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

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Abstract

We study the role of FM radio messaging in discouraging violent conflict. We collected unique information about defection messaging by local and international radio stations in the four countries (DR Congo, Central African Republic, South Sudan and Uganda) affected by the Lord's Resistance Army (LRA) insurgency. We exploit random topography-driven variation in radio coverage along with panel variation at the grid cell level to capture the causal effect of defection messaging on violence. We find that a higher intensity of defection messaging leads to a decrease in both fatalities and violence against civilians driven primarily by an increase in defections. Due to defection messaging the LRA resorts to increased looting for survival. Conflict enhancing commodity price shocks lead to higher levels of conflict and reduce the effectiveness of defection messaging in reducing violence.

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1 Introduction

How can we put an end to civil conflicts? In order to answer this question, peace-building policy since the late 1990s has made pointed efforts to go beyond macro-level policies and address individual incentives to participate in violence. A significant amount of resources and attention have focused on Disarmament, Demobilization, and Reintegration (DDR) programs to help ex-combatants transition to civilian life. Yet few formal activities within such programs effectively address issues that might prevent combatants from ever leaving the conflict and arriving into the DDR programs.[1] Defection messaging is one such initiative that has gained support and prominence in recent times (UN-DDR, 2014).

Defection messaging aims to mitigate and end conflict by providing active combatants information on the logistics of surrender, immunity offers and judicial processes, and the willingness of their families and communities to take them back. Print and digital media have limited reach in remote areas where armed groups often operate. This has prompted several policy actors to pursue 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. However, little is known about whether such defection messaging strategies can indeed be an instrument for peace.

Focussing on the Lord's Resistance Army (LRA) Insurgency in central Africa, we provide the first ever (to the best of our knowledge) evaluation of a radio defection messaging program aimed at ending an active civil conflict.[2] The LRA 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.

FM defection messaging has been employed in countering the LRA conflict since the early 2000s and has expanded dramatically since 2008. Defection programs have been largely modelled on the "*Come Home*" programs pioneered by two stations in northern Uganda in the early 2000s. Programs include interviews with surrendered combatants, personal messages from family or community members, news on the conflict, and logistical information on how to safely surrender. 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.

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

[2] The previous literature has highlighted the role of radio as a propaganda tool for inciting violence (Yanagizawa-Drott, 2014), political mobilization (Adena et al., 2015) and ethnic hatred (DellaVigna et al., 2014).

In order to study the effectiveness of the FM radio defection messaging program we constructed a novel dataset combining different primary and secondary sources of data. To start with, we designed and conducted a short survey of radio station operators to collate data on the annual expansion of defection messaging in the four countries haunted by the conflict. We combined this with the previously underexploited LRA Crisis Tracker (LRACT) database. LRACT is a high quality geo-coded database providing detailed information on events related to the LRA from the year 2008 onwards.

Next, exploiting myriad sources we collected geographically disaggregated data on a range of variables which the previous literature has found relevant for conflict. This includes data on natural resources like cash crops and minerals, as well as weather variables like temperature and precipitation. Finally, combining these aforementioned data, we come up with a grid cell level panel dataset for the period of 2008-2015.

We focus on the 2008-2015 period for several reasons. First, the LRA crisis tracker database began a detailed cataloguing of LRA activities in the year 2008. Hence, focussing on the post 2008 period allows us to do an in-depth analysis of the effects of radio messaging on conflict. In particular, we are able to go beyond just looking at the number of events or fatalities available from other conflict datasets, and explore the strategic behavior (such as looting and abductions) of the LRA under dwindling membership.

Second, 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 (UN Security Council, 2013b). The main expansion of defection messaging began around 2010 and hence the relevant variation in the data is restricted to this period.

Finally, the dispersion of the LRA outside of Uganda after 2008 caused a shift in the strategic aims of the LRA leadership. They had to abandon their aspirations of political legitimacy in Uganda, and it became clear that amnesty was unlikely for the senior leadership. The LRA started operating in small groups spread across vast expanses (Lancaster et al., 2011). Hence, defection messaging is also likely to be more relevant during this period.

In total, 18 stations (21 antennas) have partnered in these efforts, spanning an area of 400,000 square km.[3] The phased implementation of the messaging campaign and of the radio coverage expansion over time allows us to estimate the causal impact of messaging exploiting three sources of plausibly exogenous variation. Firstly, we measure radio coverage corrected by the topography of the affected area (see similar empirical strategies in Olken (2009) and Yanagizawa-Drott (2014)). Secondly, we enhance the current literature by exploiting the panel dimension of our dataset and controlling for time-invariant unobservable characteristics at a highly disaggregated level. Finally, we exploit the overlapping of radio coverage from different radios to build a measure of message

[3]We provide a detailed discussion of the timing of this expansion and its main features in section 6.4.

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. A one standard deviation increase in defection messaging 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 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.

We find that exogenous commodity price shocks, measured by cash crops and natural resources at the cell-level, reduce the effectiveness of defection messaging. The recent literature has highlighted how commodity price shocks can have opposing effects on conflict.[4] Instead of taking a stand on which crops/natural resources lead to more or less conflict, we let the data tell us which shocks are conflict-enhancing or conflict-reducing in our context. We find that a one standard deviation increase in conflict enhancing shock knocks off the effects of defection messaging on fatalities by 1 pp from 3 percent to 2 percent. This result suggests that violence and the response to defection messaging are closely related to economic incentives.

Next, exploiting the the detailed nature of our conflict database, we find a significant shift in LRA strategy as the result of defection messaging. 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 increased looting as the result of defection messaging could be an effort by the LRA to reduce the relative returns to non-military labor effort for potential recruits, while simultaneously generating spoils to reward existing recruits (Azam, 2002, 2006). However, delving further into the type of goods being looted, we find that this effect is driven primarily by an increased looting of food. This points towards looting being more of a survival strategy.

