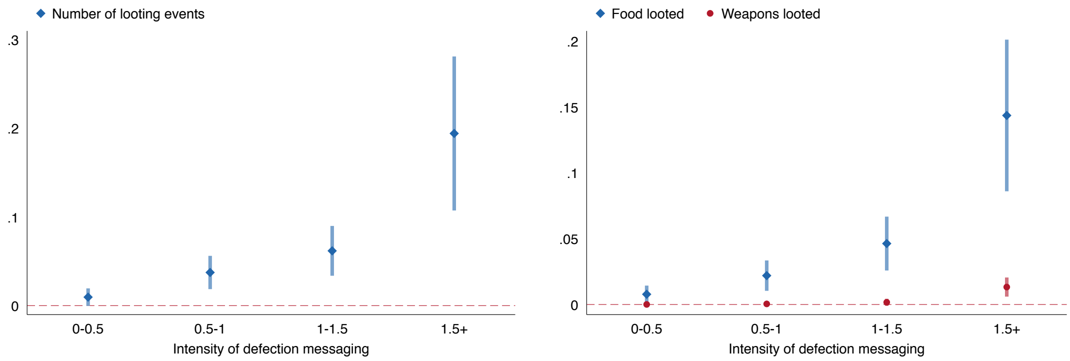
Note. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors in parenthesis are allowed to be correlated over time and space (see Conley, 1999, 2008; Hsiang, 2010). The dependent variable is the number of events characterized by looting from the LRA. Distance polynomial is a polynomial of second degree in the minimum distance from an active antenna and in the mean distance from all active antennas. Additional controls include income and weather shocks, and demographic characteristics (see section 3 for a detailed description). The time period is restricted to 2008-2015. See Appendix C.1 for a discussion about the choice of cell resolution.

standard deviation increase in the intensity of defection messaging increases looting events by roughly 0.05. This effect is again non-linear with respect to the intensity of messaging, with higher intensity causing proportionally larger increases in looting (see left panel in Figure 8).

The effect of messaging on looting can be interpreted as a strategic shift of the LRA in response to an increased number of returnees. In fact, higher incentives to fight, driven by increases in the value of conflict-enhancing commodities, leads to reductions in looting. This suggests that looting is a preferred strategy when the incentives to fight are not large enough to justify attacks against civilians and against security forces. In this case, looting can be used to compensate remaining soldiers. When these incentives are larger, the consequences of defection messaging in terms of increase looting are therefore lower, since its effectiveness is also reduced in terms of increased returns and diminished attacks against civilians.

To support the idea that looting is used for increasing non-military returns of existing soldiers, we look at the types of goods looted and at whether looting is accompanied by violence against civilians (see Appendix C.3). First, we observe that looting increases for most goods, such as food, tools, weapons, clothes, and money . However, when comparing food versus weapons, the effect is mainly driven by increases in looting of food. This suggest that looting is not targeted at increasing the military power of the group by increasing access to weapons. Secondly, we find no evidence of an increase in violence associated with the looting. Also, looting is not accompanied by destruction of property, which suggests that the increase in such activity is not driven by retaliation.

Figure 8: Non-linear effect of defection messaging on looting



Note. This figure plots the coefficients of equation (4) where intensity of defection messaging is decomposed into seven dummy variables for each group of intensity reported in the horizontal axis. The excluded variable is the dummy variable for zero-intensity. For the left panel, the dependent variable is the total number of events characterized by looting, while for the right panel, the dependent variable is the number of events where food or weapons are looted.

5.3 Robustness checks

In this section, we conduct some additional analyses and robustness tests. First, we want to understand whether defection messaging focused on the LRA has any effects on other ongoing conflicts in the area. Since the LRACT reports only events where the LRA is an actor, we cannot analyse information about other groups and actors using it. We therefore make use of the ACLED and UCDP datasets, which have information about all groups. Specifically, we estimate the effect of intensity of defection messaging using (4) and applying it to the UCDP and ACLED databases. In order to have comparability across datasets, we restrict the sample to the period of 2008-2015. Moreover, this piece of analysis allows us to check the robustness of our main results to two other widely used conflict databases.

Table 8 presents estimates of the effect of the messaging intensity on the number of violent events separated by whether they were related or not to the LRA[23], and by whether the LRA is the perpetrator of violence or it has being attacked. In columns (1)-(4) we present the results using the UCDP database, and in columns (5)-(8) using the ACLED database.

The direction of the effect of defection messaging on the LRA activity is the same as the one captured using the LRACT data. While ACLED and UCDP provide less detailed information about LRA activity and different definitions of violent events, they corroborate our main results using the LRACT. We also observe a reduction in the level of violence perpetrated by other actors (including security forces), but the coefficient is much lower. This suggest that defection messaging was indeed effective in reducing LRA-specific activities. This effect is mainly captured by a

[23]LRA events are defined by events where at least one actor is the LRA, while non-LRA events consider events where none of the actors is the LRA.

reduction in the number of attacks committed by the LRA. Therefore, while there is a reduction in overall violence, our results are primarily driven by a fall in LRA violence.

Table 8: Effect of defection messaging on LRA versus non-LRA activity

Dependent variable:	Number of violent events by ...							
Event database:	UCDP				ACLED			
	Actor involved		**LRA role**		**Actor involved**		**LRA role**	
	LRA	non-LRA	Attacking	Being attacked	LRA	non-LRA	Attacking	Being attacked
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	FE	FE	FE	FE	FE	FE	FE	FE
Intensity of messaging	-0.022***	-0.003***	-0.017***	-0.004***	-0.041***	-0.016***	-0.036***	-0.006***
	(0.004)	(0.001)	(0.004)	(0.001)	(0.011)	(0.006)	(0.010)	(0.002)
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
Cell and Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Distance polynomial	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Additional controls	No	Yes	No	Yes	No	Yes	No	Yes
Year x Macro-Region FE	No	Yes	No	Yes	No	Yes	No	Yes

Note. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. 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 (columns 1 and 5), in which none of the actors is the LRA (columns 2 and 6), in which LRA is attacking (columns 3 and 7) and in which LRA is being attacked (columns 4 and 8). Distance polynomial is a polynomial of second degree in the minimum distance from an active antenna and in the mean distance from all active antennas. Additional controls include income and weather shocks, and demographic characteristics (see section 3 for a detailed description). The time period is restricted to 2008-2015. See Appendix C.1 for a discussion about the choice of cell resolution.

We also observe a reduction in the number of events in which the LRA is attacked. This could indicate that military action from security forces concentrated in areas where topography caused higher intensity of messaging. In that case we might be capturing indirectly the effect of military actions. While it is difficult to believe that security forces could replicate the pattern of topography-corrected radio signals, to control for this mechanism we focus specifically on military activity (see Appendix C.4). Rather than observing increased military activitiy when the intensity of messaging is higher, we observe a fall in events in which state forces are perpetrators of violence. In addition, controlling for military presence in a specific cell does not affect our estimates on the effect of messaging on LRA activity. 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.

Next, we attempt to ensure that the higher intensity of defection messaging is not simply picking up the effects of higher mobile phone coverage or of the self-reported coverage (*circular coverage*).[24] We first estimate our main specification by adding the share of the cell covered by the GSM network. This allows us to control for potential variation in political mobilization. At least in the African context, mobile phones enhance both individual access to information and coordination among individuals around political and economic phenomena (Manacorda and Tesei,

[24]We do not control for these variables in our main specification due to potential endogeneity. The coverage in GSMA database is not corrected for topography and does not contain information about the position of antennas. Mobile phone coverage could therefore be endogenous to violence. Similarly, circular coverage can present issue of endogeneity since it is not corrected for topography. We therefore avoid estimating our main specification with "bad" controls (Angrist and Pischke, 2008).

2016). Secondly, we add as control a dummy variable equal to 1 if the cell is covered by at least one radio using the circular coverage and 0 otherwise. Since topography is assumed to be random, adding this control variable should not affect our main estimate if there is sufficient randomness in the topography of the region. Estimates are presented in Table 9. For all our main outcomes of interest, the coefficient on intensity of messaging is unaltered. Mobile coverage has a negative and significant coefficient on the events associated with clashes or violence against civilians.[25] The circular coverage is instead associated with increases in violence, suggesting that radio coverage was indeed targeted at areas with potential for higher levels of violence.