Finally, using an instrumental variable approach, we show that the reduction in conflict intensity is driven by a reduction in the number of returnees and quantify the effect. We find that a one standard deviation increase in the number of returnees reduces fatalities by almost 44%, abductions by around 8%, and attacks against civilians or clashes with security forces by 0.7. It also increases events characterized by looting by around 0.6. Hence, the intensity of the LRA conflict significantly went down due to defections in the LRA which was in turn driven by the radio defection messaging programs.

Our results are stable across a series of robustness tests. Our baseline specifications always control for cell level fixed effects in addition to correcting radio coverage for topography. Given the disaggregated nature of our data we have been able to take a grid cell based approach which let's us overcome the endogeneity of political borders. Our results are robust to the use of administrative units instead of grid cells. While we have based our choice of grid cell size (approximately 14

[4] See section 3 for a more detailed discussion.

$km \times 14$ km for the baseline specifications) on the geography of point patterns (Boots and Getis, 1988), our results are robust to using alternative spatial scales.

Our results are also robust to controlling for a wide range of other time varying controls including rainfall and temperature shocks. In some of our specifications we specifically control for mobile phone coverage. Mobile phone coverage can affect political mobilization and could have been a potential confounder of our results (Manacorda and Tesei, 2016). Our results are also robust to the use of alternative conflict datasets. Using these alternative data sources, we show that our results are not driven by conventional state military pressure against the LRA, a possible confounding strategy. Finally, we undertake placebo tests by randomly placing radio stations across space and show that exposure to these placebo radio stations do not affect the conflict.

We contribute to three different strands of the literature. First, we contribute to the literature studying the effects of media on social and political outcomes. Previous contributions in this field have focused on the effect of media on politician accountability (Besley and Burgess, 2002; Strömberg, 2004), crime (Dahl and DellaVigna, 2009), social capital (Olken, 2009), and female autonomy and fertility (Jensen and Oster, 2009; La Ferrara et al., 2012). More recently, the literature has highlighted the role of radio in inciting violence and hateful attitudes.[5] For instance, Yanagizawa-Drott (2014) shows how propaganda broadcast via radio played an important role during the Rwandan Genocide. Adena et al. (2015) show how radio was instrumental in ensuring support for government initiatives in Nazi Germany. Again, DellaVigna et al. (2014) show how radio was effective in shaping hateful sentiments across different ethnic groups in Croatia. In contrast, we provide the first systematic analysis of how radio messaging can be effectively used to encourage defections and reduce violent conflict.[6]

Second, we contribute to the burgeoning literature which highlights the role of economic shocks on civil conflicts. 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 (Becker, 1968). Economic conditions and the availability of resources can affect these expected returns. For instance, positive income shocks generated through an improvement in economic conditions can reduce the intensity of conflict by increasing wages and reducing the supply of labor for conflict activities (Becker, 1968; Grossman, 1991). Alternatively, they can increase conflict by increasing the returns to predation (Fearon, 2005; Dube and Vargas, 2013) or reduce conflict by improving state capacity (Fearon and Laitin, 2003; Snyder, 2006; Ross, 2012). We are the first paper to show that show that income shocks can affect active policies to disincentivize conflict.

Our final contribution relates to changes in armed group strategy which is one of the most understudied areas in the literature (Blattman and Miguel, 2010). 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 civil-

[5] 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.

[6] 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).

ians 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 survival strategy of the LRA under dwindling membership. This provides novel insights into the strategic behavior of armed groups.

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

2 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 spiritual cleansing of the nation.[7]

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 through 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.

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

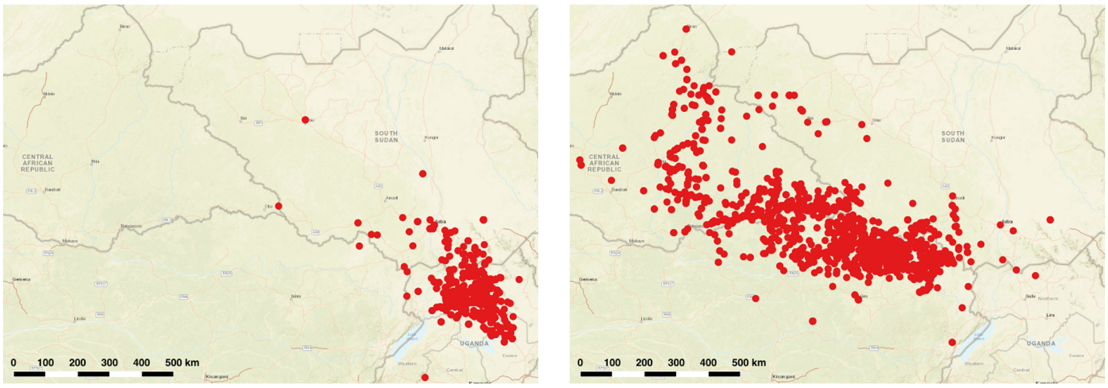
[7] For deeper reading on the historical origins of the LRA see Allen (2005); Beber and Blattman (2013); Allen and Vlassenroot (2010); Behrend (1999); Doom and Vlassenroot (1999); Finnström (2010); Lamwaka (2002); Omara-Otunnu (1987).

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.

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

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.

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).[9]

[8] Additional examples are provided in Appendix E.

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

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.

While we cannot directly observe combatants receiving defection messages through the FM radio broadcasts, qualitative evidence suggests that exposure to these messages is high. 89% of returnees have cited defection messaging as "influential in their decision to escape" (Invisible Children, 2013). 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.

In Figure 1 we plot the geographic distribution of LRA-related events for the period 1989-2015, divided into pre-2008 and post-2008 periods. This paper focusses on the expansion of the defection program at the bordering region of Uganda, DR Congo, South Sudan and CAR in the post 2008 period.

3 Conceptual Framework

In this section we provide a discussion on why defection messaging might be effective in reducing conflict and bringing rebels back. We do so by drawing on the theoretical literature. Defection messaging can be considered as an instrument of what in the literature is known as persuasive communication.[10] In this branch of the literature, communication can affect behavior through two types of models, viz. the belief based model and/or the preference based model. Let us consider them in turn.

In a belief-based model, fighters would be considered as rational agents updating their information set using Bayes' rule when processing new information received from defection messaging. The information needs to be credible and relevant for their decision making, so that fighters could change their behavior by updating their perception of costs and benefits associated with the decision to leave the armed group or keep fighting. There are three reasons why we think that in our context a belief-based model could explain why defection messaging would be effective.

Firstly, the most common source of news for LRA fighters is radio broadcasts (Lancaster et al., 2011). This suggests that at least a priori, information channelled using radio stations could reach their targeted receivers and influence their beliefs. Secondly, credibility was directly targeted in

[10]See DellaVigna and Gentzkow, 2010 for a review.

the design of defection messages. The choice of former fighters, family or community members directly signalled credibility about the content of the information broadcast, and especially about the possibility of returning to civilian life without consequences.

The issue of credibility is particularly salient in the case of defections from the LRA. This is evident from an episode in Northern Uganda, where a significant number of long-term LRA members who surrendered, refused the food offered by demobilization teams based on widespread rumours that Ugandan and international forces would poison them (Allen and Schomerus, 2006).

Thirdly, evidence suggests that defection messaging indeed had an impact on beliefs. By looking at civilians, Rigterink and Schomerus (2016) show that LRA-targeted defection messaging in South Sudan led civilians to show higher anxiety and fear of a potential LRA attack. Together, these points suggest that a revision about the cost-benefit trade-off between fighting or defecting could well be a mechanism through which defection messaging can reduce violence.

In a preference-based model, even if agents are not fully rational and messages are non-informative, communication can affect fighters' behaviors if two conditions are met. First, if they either implicitly value the act of going back to civilian life or being part of the LRA, and second, if defection messaging can impact these values.

Intrinsic motivation to fight for the LRA played an important role in the history of the armed group and needs to be considered in the study of defection messaging. In the early history of the group, fighters saw themselves as fighting for their people, the Acholi, whom they believed to be marginalized, abused, and excluded from Uganda's oppressive regime (Schomerus, 2007). Also religion, a unique blend of Christian and traditional beliefs, played a central role in motivating the group in its early stages (Lancaster et al., 2011).

The LRA used violence and the threat of punishment as the main instruments to control abducted individuals. However, indoctrination played an important role in shaping their motivation, especially in the context of child soldiers (Beber and Blattman, 2013). While ideology and spirituality provided motivation for fighters to remain in the armed group, it was the *status* reached by fighters that was driving their decision to continue fighting in the later stages of the conflict (Titeca, 2010). The choice of emotional messages during defection broadcasting specifically targeted such intrinsic motivation. The appeal to emotions and a non-confrontational approach (attempting to de-escalate the situation) can indeed play a complementary role to the informative content of messages by influencing the intrinsic motivation among fighters.

In both the belief-based and the preference-based models, we also need to consider how social interactions can influence the effect of mass media (see, for instance, Katz and Lazarsfeld, 1955). In the case of armed groups, decisions among peer fighters are linked and dependent on each other. Hence, defection messaging can have important spillovers through peer group effects (see Durlauf, 2004, for a review on social interactions).

Firstly, interdependencies in either the constraints that individuals face or psychological factors can influence the effectiveness of messaging. If the marginal net benefit of leaving the LRA is increasing in the number of other fighters in the same group, because of strategic complementaries in the decision (for instance, for safety in numbers), then one would expect positive spillovers.

Secondly, in the presence of interdependencies in information transmission, social interactions might facilitate the diffusion of defection messaging among non-listeners. This is the case in which not all fighters have access to radio and cannot listen to the message directly. If information can circulate by word of mouth, social interactions can also generate positive spillovers. This is possibly a mechanism at play for lower-ranked fighters, since the monologues are predominantly in the Acholi language, targeting mid-level commanders who are almost exclusively Acholi Ugandans and are more likely to have access to radios (Ross, 2016).[11]

Since defection messages targeted both beliefs and preferences of fighters, we cannot disentangle the relative role of each mechanism in encouraging defections. It is plausible that both mechanisms were at play in our setting. However, regardless of which mechanism was at play, clearly economic incentives should affect the effectiveness of defection messaging.[12]

If fighters are driven not only by intrinsic motivation, but also by economic incentives, it is reasonable to believe that changes in the relative trade-off between fighting or leaving the group, could influence the effectiveness of messaging. Recent evidence suggests that while economic shocks do not trigger new wars, they are central in explaining the persistence and intensity of existing conflicts (Bazzi and Blattman, 2014). The economic incentives literature has focused widely on the role of commodity price shocks as a source of income shock (Berman et al., 2017; Dube and Vargas, 2013). Commodity price shocks can affect civil conflicts in different ways and indeed different directions.

Firstly, one mechanism relates to the *opportunity cost* of fighting. In particular, an individual's willingness to engage within an armed group can be related to the expected returns to different alternatives, such as fighting or returning to the civil society, often as farmers. In this setting, commodity price shocks can reduce the intensity of conflict by increasing wages and reducing the labor supply for conflict activities (Becker, 1968; Grossman, 1991; Hirshleifer, 1995). Alternatively, they can increase conflict by increasing the returns to predation (Fearon, 2005; Dube and Vargas, 2013).