5.4 Timing of expansion versus location of antennas

To check the robustness of our estimates, we perform a placebo test using random spatial reallocation of the radio antennas. Comparing the effect of actual defection messaging with hypothetical exposure allows us understanding the role of antenna location on the reduction of LRA violence. Within the original area of analysis, we randomly generate new locations for the set of antennas in our data and calculate hypothetical intensity of messaging. We perform 250 simulations using this method. For each simulation, we then estimate equation (4) using our main outcomes as dependent variables and we compute the marginal effect of the (placebo) message intensity.[26]

For all variables under analysis, the effect of defection messaging with random antennas is on average zero, with the 5^{th}-95^{th} percentiles interval including zero (see Appendix Table D10). As an example, we focus on the number of events characterized by violence against civilians or clashes with security forces, as reported in the LRACT database, and the number of violent events as reported in the ACLED and UCDP databases. Figure 9 shows the distribution of the coefficient on intensity of messaging in the placebo simulations for these variables, with the solid vertical line representing the point estimate obtained using real intensity of messaging. The distributions are slightly left-skewed, indicating that, if anything, the expansion of defection messaging was related to increases rather than decreases in violence.

The results from the placebo test suggest that the effect captured using the real intensity of defection messaging is therefore not driven by the timing of expansion of defection messaging, but rather by the combination of timing and antenna location. This is true when analysing outcome variables individually. However, to understand whether this conclusion is also valid when we analyse outcomes jointly, we look at the joint distribution of the marginal effects of intensity of messaging in the placebo regressions. The left panel in Figure 10 shows the joint distribution of the

[25] When we interact GSM coverage with the intensity of messaging, we observe that higher mobile phone coverage tends to amplify the effect of radio messaging in the same direction. This suggests that, in this setting, mobile phone coverage is a complement of radio messaging in fighting the LRA. We take this result only as suggestive evidence due to the endogeneity of mobile phone coverage.

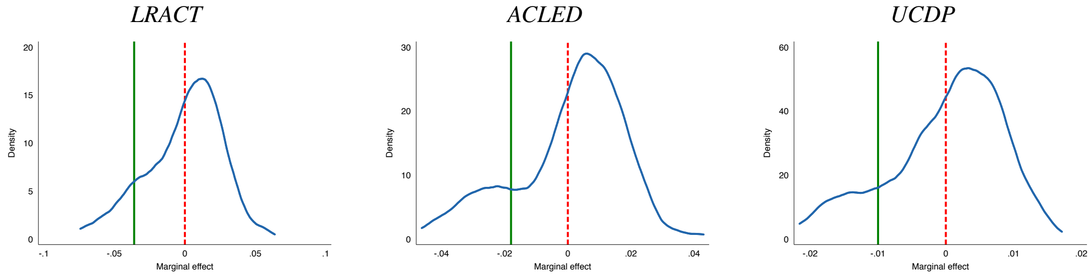
[26] Figure D11 in Appendix presents a comparison between the original location of antennas and the placebo locations in terms of minimum/mean distance from cell's centroid to active antennas. The minimum and mean distances are computed over the period 2008-2015. The distribution of minimum and mean distance are comparable, with minimum distance being larger for the original location.

Table 9: Defection messaging and alternative coverage

Dependent variable:	**Number of fatalities (log)**		**Number of individuals...**				**Number of events involving...**			
			Returning		Being Abducted		Clashes and violence against civilians		Looting	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	FE	FE	FE	FE	FE	FE	FE	FE	FE	FE
Intensity of messaging	-0.033***	-0.038***	0.010***	0.011***	-0.006	-0.008*	-0.053***	-0.064***	0.045***	0.050***
	(0.004)	(0.005)	(0.003)	(0.003)	(0.004)	(0.004)	(0.009)	(0.011)	(0.010)	(0.012)
GSM coverage (% cell)	-0.034***		-0.000		-0.012		-0.102**		0.017	
	(0.013)		(0.014)		(0.020)		(0.040)		(0.037)	
Circular coverage		0.054***		-0.002		0.023***		0.095***		-0.048***
		(0.008)		(0.005)		(0.009)		(0.017)		(0.013)
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
Cell and Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Distance polynomial	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Additional controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year x Macro-Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. 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 (columns 1 and 2) and the number of violent events involving different LRA activities (columns 3-10). Distance polynomial is a polynomial of second degree in the minimum distance from an active antenna and in the mean distance from all active antennas. Additional controls include income and weather shocks, and demographic characteristics (see section 3 for a detailed description). The time period is restricted to 2008-2015. See Appendix C.1 for a discussion about the choice of cell resolution.

Figure 9: Distribution of marginal effects of intensity of messaging on violent events

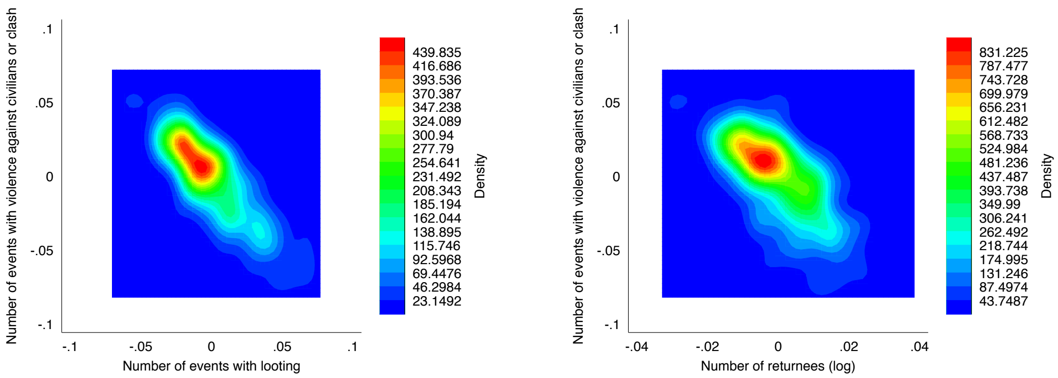


Note. The figures show the distribution of the coefficient on intensity of defection messaging in the placebo samples. Outcome variables are events characterized by violence against civilians or clashes with security forces as defined by the LRACT database (left figure), and the number of violent events as reported in the ACLED database (middle figure) and the UCDP database (right figure). We perform 250 simulations. The dotted red line indicates zero, while the solid green line indicates the point estimate in our original radio coverage (see Tables 5 and 8).

marginal effect for events characterized by violence against civilians or clashes with security forces (vertical axis) and for events characterized by looting (horizontal axis). The right panel compares instead the marginal effect for events characterized by violence against civilians or clashes with security forces and for the number of returnees.

With random location of antennas, when the marginal effect is positive for violence against civilians and clashes with security forces, it also tends to be negative for events with looting. The highest density of the joint distribution is concentrated in an area with a positive effect on the first variable and and a negative effect on the second. This is the opposite of what we observe using the real location of antennas, suggesting again that the timing of defection messaging is not driving our results alone. A similar result is also found for the number of returnees.

Figure 10: Joint distribution of marginal effects of messaging intensity in the placebo regressions



Note. The figures show the joint distribution of the coefficient on intensity of defection messaging in the placebo samples when comparing violent events with events with looting and with events with returnees. Outcome variables are drawn from the LRACT database. We perform 250 simulations.

6 Conclusion

The LRA Insurgency has been a costly and bloody conflict. It has impacted thousands of communities across four countries and exerted immense human and economic costs on communities living in them. Like most armed groups operating in remote areas, it has also been very difficult to fight, especially with conventional military operations and especially in phases of the conflict characterized by the dispersion of the group in larger areas. In these settings, FM radio defection messaging has the potential of encouraging defections among rebels, and reducing overall violence. Our findings are more relevant than ever as the main state actor in the fight against the LRA (the Ugandan Peoples' Defence Forces) announced a withdrawal of its remaining military resources from the region in 2017, which will place greater importance on defection messaging and other non-military strategies to end the insurgency.

While little was known about whether and when defection programs are most successful, this paper provides evidence on the conditions for this approach to be more effectively replicated. Firstly, defection programs should focus on the incentive of fighters to commit violence against civilians. We showed that, not only commodity price shocks can predict the activity of the LRA in terms of increased violence, but that economic incentives are important determinants for the effetiveness of defection messaging. This suggests that programs targeting the end of armed conflicts should not only focus on the pathway to leave the conflict, but also on the economic incentives that keep fighters in the group. Secondly, more attention and consideration should be directed to the effects of defection on remaining members. While fatalities can be considered the main indicator of violence intensity in a conflict, other actions of armed groups, such as looting, can also be violent and costly for the communities. In the LRA conflict, a higher intensity of defection messaging also caused increases in looting in the same areas where the program was indeed more effective in reducing fatalities. This suggests that defection messaging operations should be complemented by interventions reducing the incentives of fighters to loot.