Secondly, rising commodity prices also have two opposite effects in relation to state control. Commodity prices increase *resource rents*, making the state a more valuable prize, and increasing incentives to seize it (Grossman, 1995; Bates et al., 2002). Alternatively, rising revenues can also increase *state capacity* and its ability to defend and strengthen control over the territory (Fearon and Laitin, 2003; Snyder, 2006; Ross, 2012).

If any of these mechanisms are at play then the effectiveness of defection messaging crucially depends on these shocks. In other words, we should observe interaction effects between disincentives to fight created by messaging and incentives to fight generated by income shocks. If defection messaging indeed turns out to be a function of economic shocks, then the underlying theoretical

[11] Peer effects can also have negative effect on the effect of defection messaging. This would be the case if observing some of the fighters leaving the LRA would induce others to remain and fight. We exclude this possibility in our setting

[12] 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.

framework cannot be one based exclusively on intrinsic motivation. It would rather be either a belief-based or a preference-based framework that includes the role of economic rewards.

The literature has also devoted some attention to understanding under what conditions armed groups are more or less likely to use violence against civilians. The two factors that have been found to be important for explaining violence against civilians are the ability of armed groups to control territory and their sources of financing (Kalyvas, 2006; Wood, 2014). Once armed groups are able to control and defend a territory they stop attacking civilians. On the other hand, if they have weak control over territory, they become more mobile and use attacks against civilians to obtain support from the local communities (Wood, 2010, 2014).

Depending on the type of resources, resource gains can have contradictory effects on violence. On the one hand, for certain types of resource gains which can be easily taxed, armed groups might provide protection instead of violence (Tilly, 1985; Sanchez de la Sierra, 2014). On the other hand, groups rich in material resources could also be more prone to committing violence against civilians as they are joined by members with little commitment to civilian populations (Weinstein, 2005).

4 Data

In this paper we make use of data from different sources. We combine a 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.

4.1 FM Radio Stations and coverage

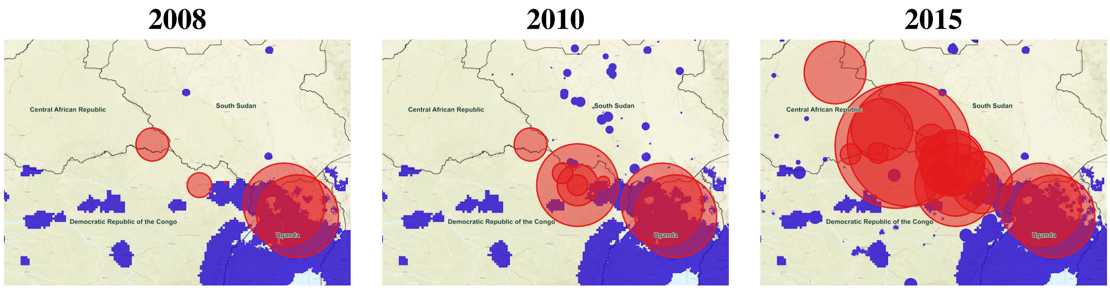
To acquire data on broadcast exposure, we designed a short questionnaire for participating stations.[13] The set of participating stations was generated by cross-referencing policy reports and through direct exchanges with international actors and radio operators to identify any station that broadcasted 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 such as the Catholic Radio Network in South Sudan and other independent stations in Uganda were reached through direct contacts. 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

[13] See Appendix B for a detailed description.

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 are FM radio stations that broadcast defection messaging at least once in their history. Stations in the area of study that have not broadcast defection content are not included in our dataset due to data collection constraints. Figure 2 also plots the extension of GSM mobile phone network coverage for the same period, which remained relatively unchanged.[14]

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.

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 5. Where stations' technical characteristics were 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.[15] 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

[14] 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.

[15] 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.

receive signal from the station and at what strength at a 90m resolution. Figure C5 in Appendix shows the coverage of defection messaging using this correction.[16]

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.

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.

4.2 Conflict intensity

Our primary LRA related conflict data are based on the LRA Crisis Tracker (LRACT) database. LRACT is an event-based data collection project that began in 2008 through the efforts of two policy NGOs, The Resolve LRA Crisis Initiative and Invisible Children. The goal of LRACT is to provide detailed and disaggregated data on LRA activities to better inform policy actors' strategies and activities. It provides geo-coded information about LRA-related events, including fatalities, looting, abductions, and defections across space and time. Nearly all the events are

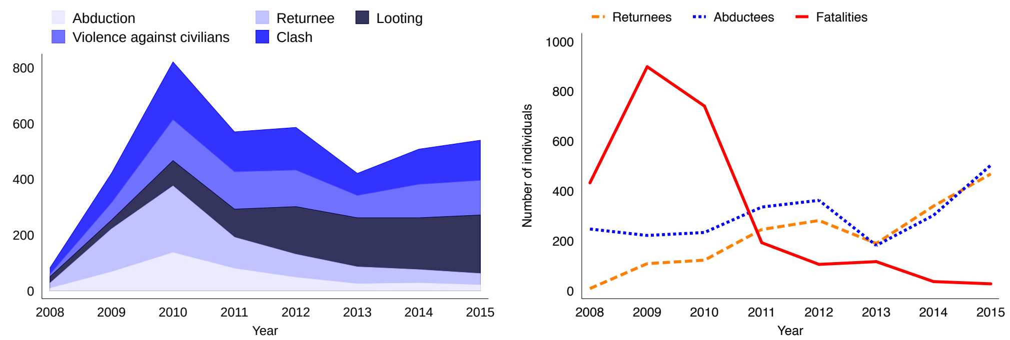
[16]Coverage is calculated using CloudRF (cloudrf.com), a commercial radio planning tool.

located in Central African Republic, Democratic Republic of Congo, South Sudan, and Uganda. LRACT reports events at the maximum spatial resolution of the population center where the event occurred and at maximum temporal resolution of the day of the event.

The LRA Crisis Tracker database collects its data using methods similar to other widely used conflict event databases like the 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., 2010). The data collection methods 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.

The LRACT dataset provides detailed information on events related to the LRA conflict. We classify these events into different categories such as clashes with government forces, violence against civilians, abductions, and looting, among others. 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 plots the series of the number of returnees, abductees and fatalities over the period of analysis.

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



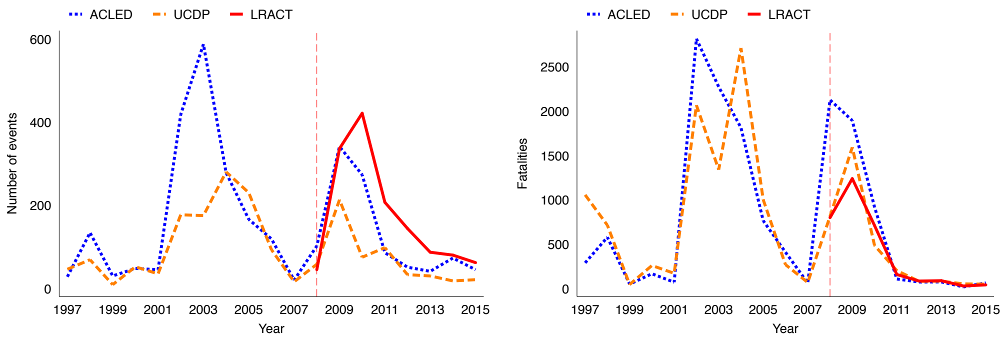
Note. The figures show the time series of conflict events and involved individuals as measured by the LRACT database. The left panel presents the composition of total events per year, while the right panel focuses on the number of returnees, abductees and fatalities.

As part of the robustness exercises and for conducting additional analyses, we supplement the LRACT data with conflict data from the UCDP and ACLED databases. Each of these datasets include 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 in 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 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." On the other hand, ACLED collects and codes all events identified as political violence in the developing world, focusing on civil and communal conflicts, violence against civilians, rioting and protesting.

In Figure 4 we plot and compare the evolution of violence related to the LRA from the three different datasets for the years 1997 to 2015. 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 our units of observation, we superimpose a grid of equally-sized cells over the territory affected by the LRA and hold this stable over the entire period of analysis. For our baseline specifications, we consider grid cells of 0.125 degrees of latitude by 0.125 degrees of longitude, which is around 14 km by 14 km at the equator. We base our choice of grid cell size on the geography of point patterns (Boots and Getis, 1988), but our results are robust to using alternative grid resolutions. We provide a more detailed discussion about the choice of cell resolution, including its effect on our main estimates, and the Modifiable Areal Unit Problem (MAUP) in Appendix C.1. See Figure C4 for a graphical representation of the grid resolution.

Defining the extent of the grid is another discretionary decision with no clear precedent in the literature. In our case, we select all events where the LRA is an actor and look at the distribution of their coordinates (latitudes and longitudes) across space for the 1997-2015 period. While our period of analysis is from 2008 to 2015, instead of restricting our study area only to this period, we look at a wider area to take into account the entire area in which the LRA has historically operated. We then select a geographical area that is defined by the 1st percentile minus 0.5 degrees and 99th percentile plus 0.5 degrees of both latitude and longitude of the events. Our results are robust to expanding our study area further (see Appendix C.2).

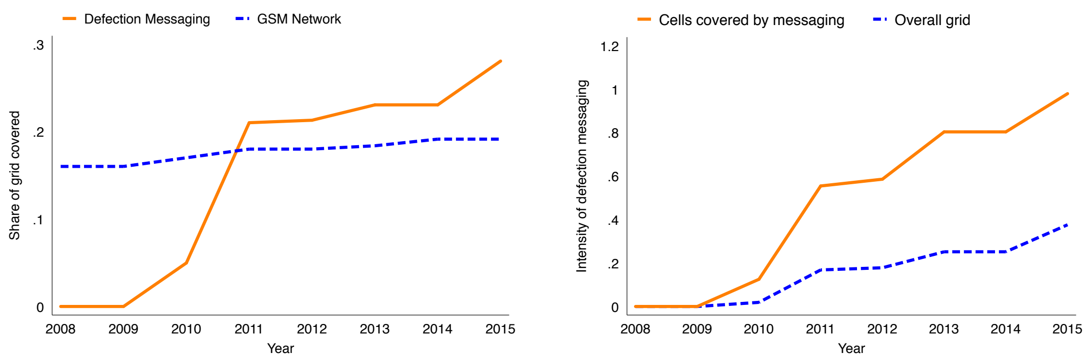
A grid-cell based approach avoids the potential of political boundaries to be endogenous to violence and has been frequently used in the literature (Michalopoulos, 2012; Harari and La Ferrara, 2013; Montalvo and Reynal-Querol, 2016). Some related studies have relied on administrative divisions as units of analysis (Yanagizawa-Drott, 2014). One advantage of using administrative units could be the availability of data collected at the administrative unit level for instance, on demographics or other time varying characteristics. Such data are hard to come by in our context, particularly given the international extent of the conflict. On the other hand, the advantage of using a grid cell based approach is that 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.[17]

Events are aggregated at the cell-year level over the period 2008-2015. Aggregating events reduces 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.

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

Coverage *Intensity of defection messaging*



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.

4.3 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.

[17]While we prefer a grid cell based approach, we will later show that our results are robust to the use of district-level administrative boundaries instead. 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.

4.3.1 Commodities and income shocks

We measure income shocks which might be driving LRA activity and the effectiveness of messaging, by using shocks to commodity prices. We construct these data by combining the geographical distribution of commodities with yearly commodity-specific price variation in international markets (see for instance, Dube and Vargas, 2013).