References

Adena, M., R. Enikolopov, M. Petrova, V. Santarosa, and E. Zhuravskaya (2015). Radio and the rise of the nazis in prewar germany. *The Quarterly Journal of Economics 130*(4), 1885–1939. 2, 5

Allen, T. (2005). War and justice in northern uganda: an assessment of the international criminal court's intervention. *London: Crisis States Research Centre, Development Studies Institute, London School of Economics*. 6

Allen, T. and M. Schomerus (2006). A hard homecoming: Lessons learned from the reception center process in northern uganda. *Washington, DC: Management Systems International*, 62. 7

Allen, T. and K. Vlassenroot (2010). *The Lord's Resistance Army: myth and reality*. Zed Books. 6

Angrist, J. D. and J.-S. Pischke (2008). *Mostly harmless econometrics: An empiricist's companion*. Princeton university press. 27

Annan, J., C. Blattman, and R. Horton (2006). The state of youth and youth protection in northern uganda. *Uganda: UNICEF*. 23

Azam, J.-P. (2002). Looting and conflict between ethnoregional groups lessons for state formation in africa. *Journal of Conflict Resolution 46*(1), 131–153. 4

Azam, J.-P. (2006). On thugs and heroes: Why warlords victimize their own civilians. *Economics of Governance 7*(1), 53–73. 4

Beber, B. and C. Blattman (2013). The logic of child soldiering and coercion. *International Organization 67*(01), 65–104. 6

Becker, G. S. (1968). Crime and punishment: An economic approach. *Journal of Political Economy 76(2)*, 169–217. 4

Behrend, H. (1999). Alice lakwena and the holy spirits: war in northern uganda, 1985-97. 6

Besley, T. and R. Burgess (2002). The political economy of government responsiveness: Theory and evidence from india. *The Quarterly Journal of Economics 117*(4), 1415–1451. 4

Blattman, C. and E. Miguel (2010). Civil war. *Journal of Economic literature 48*(1), 3–57. 2, 5

Boots, B. N. and A. Getis (1988). *Point pattern analysis*, Volume 8. Sage Publications, Inc. 3

Ciccone, A. (2011). Economic shocks and civil conflict: A comment. *American Economic Journal: Applied Economics 3*(4), 215–227. 16

CIESIN-CIAT (2005). Gridded population of the world, version 3 (gpwv3) - population count grid. *Palisades, NY*. 16, 20, 10

Conley, T. G. (1999). Gmm estimation with cross sectional dependence. *Journal of econometrics 92*(1), 1–45. 18, 20, 21, 22, 24, 25, 27, 29, 7, 8, 9, 10, 13

Conley, T. G. (2008). Spatial econometrics. In *New Palgrave Dictionary of Economics - 2nd Edition*. Springer. 18, 20, 21, 22, 24, 25, 27, 29, 7, 8, 9, 10, 13

Croicu, M. and R. Sundberg (2016). Ucdp ged codebook version 5.0. *Department of Peace and Conflict Research, Uppsala University*. 9, 1

Dahl, G. and S. DellaVigna (2009). Does movie violence increase violent crime? *The Quarterly Journal of Economics 124*(2), 677–734. 4

DellaVigna, S., R. Enikolopov, V. Mironova, M. Petrova, and E. Zhuravskaya (2014). Cross-border media and nationalism: Evidence from serbian radio in croatia. *American Economic Journal: Applied Economics 6*(3), 103–132. 2, 5

Doom, R. and K. Vlassenroot (1999). Kony's message: a new koine? the lord's resistance army in northern uganda. *African affairs 98*(390), 5–36. 6

Dube, O. and J. F. Vargas (2013). Commodity price shocks and civil conflict: Evidence from colombia. *The Review of Economic Studies 80*(4), 1384–1421. 4, 13

Eck, K. (2012). In data we trust? a comparison of ucdp ged and acled conflict events datasets. *Cooperation and Conflict 47*(1), 124–141. 10

Fearon, J. D. (2005). Primary Commodity Exports and Civil War. *Journal of Conflict Resolution 49*(4), 483–507. 4

Finnström, S. (2010). An african hell of colonial imagination?: The lord's resistance army in uganda, another story. *The Lord's Resistance Army: myth and reality*. 6

Fotheringham, A. S. and D. W. Wong (1991). The modifiable areal unit problem in multivariate statistical analysis. *Environment and planning A 23*(7), 1025–1044. 5

Fujiwara, T., K. Meng, and T. Vogl (2016). Habit formation in voting: Evidence from rainy elections. *American Economic Journal: Applied Economics 8*(4), 160–188. 15

Funk, C., P. Peterson, M. Landsfeld, D. Pedreros, J. Verdin, S. Shukla, G. Husak, J. Rowland, L. Harrison, A. Hoell, et al. (2015). The climate hazards infrared precipitation with stations–a new environmental record for monitoring extremes. *Scientific data 2*, 150066. 15

Grossman, H. (1991). A general equilibrium model of insurrections. *American Economic Review 81(4)*(912-921). 4

GSMA (2012). *GSMA Network Coverage Maps - Submission Guide January 2012*. 8, 1

Harari, M. and E. La Ferrara (2013). Conflict, climate and cells: A disaggregated analysis. 11, 18

Hengl, T. (2006). Finding the right pixel size. *Computers & Geosciences 32*(9), 1283–1298. 3

Hidalgo, F. D., S. Naidu, S. Nichter, and N. Richardson (2010). Economic determinants of land invasions. *The Review of Economics and Statistics 92*(3), 505–523. 15

Hsiang, S. M. (2010). Temperatures and cyclones strongly associated with economic production in the caribbean and central america. *Proceedings of the National Academy of sciences 107*(35), 15367–15372. 18, 20, 21, 22, 24, 25, 27, 29, 7, 8, 9, 10, 13

Humphreys, M. and J. M. Weinstein (2007). Demobilization and reintegration. *Journal of conflict resolution 51*(4), 531–567. 2

Invisible Children (2013). “come home” broadcasts. *Retrieved from http://invisiblechildren.com/program/come-home- broadcasts/*. 18

Jensen, R. and E. Oster (2009). The power of tv: Cable television and women’s status in india. *The Quarterly Journal of Economics 124*(3), 1057–1094. 5

Kalyvas, S. N. (2006). *The logic of violence in civil war*. Cambridge University Press. 21

Kenny, P. D. (2008). Discipline, identity and cohesion in armed organizations. *Unpublished working paper, Yale University*. 4

La Ferrara, E., A. Chong, and S. Duryea (2012). Soap operas and fertility: Evidence from brazil. *American Economic Journal: Applied Economics 4*(4), 1–31. 5

Lamwaka, C. (2002). The peace process in northern uganda, 1986-1990. *Accord: An International Review of Peace Initiatives* (11). 6

Lancaster, P. and L. Cakaj (2013). Loosening kony’s grip: Effective defection strategies for today’s lra. *Washington, DC: The Resolve LRA Crisis Initiative*. 5

Manacorda, M. and A. Tesei (2016, March). Liberation technology: mobile phones and political mobilization in africa. *CEP Discussion Paper* (1419). 4, 27

Michalopoulos, S. (2012). The origins of ethnolinguistic diversity. *The American economic review 102*(4), 1508–1539. 11

Miguel, E., S. Satyanath, and E. Sergenti (2004). Economic shocks and civil conflict: An instrumental variables approach. *Journal of political Economy 112*(4), 725–753. 16

Monfreda, C., N. Ramankutty, and J. A. Foley (2008). Farming the planet. part 2: Geographic distribution of crop areas, yields, physiological types, and net primary production in the year 2000. *Global Biogeochemical Cycles 22*. 13, 1

Montalvo, J. G. and M. Reynal-Querol (2016). Ethnic diversity and growth: Revisiting the evidence. *UPF, mimeo*. 11

Olken, B. A. (2009). Do television and radio destroy social capital? evidence from indonesian villages. *American Economic Journal: Applied Economics 1*(4), 1–33. 3, 4, 16

Omara-Otunnu, A. (1987). *Politics and the Military in Uganda, 1890–1985*. Springer. 6

Paluck, E. L. and D. P. Green (2009). Deference, dissent, and dispute resolution: An experimental intervention using mass media to change norms and behavior in rwanda. *American Political Science Review 103*(4), 622–644. 5