We focus on two types of commodities whose values are particularly linked to prices in international markets: cash-crops and extractive resources. We select the main cash crops and natural resources for each country covered by the study area from the CIA Factbook.[18] The area under

[18] See Table C10 in Appendix

consideration is not a world-leading producer in any of these commodities, which lets us assume that international prices are exogenous to local production.

Understanding the direction of the effect of commodity price shocks on the intensity of LRA conflict is not straightforward. Existing studies focusing on the role of commodity price shocks on conflict reach seemingly different conclusions. Some find no relationship (Deaton et al., 1995), some a positive relationship (Ciccone, 2011; Savun and Cook, 2010), while others a negative relationship (Besley and Persson, 2008). These contrasting findings might be due to the selection and coverage of the commodities considered (Bazzi and Blattman, 2014; Dube and Vargas, 2013). Commodity price shocks can generate opposing effects on conflict depending on the type of commodity. Shocks that disproportionately increase household income compared to state income are expected to reduce conflict intensity through an opportunity cost mechanism. This is the case of labor-intensive, smallholder-owned, and difficult-to-tax commodities, such as annual agricultural crops (Dal Bó and Dal Bó, 2011). On the other hand, capital-intensive or appropriable commodities accrue mainly to the state due to high taxability and licensing fees. These can lead to both an increase in conflict, through an increase in resource rents, or a decrease in conflict, through a state capacity effect. This category includes capital-intensive extractive commodities, but also rubber and perennial tree crops, like coffee, which requires larger investments.

Since the goal of the study is to understand how economic shocks affect the effectiveness of radio, we follow an empirical procedure to select commodities that are either increasing or decreasing the intensity of LRA violence. 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, proxied as standard in the literature with the number of fatalities. In line with Dube and Vargas (2013) and Berman et al. (2017), 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 detailed results and a discussion on the role of each commodity 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 shocks 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.

To build ω_{ik}, which identifies whether a particular crop is farmed or a natural resource is extracted in a particular cell, we use data on the geographical distribution of agricultural crops obtained from the M3-Crops database (Monfreda 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. 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 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.

To build p_{kt}, we use price series 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.

4.3.2 Weather and demographics

To control for possible confounders of commodity price shocks presented in section 4.3.1, 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 precipitation 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 ensure comparability of the effect of rainfall on LRA activity across cells, we construct 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.[19]

We compute temperature deviations using a similar procedure, but restricting the standardization to the 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.

5 Empirical Strategy

Putting together the data from the different sources mentioned above, we construct a cell-level dataset spanning across the four countries of DR Congo, South Sudan, CAR and Uganda for the 2008-2015 period.[20] For the baseline specifications, we consider cells of 0.125×0.125 degrees which is around 14 km by 14 km near the equator.

For identification, we rely on three sources of plausibly exogenous variation. Firstly, following Yanagizawa-Drott (2014), we exploit local topographic variation as a random determinant of signal reception. The propagation of FM radio signal depends on the height and power of each antenna. Without obstacles the attenuation of the signal is proportional to the square of the distance from the antenna. In the presence of physical obstacles such as hills, mountains, or buildings, the signal can be physically blocked, creating patterns in 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 any particular point of time certain cells could experience violence either due to their topography or due to other characteristics that do not change over time. This strategy is in line with Olken (2009), who uses a similar type of variation, in addition to topographic variation, to study 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 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

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

[20]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.

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:

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

where c_{ijt} is the percentage of cell i covered by radio j at time t and h_{jt} is the number of hours of defection messaging daily broadcast by radio j at time t. 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.

Our measure of radio intensity is constructed by summing up the proportion of cell coverage times the hours of messaging for each cell as defined by equation (3). Another alternative would be to consider the cell level intensity averaged over the number of radio stations messaging in a particular cell. While our preferred measure is the absolute intensity given by equation (3), we also present our main results using an average measure by dividing equation (3) by the number of radios covering the cell. Our results are robust to this specification (see Appendix C.6). In Section 6.4, we also discuss the possibility that each radio responded to expected reduction in violence with increased radio messaging. We do not find evidence of this possibility.[21]

Our primary objective is to measure the effect of the intensity of defection messaging on an outcome variable y_{irt}, which captures violence intensity (or LRA activity) in cell i in macro-region r at time t. To this end, we estimate the following model as our main specification:

$$y_{irt} = \alpha_0 + \alpha_1 dm_{it} + \mathbf{X'}_{it}\beta + d_t + d_t m_r + \gamma_i + u_{it} \tag{4}$$

where $\mathbf{X}_{it}$ is a vector of cell-level time-varying characteristics, d_t are time fixed effects, γ_i are cell fixed effects and u_{it} are idiosyncratic error terms. We include macro-region specific 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 measure radio signal coverage corrected for topography, it is plausible to assume that defection messaging intensity is exogenous to conflict.

[21] 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.

To give a causal interpretation to α_1 we also need to rule out the possibility that antennas have been placed endogenously to the conflict. This would be the case if antennas have been placed in locations where violence increased (or decreased) and the distance from the antennas hide unobserved determinants of violence. We overcome the possibility of endogenous location of antennas by controlling for distance from active antennas.

Since the 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. In Appendix Figure D11 we present the distribution of these two variables. We allow for a flexible functional form in the way distance enters our main estimating equation since this variable is important for our identification strategy. Our results are robust to less flexible forms, such as controlling only for the minimum distance from active antennas.

Since we cannot directly observe LRA members receiving the radio message, our estimates can be interpreted as an Intent-to-Treat effect of defection messaging. Available qualitative evidence suggests that exposure to defection messaging is widespread, and almost 90% of returnees cite defection messaging as being influential in their decision to return. (Invisible Children, 2013)

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.[22]

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.