Raleigh, C., A. Linke, H. Hegre, and J. Karlsen (2010). Introducing acled: An armed conflict location and event dataset special data feature. *Journal of peace research 47*(5), 651–660. 9, 1

Rigterink, A. S., J. J. Kenyi, and M. Schomerus (2016). Report on jsrp survey in ezo and tambura counties, south sudan. Technical report, The Justice and Security Research Programme. 18

Rigterink, A. S. and M. Schomerus (2016). The fear factor is a main thing: How radio influences anxiety and political attitudes. *The Journal of Development Studies*, 1–24. 2

Ross, S. (2016). Encouraging rebel demobilization by radio in uganda and the dr congo: The case of "come home" messaging. *African Studies Review 59*(01), 33–55. 5, 7

Strömberg, D. (2004). Radio's impact on public spending. *The Quarterly Journal of Economics 119*(1), 189–221. 4

Sundberg, R. and E. Melander (2013). Introducing the ucdp georeferenced event dataset. *Journal of Peace Research 50*(4), 523–532. 9, 1

Tollefsen, A. F., H. Strand, and H. Buhaug (2012). Prio-grid: A unified spatial data structure. *Journal of Peace Research 49*(2), 363–374. 14

UN-DDR (2014). *Operational Guide to the Integrated Disarmament, Demobilization, and Reintegration Standards*. unddr.org/uploads/documentsOperationalInter-Agency Working Group on DDR. 2

UN Security Council (2013a, May). Report of the secretary-general on the activities of the united nations regional office for central africa and on the lord's resistance army-affected areas. Technical Report S/2013/297, United Nations. 2

UN Security Council (2013b, November). Report of the secretary-general on the activities of the united nations regional office for central africa and on the lord's resistance army-affected areas. Technical Report S/2013/297, United Nations. 3

USGS (2016). Historical statistics for mineral and material commodities in the united states, data series 140. *Data Source 2016*. 14, 1

Weinstein, J. M. (2005). Resources and the information problem in rebel recruitment. *Journal of Conflict Resolution 49*(4), 598–624. 5

Yanagizawa-Drott, D. (2014). Propaganda and conflict: Evidence from the rwandan genocide. *The Quarterly Journal of Economics 129*(4), 1947–1994. 2, 3, 5, 9, 12, 16

ONLINE APPENDIX for "The Reach of Radio"

A Summary of data

Table A1 presents a summary of the variables used in the paper, their respective sources and a short description.

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. We obtain these data from three distinct databases providing detailed information on violent events (including their geo-location). Namely, we use the LRA Crisis Tracker (LRACT) database, the Uppsala Conflict Data Program (UCDP) database (Sundberg and Melander, 2013; Croicu and Sundberg, 2016) and the Armed Conflict Location & Event Data Project (ACLED) database (Raleigh et al., 2010).
Mobile phone coverage	GSMA and Collins Bartholomew	The variable is a dummy variable equal to 1 if at time t the cell is covered by the 2G (GSM) network. We make use of the Collins Mobile Coverage Explorer, provided by GSMA and Collins Bartholomew (GSMA, 2012).
Crop coverage	M3-Crops	We compute for each cell the share covered by each crop. M3-Crops Data by Monfreda et al. (2008) offers a raster dataset at the 5 minute by 5 minute latitude/longitude grid and information for 175 crops.
Commodity prices	GEM and USGS	Commodity prices in international markets are obtained from two sources: the Global Economic Monitor (GEM) Commodities dataset, provided by the World Bank, and the Historical Statistics for Mineral and Material Commodities in the United States (USGS, 2016), provided by the U.S. Geological Survey (USGS).
Diamond presence	PRIO Diadata	The variable includes any site with known activity, meaning production or confirmed discovery. For each cell we calculate the presence of a diamond mine in GIS.
Oil presence	PRIO Petrodata	The petroleum dataset groups oil fields in polygons within a buffer distance of 30 km. For each cell we calculate the percentage that is covered by an oil-field in GIS.
Mineral presence	MRDS-USGS	Dummy variable whether mineral is present in the cell. The database provides geolocated extraction sites by type of mineral and the magnitude of production.
Commodity prices	GEM World Bank / USGS	International commodity prices. The series are obtained from two sources: the Global Economic Monitor (GEM) Commodities dataset, provided by the World Bank, and the Historical Statistics for Mineral and Material Commodities in the United States (USGS, 2016), provided by the U.S. Geological Survey (USGS).
Temperature	PRIO-GRID	Yearly mean temperature (in degrees Celsius) in the cell, based on monthly meteorological statistics from GHCN/CAMS, developed at the Climate Prediction Center, NOAA/National Weather Service. Data is available for the period 1948-2014.
Precipitation	PRIO-GIRD	Total amount of precipitation (in millimeter) in the cell, based on monthly meteorological statistics from the GPCP v.2.2 Combined Precipitation Data Set. It provides information for the period 1979-2014.

B The Radio Questionnaire

This questionnaire was filled by station staff or associates that could accurately and fully respond to all questions. The interview was introduced by a statement guaranteeing the confidentiality of the answers. Figure B1 presents the content of the questionnaire that was collected during the interviews with the radios.

Figure B1: Questionnaire content

Station Defection Messaging Questionnaire

General Station information

Q1	Station Name:	
Q2.A	Country:	UGA CAR SSD DRC
	Q2.B Locale:	
Q3	Institutional affiliations and or funders:	
Q4	All broadcast languages (list):	
Q5	Predominant broadcast language:	
Q6	Majority of programming (circle):	News and Politics Music/entertainment Defection Messaging / Information
Q7	Average hours on-air per day (circle):	0-3 3-12 12+ Not sure
Q8	Produces or produced defection content:	Yes No Not sure
	Q8.B If no, please list major source(s):	

Annual Broadcast Activity

For Questions 9 and 10, please mark each cell with 'Y' (for 'yes') or 'N' (for 'no') for each year. If known, please note sustained interruptions in broadcasting in Q12.

			2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
Q9	Was the station broadcasting its normal content?																			
Q10	Was it broadcasting LRA defection content?																			
	Q10.B	If yes, what was the frequency of LRA-targeted content (in hrs/week)?																		
	Q10.C	What type of LRA targeted content was broadcasted?	Please check all that apply. If you respond "Other", or one type in particular was more relevant, please make note of this in Q12.																	
	Q10.C1	Ex-LRA interviews																		
	Q10.C2	Family/community member interviews																		
	Q10.C3	Safe reporting information																		
	Q10.C4	Other																		
Q11	Q11.A Broadcast radius (km)																			
	Q11.B Tower Height (m)																			
	Q11.C Tranmitter Power (kW)																			

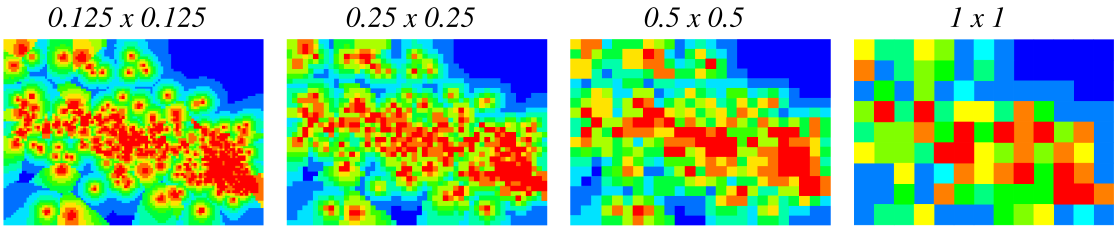
Q12	Please describe any relevant aspects of the station's history and the context where it has/does operate(d):
Q13	If you feel any part of Question 9 or 10 (Q9/Q10) needs further explanation please describe here with reference to the year and month:
Q14	Any further reflections on the station, its operators, motivations, relevance, and efficacy:

C Additional Analysis

C.1 Cell size analysis and the Modifiable Areal Unit Problem

We are analyzing a two-dimensional spatial point pattern S defined as a set of points s_i with $i = 1, ..., n$. Points are located in a two-dimensional region R and have coordinates (s_{i1}, s_{i2}). Each point s_i represents the location in R of a violent event where the LRA is an actor. The objective of this section is to understand the correct grid for our analysis. A grid is a regular tessellation of the study region R that divides it into a set of contiguous cells whose centers are referred to as the grid points. While looking at the spatial pattern of events across the grid, we are interested in understanding whether events are geographically clustered or whether they are uniformly distributed in the region R. We therefore look at the probability density function, $\rho(s)$, defining the probability of observing an event in cell $s \in R$. We estimate $\rho(s)$ using a Kernel estimator. Figure C2 presents the geographic distribution of $\rho(s)$ in the region R.