6 Results

In this section we present the estimates for the effect of defection messaging on different indicators of conflict. We first focus on the effectiveness of defection messaging in reducing violence (section 6.1) and we then examine the effects of messaging on the strategic behavior of the LRA (section 6.2). Finally, we undertake a host of robustness exercises (section 6.3).

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

6.1 Effectiveness of defection messaging

Encouraging defections among rebels is ultimately motivated by the desire to reduce violence, either by directly altering combatant behavior, or by 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. 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.[23]

Table 3: Effect of defection messaging on fatalities

Dependent variable:	**Number of fatalities (log)**				
	(1)	(2)	(3)	(4)	(5)
	FE	FE	FE	FE	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 4 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 one standard deviation increase in messaging intensity leads to a reduction in the number of fatalities by around 3 percent. As expected, conflict enhancing commodity price shocks lead to higher conflict and conflict reducing shocks lead to lower conflict. The effectiveness of defection messaging is itself a function of conflict-enhancing commodity price shocks. When intensity of

[23] 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). In Appendix C.7, we show the robustness of the result to different specifications, such as using as dependent variable the number of fatalities normalized by the population or the available land in the cell or restricting the sample to cells that have experienced defection messaging.

messaging increases by one standard deviation, a one standard deviation increase in the value of conflict-enhancing commodities leads to a 1 percent point reduction in the effectiveness of defection messaging in reducing fatalities. This implies that economic incentives directly affect violence and also reduce the effectiveness of defection messaging to reduce violence.

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 returnees 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 wilfully defected or captured within the incident reported."[24] In Table 4, we show how defection messaging impacted the total number of returnees.

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 4 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.

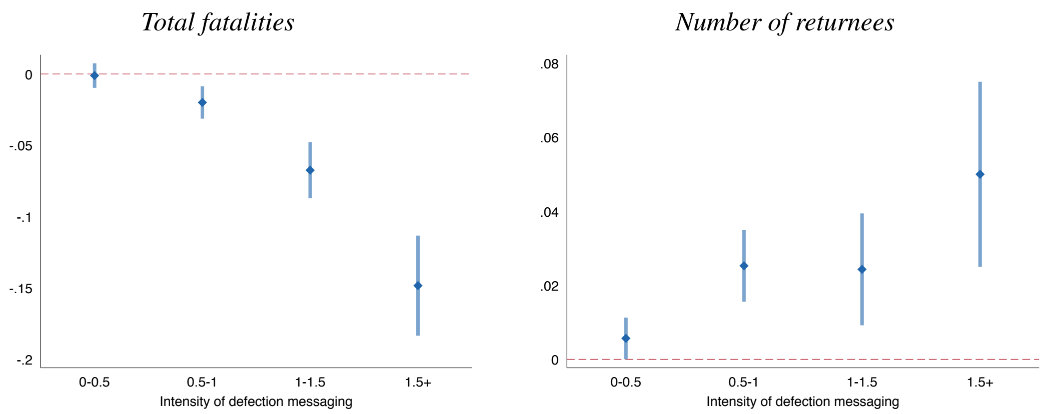
A higher intensity of defection messaging leads to a statistically significant increase in the total number of returnees. A one standard deviation increase in defection messaging intensity leads to an increase of returnees by 1 percent. These results suggest that defection messaging was indeed effective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

[24] In our data, we cannot distinguish between forced recruits and intrinsically motivated fighters who are returning from the LRA. Hence, we use the total number of individuals returning as the dependent variable. Our results are similar if we instead consider the number of events involving at least one individual returning.

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. More specifically we use five 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. 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 a 2 percent increase in returnees.

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.

6.2 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 behavior of the LRA and its members to understand the mechanism behind the impact of defection messaging.

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.

6.2.1 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. In guerrilla conflict, evidence shows that armed groups prefer selective and strategic violence rather than indiscriminate violence (Kalyvas, 2006).

We focus on the number of events defined either as "LRA violence" or "clash" in the database.[25] 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 4 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 messaging translates into a reduction in fatalities is through a decrease in the attacks carried out

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

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, similar 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 suggests that incentives for fighting are strongly associated with higher levels of violence, and that stronger economic incentives to fight makes defection messaging less effective in reducing violence.

6.2.2 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 due to the ease of indoctrinating children (Annan et al., 2006; Beber and Blattman, 2013). 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 of radio messaging on abductions by the LRA.[26]

Since abduction provides an injection in the supply of fighters or slave labor that the LRA can use for different tasks, it is not surprising that, when incentives for fighting are higher, abductions increase. 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. Higher rents can require additional labor supply for the group, but also provide additional means to coerce new fighters and motivate them into the group. 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 significant non-linear effect of radio messaging on abductions (see Figure 7).

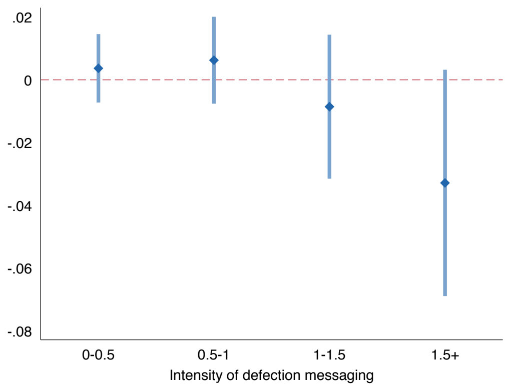
[26] Information about returnees and abductions dis-aggregated by age and gender is not always available in the dataset (around 50 percent of observations have this information). Due to the high sample selection of dis-aggregated data, we rely on total numbers as our main outcome variable.

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 4 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.

6.2.3 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) 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 leads to decreases of attacks against civilians, it increases the incidence of looting associated with the LRA. A one 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).