Figure C2: Probability of observing a violent event per cell, by cell resolution



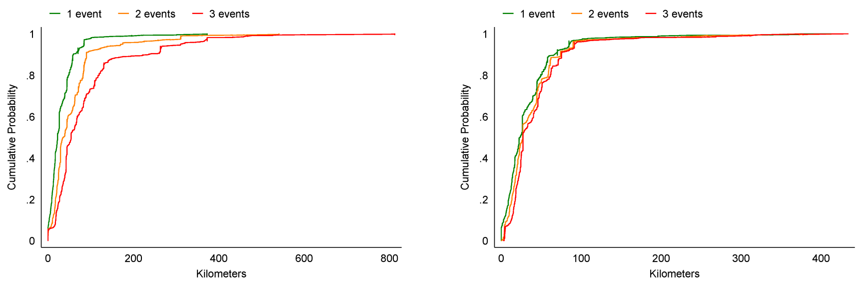
Note. Cell resolution is expressed in degrees per side. Results are produced using Stata command *spkde*. Kernel is estimated using a quartic distribution and assuming as bandwidth the minimum number of data points method (k = 1). We use ACLED database for the period 1996-2015 to compute these statistics.

Given the clustering of events and the full extent of the area observed, a finer resolution allows capturing a much larger variation compared to worse resolutions, such as 1 degree by 1 degree. The selection of the size of our unit of observation is artificial. Aggregating and disaggregating cells affect the overall information contained by the grid. While no ideal resolution exists (Hengl, 2006), grid resolution can be related to geometry of point patterns, i.e. the distance between the sampled points (Boots and Getis, 1988). The grid resolution should therefore be at most half the average of the mean shortest distance, i.e. the mean spacing between the closest point pairs. In our case, each point corresponds to an event related to the LRA. In a more conservative approach, we will look at the median, rather than the average of the shortest distance. Figure C3 plots the empirical cumulative distribution function for distance between one event and the closest, the second closest and the third closest events. When we include events happening in the same location, the 0.5 probability distance of finding one neighbor is at about 22 km, while the 1.0 probability distance of finding one neighbor is at 373 km. When we exclude events happening in the same location, these are equal to 25 km and 431 km respectively.

Following this analysis, we select a cell resolution of 0.125x0.125 degrees per side. This corresponds roughly to 14 km per side. Figure C4 graph the area covered by the grid and its

Figure C3: Cumulative distribution function of proximity across events

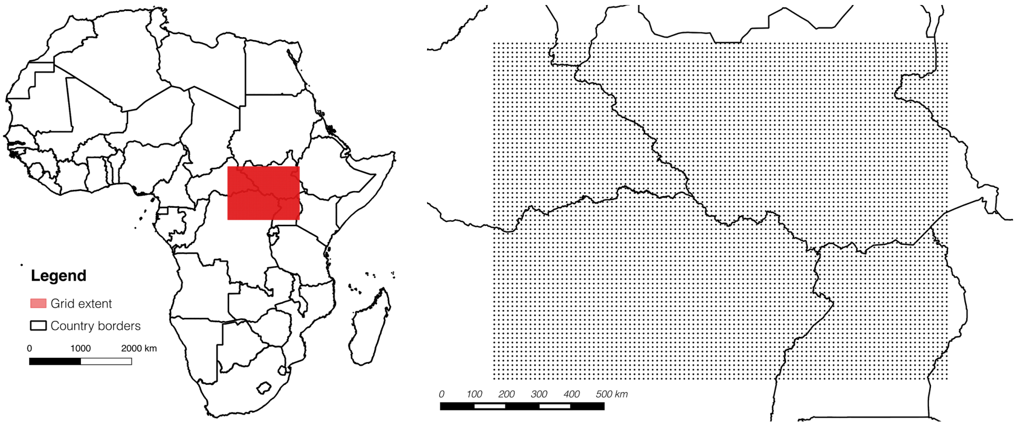
Includes same-location points *Excludes same-location points*



Note. The graphs show the empirical cumulative distribution function for distance between one event and the closest, the second closest and the third closest events. In the left panel, we include events happening in the same location, while in the right panel we excludes these events and we focus on distance across different locations where events are happening. We use ACLED database for the period 1996-2015 to compute these statistics.

resolution.

Figure C4: Geographical coverage and grid resolution



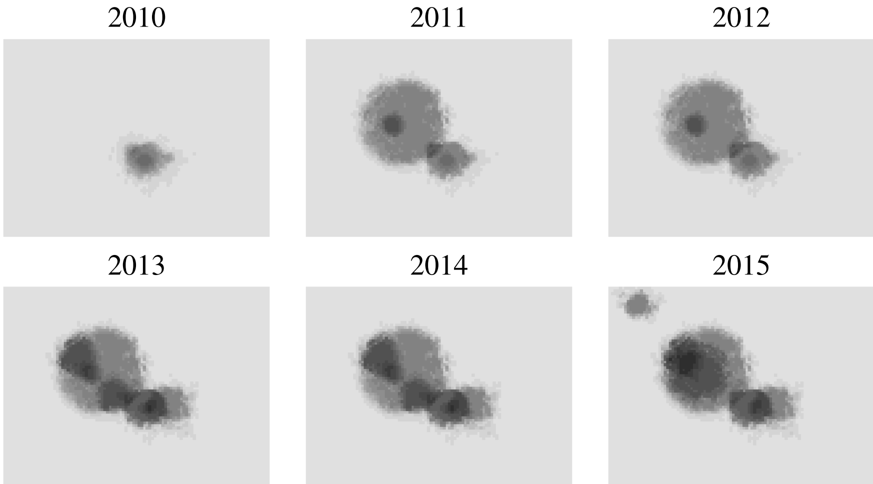
Note. The left panel shows the area covered by the selected grid. The right panel shows its resolution. Each dot represents the centroid of a 0.125x0.125 degrees cell.

The choice of a resolution of 0.125x0.125 degrees additionally allows us to observe variation in terms of our main independent variable, the intensity of radio messaging. Figure C5 presents the intensity of defection messaging. Different colors represent the number of hours broadcast daily. Cells in light grey have zero or negligible intensity, while cells where higher intensity of messaging is occurring are shown as darker.

The Modifiable Areal Unit Problem (MAUP) happens when cell sizes are chosen in order to provide a pre-selected type of result. To support our results, we estimate our model using different cell sizes. We construct cells of 0.0625, 0.125, 0.25, and 0.5 degrees per side. We then estimate our main specification for each of these grids. Figure C6 shows how our main estimate for the effect of intensity of defection messaging on fatalities changes with cell size.

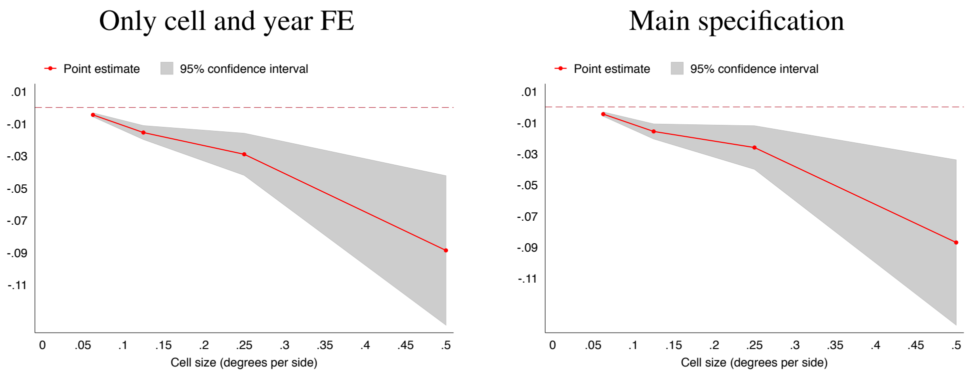
The direction of the effect is not affected by the size of each cell. However, the coefficients

Figure C5: Geographic distribution of messaging intensity



Note. The graph represents the geographic distribution of defection messaging based on intensity (total number of hours of daily broadcast). Darker shades represent higher intensity, while lighter shades represent less intensity (with the lightest showing zero coverage). Cell resolution is 0.125 degrees per side (see Figure C4 for the grid extent).

Figure C6: The effect on defection messaging on total fatalities: estimates and cell size



Note. The figures show the variation of estimates (and standard errors) of equation (4) where the dependent variable is total fatalities and when the resolution of the grid changes. The resolution is reported on the horizontal axis.

increase with the cell size. The magnitude of the effect changes quite dramatically from a cell of 0.125 degrees per side to a cell of 0.50 degrees per size.[2]

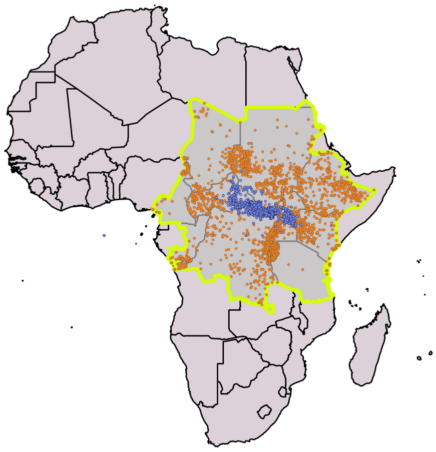
C.2 Geographical extent of study

Figure C7 presents the geographical extent of the LRA violence as compared to other violence in the region.

As no clear precedent exists in the literature in selecting the geographic extent of our analysis, we implement a rule based on the latitudinal and longitudinal distribution of events from 1989-

[2]This result is 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 at play following averaging across cells. The correlation between two variables is expected to increase when the variance is reduced and the covariance is stable.

Figure C7: Extent of LRA violence in the region (1989-2015)

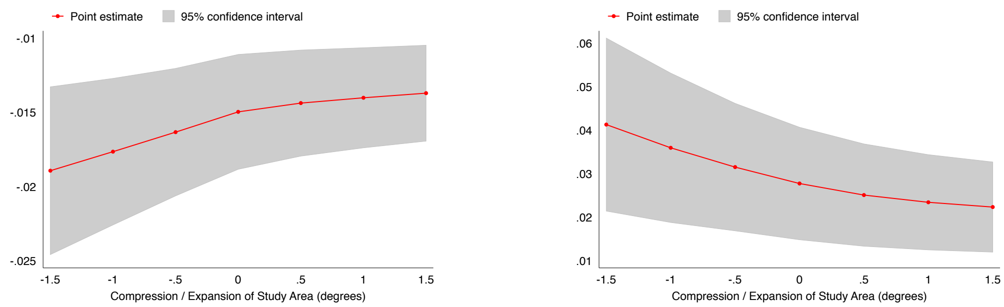


Note. The figure shows the geographical distribution of violent events in the countries of our study region highlighted in yellow. Each dot represents an event as defined in the UCDP dataset. Blue dots are LRA violent events, while orange dots are non-LRA events.

2015. In the main analysis, this area is bounded by the 1st and 99th percentiles of both latitude and longitude of the geographical distribution of LRA events, minus and plus 0.5 degrees respectively. The parameter 0.5 is chosen to allow a buffer around the events that fall on the edge of the grid, such that our analysis accounts for the spatial processes that might have cause it. Figure C8 shows the effect of defection messaging on the number of fatalities (left panel) and on the number of events with looting (right panel), when increasing and reducing the geographic extent.

Figure C8: Size of study area and sensitivity of estimates

Number of fatalities *Number of events with looting*



Note. The figures show the variation of estimates (and standard errors) of equation (4) when the size of the study area changes. The dependent variables are total fatalities (left panel) and the number of events with looting (right panel). The expansion and compression of the area is reported on the horizontal axis in degrees.

C.3 Heterogeneity of effect with respect to looting

We look at the effect of defection messaging on the different specific types of goods looted. We therefore estimate equation (4), using the number of events characterized by looting of a specific good as the dependent variable. We distinguish between food, tools, weapons, clothes, money, medicines and other goods. We observe that looting increases for all goods, apart from medicines, for which we do not observe any statistically significant effect of defection messaging.

Table C3: Effect of defection messaging on types of looted goods

Dependent variable:	Number of events characterized by looting of...						
	Food	**Tools**	**Weapons**	**Clothes**	**Money**	**Medicines**	**Other**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	FE	FE	FE	FE	FE	FE	FE
Intensity of messaging	0.034***	0.013***	0.003***	0.011***	0.006***	0.000	0.015***
	(0.007)	(0.003)	(0.001)	(0.003)	(0.002)	(0.000)	(0.005)
Observations	60600	60600	60600	60600	60600	60600	60600
Number of Years	8	8	8	8	8	8	8
Number of Cells	7575	7575	7575	7575	7575	7575	7575
Cell and Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Distance polynomial	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Additional controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year x Macro-Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. 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 looting, by category of looted good. "Other" includes goods that are not specified in the dataset. Distance polynomial is a second degree polynomial in the minimum distance from an active antenna and in the mean distance from all active antennas. Additional controls include income and weather shocks, and demographic characteristics (see section 3 for a detailed description). The time period is restricted to 2008-2015.

Table C4 shows how the number of events characterized by looting is associated to other violent events. We build the number of events where looting takes place distinguishing whether the looting is either associated with or not not associated with death, injury, and abduction. We observe that the increase in looting is mainly observed with minimal physical harm to civilians. However, the increase in looting is most associated with events that are also coded for abductions.

Table C4: Effect of defection messaging on violent looting

Dependent variable:	Number of events characterized by looting and...					
	No death	**No death and no injury**	**No death, no injury and no abduction**	**At least one death**	**At least one injury**	**At least one abduction**
	(1)	(2)	(3)	(4)	(5)	(6)
	FE	FE	FE	FE	FE	FE
Intensity of messaging	0.048***	0.045***	0.031***	-0.002***	0.002	0.014***
	(0.010)	(0.010)	(0.007)	(0.001)	(0.001)	(0.003)
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
Cell and Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Distance polynomial	Yes	Yes	Yes	Yes	Yes	Yes
Additional controls	Yes	Yes	Yes	Yes	Yes	Yes
Year x Macro-Region FE	Yes	Yes	Yes	Yes	Yes	Yes

Note. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. 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 where looting is happening in association (or not) with other violent events, such as a death, an injury or an abduction. Distance polynomial is a polynomial of second degree in the minimum distance from an active antenna and in the mean distance from all active antennas. Additional controls include income and weather shocks, and demographic characteristics (see section 3 for a detailed description). The time period is restricted to 2008-2015.

We then focus on the role of destructive versus non-destructive looting to check whether the increase in looting is driven more by retaliation or by appropriation of private property. To this purpose, we looked at the description of events characterized by looting and we define a looting event as destructive looting, if the event's description contains one of the following strings: burn, destroy, broke, break, damage, dismantle, sabotage, spill, smash, ruin, demolish, wreck, shatter, or fire. We observe that destructive looting is very limited. Overall, it accounts for around 0.6% of all looting events.

C.4 Military intervention

We look at violent events in which an army is the perpetrator using the UCDP and the ACLED datasets. Columns (1) and (2) in Table C5 provides estimates of equation (4) where the dependent variable is the number of events where an army actor (including United Nations operations) is the perpetrator of the action. In columns (3)-(6), we also look at the effect of intensity of messaging on fatalities associated with LRA activity, but controlling for (potentially endogenous) military presence at cell level. We build military presence using again the UCDP and the ACLED datasets. 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 which an army is involved and 0 otherwise. Our estimates are unaffected by controlling for army presence.

Table C5: Effect of defection messaging and army presence

Dependent variable:	**N. of violent events where the army is the perpetrator**		**Number of LRA-associated fatalities (log)**			
Event database:	UCDP	ACLED	LRACT	LRACT	LRACT	LRACT
	(1)	(2)	(3)	(4)	(5)	(6)
	FE	FE	FE	FE	FE	FE
Intensity of messaging	-0.006***	-0.010***	-0.033***	-0.033***	-0.032***	-0.032***
	(0.002)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)
Army presence (ACLED)			0.062***	0.178***		
			(0.018)	(0.058)		
* Minimum distance				-0.000***		
				(0.000)		
Army presence (UCDP)					0.186***	0.493***
					(0.054)	(0.140)
* 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
Cell and Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Distance polynomial	Yes	Yes	Yes	Yes	Yes	Yes
Additional controls	Yes	Yes	Yes	Yes	Yes	Yes
Year x Macro-Region FE	Yes	Yes	Yes	Yes	Yes	Yes

Note. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. 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). Distance polynomial is a polynomial of second degree in the minimum distance from an active antenna and in the mean distance from all active antennas. Additional controls include income and weather shocks, and demographic characteristics (see section 3 for a detailed description). The time period is restricted to 2008-2015.

C.5 Administrative-level analysis

We control for robustness of our estimates using administrative divisions instead of cells. We make use of third-level administrative units (corresponding to districts) from the Global Administrative

Areas (GADM) database. Since the unit area is most often larger than the cell size in our main analysis, we focus here on per capita fatalities from the LRACT database, though general findings apply to other outcome variables. At this level of analysis, one standard deviation in intensity of messaging corresponds to roughly 0.09 hours of messaging at full district coverage. Table C6 presents the results.

Table C6: Effect of defection messaging using administrative divisions as unit of observation

Dependent variable:	**Number of fatalities per 1000 inhabitants (log)**			
	(1)	(2)	(3)	(4)
	FE	FE	FE	FE
Intensity of messaging	-0.014***	-0.014***	-0.013***	-0.013***
	(0.003)	(0.003)	(0.003)	(0.003)
Observations	3664	3664	3664	3664
Number of Years	8	8	8	8
Number of Administrative Areas	458	458	458	458
Cell and Year FE	Yes	Yes	Yes	Yes
Distance polynomial	Yes	Yes	Yes	Yes
Additional controls	No	Yes	Yes	Yes
Year x Country FE	No	No	Yes	No
Year x Macro-Region FE	No	No	No	Yes

Note. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. 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. Distance polynomial is a polynomial of second degree in the minimum distance from an active antenna and in the mean distance from all active antennas. Distances are computed as average of cell-level distances within a defined administrative area. Additional controls include income and weather shocks, and demographic characteristics (see section 3 for a detailed description). The time period is restricted to 2008-2015.

C.6 Contemporaneous versus lagged intensity of messaging

In the main text we focused on the contemporaneous effect of defection messaging on different indicators of violence and of LRA strategic behavior. In this section, we estimate the effect of defection messaging on all these outcomes, but focusing on the lagged intensity of messaging. Table C7 presents the results.

C.7 Per capita outcomes

In the main text, we focused on the overall number of fatalities in each cell. In this section, we show robustness of our results when considering per capita fatalities. Table C8 presents the results.

C.8 Commodities and Income shocks

Table C9 presents the list of the main cash crops and of natural resources for each country affected by LRA violence. For each commodity, we present the source for prices and the source for geo-location. To build income shocks, we supplement information about the geographical distribution of commodities with prices in the international market. Figure C9 presents the historical series for the prices of the selected commodities. Prices are normalized using the year 2010 as base equal to 100. The dashed line is a moving average of the time series using a plus/minus 5 years as window.

Table C7: Defection messaging and lagged intensity of messaging

Dependent variable:	**Number of fatalities (log)**	**Number of individuals...**		**Number of events involving...**	
		Returning	Being abducted	Clashes and violence against civilians	Looting
	(1)	(2)	(3)	(4)	(5)
	FE	FE	FE	FE	FE
Intensity of messaging (t - 1)	-0.037***	0.011***	-0.007	-0.074***	0.050***
	(0.004)	(0.004)	(0.005)	(0.012)	(0.013)
Observations	60600	60600	60600	60600	60600
Number of Years	8	8	8	8	8
Number of Cells	7575	7575	7575	7575	7575
Cell and Year FE	Yes	Yes	Yes	Yes	Yes
Distance polynomial	Yes	Yes	Yes	Yes	Yes
Additional controls	Yes	Yes	Yes	Yes	Yes
Year x Macro-Region FE	Yes	Yes	Yes	Yes	Yes

Note. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. 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) and the number of violent events involving different LRA activities (columns 2-5). Distance polynomial is a polynomial of second degree in the minimum distance from an active antenna and in the mean distance from all active antennas. Additional controls include income and weather shocks, and demographic characteristics (see section 3 for a detailed description). The time period is restricted to 2008-2015. See Appendix C.1 for a discussion about the choice of cell resolution.

Table C8: Effect of defection messaging on per capita fatalities

Dependent variable:	**Number of fatalities per 1000 inhabitants (log)**				
	(1)	(2)	(3)	(4)	(5)
	FE	FE	FE	FE	FE
Intensity of messaging	-0.036***	-0.033***	-0.034***	-0.032***	-0.026***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
* Conflict-reducing shock			0.004*		-0.011**
			(0.003)		(0.004)
* Conflict-enhancing shock				0.007***	0.017***
				(0.003)	(0.005)
Observations	60600	60600	60600	60600	60600
Number of Years	8	8	8	8	8
Number of Cells	7575	7575	7575	7575	7575
Cell and Year FE	Yes	Yes	Yes	Yes	Yes
Distance polynomial	Yes	Yes	Yes	Yes	Yes
Additional controls	No	Yes	Yes	Yes	Yes
Year x Macro-Region FE	No	Yes	Yes	Yes	Yes

Note. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. 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, normalized by the population in the same cell at time t. Cell-level population is built using data from the Center for International Earth Science Information Network and the International Center for Tropical Agriculture (CIESIN-CIAT, 2005). Distance polynomial is a polynomial of second degree in the minimum distance from an active antenna and in the mean distance from all active antennas. Additional controls include income and weather shocks, and demographic characteristics (see section 3 for a detailed description). The time period is restricted to 2008-2015. See Appendix C.1 for a discussion about the choice of cell resolution.

To identify commodities linked to increases or decreases in fatalities associated with LRA, we follow a regression procedure. We estimate the following equation:

$$y_{it} = \alpha_0 + \sum_{k=1}^{K} \phi_k \omega_{ik} p_{kt} + \mathbf{X'}_{it}\beta + \sum_{t=2}^{T} \gamma_t d_t + \sum_{t=2}^{T} \sum_{r=2}^{R} \psi_{tr} d_t m_r + c_i + u_{it} \tag{5}$$

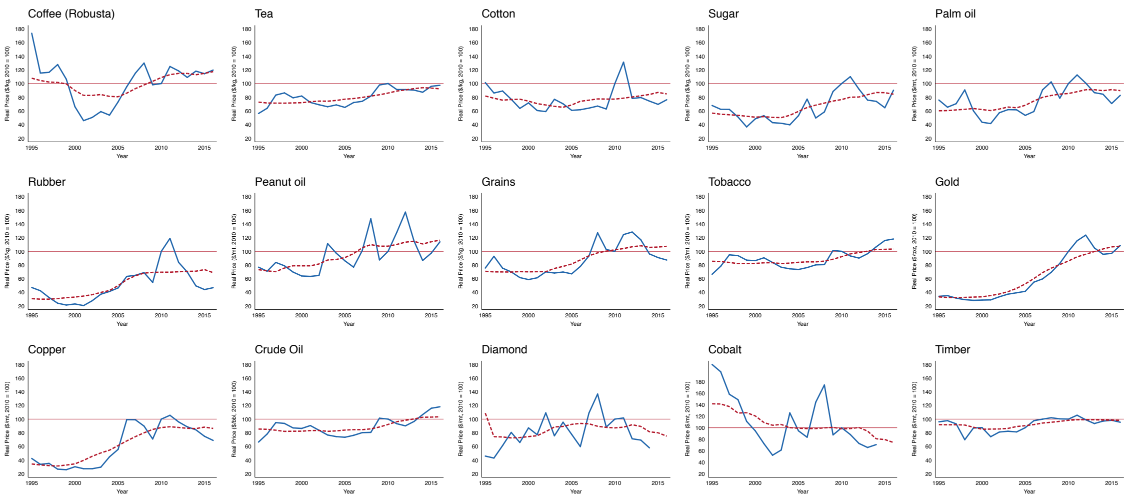
where y_{it} is the number of LRA fatalities at time t in cell i, ω_{ik} is an indicator variable equal to one if the crop k is farmed or extracted in cell i, and p_{kt} is the natural log of the price of crop k in the international market. $\mathbf{X}_{it}$ is a vector of cell-level time-varying characteristics, d_t are year-specific

Table C9: Main exported crops and natural resources present in LRA-affected countries

Country	Type	Commodity	Price	Source	Geo-location
CAR	Cash Crops	Cotton	Cotton, A Index, $/kg, real 2010$	GEM	M3-Crops
		Coffee	Coffee, Robusta, $/kg, real 2010$	GEM	M3-Crops
		Tobacco	Tobacco, $/mt, real 2010$	GEM	M3-Crops
	Natural resources	Diamonds	Industrial Diamonds, $/g, real 1998$	USGS	PRIO Diamonds
		Wood	Timber, 2010=100, real 2010$	GEM	PRIO Globcover
DR CONGO	Cash Crops	Coffee	Coffee, Robusta, $/kg, real 2010$	GEM	M3-Crops
		Sugar cane	Sugar, world, $/kg, real 2010$	GEM	M3-Crops
		Oil palm	Palm oil, $/mt, real 2010$	GEM	M3-Crops
		Rubber	Rubber, Singapore, $/kg, real 2010$	GEM	M3-Crops
	Natural resources	Diamonds	Industrial Diamonds, $/g, real 1998$	USGS	PRIO Diamonds
		Copper	Copper, $/mt, real 2010$	GEM	MRDS
		Gold	Gold, $/toz, real 2010$	GEM	PRIO Goldata
		Cobalt	Cobalt, $/mt, real 1998$	USGS	MRDS
		Crude oil	Crude oil, avg, spot, $/bbl, real 2010$	GEM	PRIO Petroleum
SOUTH SUDAN	Cash Crops	Cotton	Cotton, A Index, $/kg, real 2010$	GEM	M3-Crops
		Sesame	Grains, 2010=100, real 2010$	GEM	M3-Crops
		Peanuts	Groundnut oil, $/mt, real2010$	GEM	M3-Crops
		Sugar	Sugar, world, $/kg, real 2010$	GEM	M3-Crops
	Natural resources	Gold	Gold, $/toz, real 2010$	GEM	PRIO Goldata
		Crude Oil	Crude oil, avg, spot, $/bbl, real 2010$	GEM	PRIO Petroleum
UGANDA	Cash Crops	Coffee	Coffee, Robusta, $/kg, real 2010$	GEM	M3-Crops
		Tea	Tea average, $/kg, real 2010$	GEM	M3-Crops
		Cotton	Cotton, A Index, $/kg, real 2010$	GEM	M3-Crops
		Tobacco	Tobacco, $/mt, real 2010$	GEM	M3-Crops
	Natural resources	Gold	Gold, $/toz, real 2010$	GEM	PRIO Goldata

Note. Commodities are listed in order of relative importance. South Sudan includes the information for Sudan. Source: CIA World Factbook. We exclude from our analysis diamonds and crude oil since they are not present in the area of analysis.

Figure C9: Price series of commodities present in LRA-affected areas

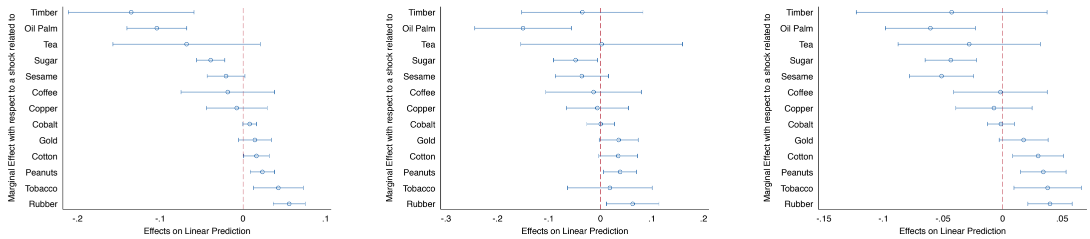


Note. The figures show the time series of commodity prices. We select commodities that are present in the area affected by LRA violence. Prices are reported in real values using US$ per the corresponding unit. Prices are normalized using the year 2010 as base. The horizontal line shows the base value of 100. The dashed line is a moving average of the time series using a plus/minus 5 years. Source: World Bank Global Economic Monitor (GEM) Commodities dataset.

dummy variables, c_i are cell fixed effects and u_{it} are idiosyncratic error terms. We include macro-region time fixed effects by dividing our grid into 8 macro-regions and introducing interaction terms between d_t and macro-region indicators, m_r. The coefficients ϕ_k identify the effect of each commodity on fatalities. We then define commodity k as a conflict-enhancing commodities if is $\phi_k > 0$ or as a conflict-reducing commodity if $\phi_k > 0$. We exclude from this definition commodities for which ϕ_k is not statistically significant at 10% level. The left panel in Figure C10 presents estimates of ϕ_k when using the LRACT. We supplement the results by presenting estimates of equation (5) where the dependent variable is the number of events where LRA is an actor. To this purpose, we use the UCDP and the ACLED data sets.

Figure C10: Marginal Effects of individual income shocks on fatalities and events

Fatalities (LRACT) *Number of events (ACLED)* *Number of events (UCDP)*

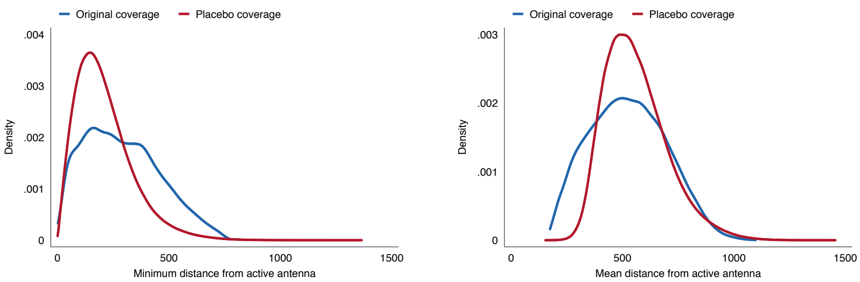


Note. The figures shows the estimates ϕ_k for each commodity using equation (5). The dependent variables are: log-number of fatalities from the LRACT database (left panel), number of events from the ACLED database (middle panel), and the number of events from the UCDP database (right panel). We consider the period 2008-2015. Confidence intervals are computed at 10% level of confidence.

D Additional Figures and Tables

Figure D11: Distribution of minimum and mean distance from active antennas

Minimum distance *Mean distance*



Note. The figures shows the distribution of the minimum distance from a cell's centroid to an active antenna and the mean distance from active antennas. We consider the period 2008-2015. The red line represents the minimum distance for all placebo simulations, while the blue line presents the distribution with the original location of antennas.

Table D10: Placebo test descriptive statistics

	Coefficient on intensity of defection messaging				
			Percentiles		
	Mean	Std.Dev.	5^{th}	50^{th}	95^{th}
	(1)	(2)	(3)	(4)	(5)
Total fatalities (log)	0.000	0.017	-0.034	0.005	0.021
Number of returnees (log)	-0.000	0.010	-0.015	-0.001	0.017
Number of abductees (log)	-0.000	0.009	-0.013	-0.001	0.013
Number of events with violence against civilians or clash	-0.001	0.027	-0.049	0.004	0.034
Number of LRA events (ACLED)	0.001	0.017	-0.034	0.004	0.022
Number of Non-LRA events (ACLED)	-0.003	0.053	-0.092	-0.001	0.085
Number of LRA events (UCDP)	-0.000	0.008	-0.017	0.002	0.011
Number of Non-LRA events (UCDP)	-0.003	0.057	-0.099	0.003	0.092
Number of events with looting	-0.001	0.024	-0.034	-0.005	0.047

Note. The table presents descriptive statistics of the coefficient on intensity of defection messaging in the placebo test. Each observation is an estimated coefficient in equation (4) where radio coverage is generated by randomly allocating antennas in the original grid. We perform 250 simulations.

Table D11: Effect of defection messaging on returnees and abductions, by age group

Dependent variable:	Number of returnees (log)		Number of abductees (log)	
Group:	Adults	Children	Adults	Children
	(1)	(2)	(3)	(4)
	FE	FE	FE	FE
Intensity of messaging	0.013***	-0.000	0.011***	-0.007***
	(0.002)	(0.002)	(0.003)	(0.002)
Observations	60600	60600	60600	60600
Number of Years	8	8	8	8
Number of Cells	7575	7575	7575	7575
Cell and Year FE	Yes	Yes	Yes	Yes
Distance polynomial	Yes	Yes	Yes	Yes
Additional controls	Yes	Yes	Yes	Yes
Year x Macro-Region FE	Yes	Yes	Yes	Yes

Note. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. 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 returnees (columns 1 and 2) and the number of abductees (columns 3 and 4), both reported in logarithm. Distance polynomial is a polynomial of second degree in the minimum distance from an active antenna and in the mean distance from all active antennas. Additional controls include income and weather shocks, and demographic characteristics (see section 3 for a detailed description). The time period is restricted to 2008-2015. See Appendix C.1 for a discussion about the choice of cell resolution.

E Examples of defection messages

In this section, we present some examples of messages broadcast during the defection messaging campaing. The following examples are drawn from a small 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 instead 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 Organisation] 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.