Table 7: Effect of defection messaging on looting

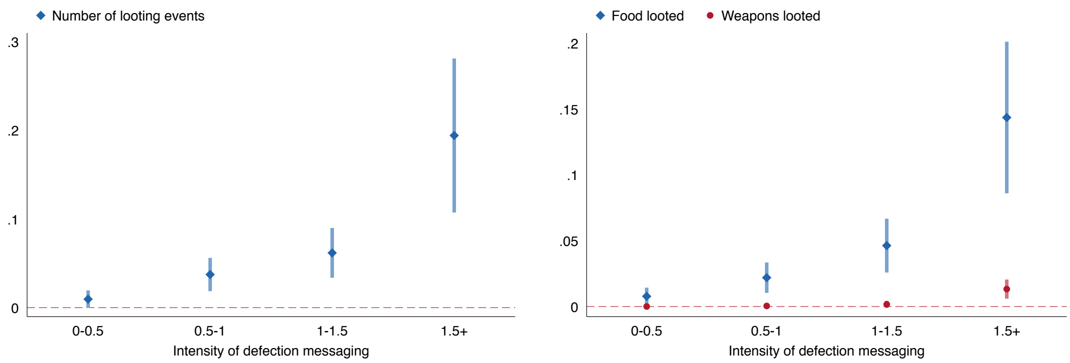
Dependent variable:	Number of events involving looting by LRA				
	(1)	(2)	(3)	(4)	(5)
	FE	FE	FE	FE	FE
Intensity of messaging	0.045***	0.045***	0.046***	0.042***	0.045***
	(0.010)	(0.010)	(0.011)	(0.010)	(0.011)
* Conflict-reducing shock			-0.002		-0.007
			(0.005)		(0.005)
* Conflict-enhancing shock				-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 4 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.

This is consistent with two potential mechanisms. First, looting could be used as a *reward* to reduce the relative returns to non-military labor effort for potential recruits, while simultaneously generating spoils to reward existing recruits (Azam, 2002, 2006). Since most of the recruits within the LRA are forced abductions, we can exclude the use of looting to increase rewards for new recruits. However, we cannot exclude that looting was used as a rational decision to reduce the expected returns from leaving the LRA by increasing the benefits of being part of the group, reinforcing the membership.

Second, looting can be considered as a survival strategy. Groups that have been significantly reduced by defections might be unable to control the territory by attacking civilians. Their only alternative is to either defect or to engage in looting as a means of survival. Both mechanisms are consistent with the observed reduction in looting when the value of conflict-enhancing commodities increases. In these situations, the LRA has access to sufficient resources to reward its fighters without the necessity to loot, making defection messaging less effective.

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.

To test whether one mechanism prevails over the other, we examine the types of goods being looted as the result of more intense defection messaging. If looting is primarily a strategy to reward members then we would expect the LRA to increase looting of all types of goods. On the contrary, if looting is a survival strategy, we would expect the LRA to focus more on looting food.

We find that as the result of defection messaging looting increases for most goods, such as food, tools, weapons, clothes, and money. Therefore, we cannot rule out one mechanism over another. Nevertheless, when comparing food versus weapons, we find that the effect is mainly driven by increases in looting of food (figure 8). This suggests that even if we cannot entirely rule out other mechanisms, it is likely that looting is used more as a survival strategy (see Appendix C.3).

Additional evidence about this mechanism comes from the level of violence associated with looting. Since the LRA operates in small groups with high mobility, regular access to food has been a problem throughout its history. Desperation from hunger among LRA fighters led them to frequently kill civilians for their food (Lancaster et al., 2011). To test whether this is the case in our setting, we look at the level of violence associated with looting. 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 also not driven by retaliation.

6.2.4 IV estimates and the effect of returnees

So far we have seen that radio messaging reduces fatalities, abductions (not statistically significantly), clashes and violence against civilians, and increases looting. We have argued and shown that this happens because radio defection messaging encourages returnees. Using an Instrumental variable approach we now estimate how much of the change in the conflict variables is driven by returnees.

In Table 8 we present the estimates of the IV model, instrumenting the number of returnees in cell i at time t with the intensity of messaging. The number of returnees is presented in logarithms and standardized, such that the coefficients are relative to an increase in 13% in the total number of returnees.

A one standard deviation increase in the number of returnees reduces fatalities by almost 44%, abductions by around 8%, and attacks against civilians or clashes with security forces by 0.7. It also increases events characterized by looting by around 0.6. Overall, this suggests that the intensity of the LRA conflict significantly went down due to defections in the LRA which was in turn driven by the radio defection messaging programs.

Table 8: Effect of returnees on conflict intensity and LRA activity

Dependent variable:	**Number of fatalities (log)**	**Number of individuals...**	**Number of events involving...**	
		Being abducted	Clashes/Violence against civilians	Looting
	(1)	(2)	(3)	(4)
	IV FE	IV FE	IV FE	IV FE
Number of Returnees	-0.437***	-0.078***	-0.723***	0.598***
	(0.048)	(0.026)	(0.085)	(0.057)
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. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Number of returnees is reported in logarithm and standardized. The dependent variables are the number of fatalities linked to LRA (column 1), the number of individuals being abducted (column 2) and the number of violent events involving different LRA activities (columns 4-5). 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 4 for a detailed description). The time period is restricted to 2008-2015.

6.3 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 (4) to understand the effect of intensity of defection messaging using conflict data from the UCDP and ACLED databases instead of the LRACT database. In order to have comparability across datasets, we restrict the sample to the period of 2008-2015. This piece of analysis also allows us to check the robustness of our main results to two other widely used conflict databases.

Table 9 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, and by whether the LRA is the perpetrator of violence or it has being attacked.[27] In columns (1)-(4) we present the results using the UCDP database, and in columns (5)-(8) using the ACLED database.

[27]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.

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 smaller. This suggests that defection messaging was particularly effective in reducing LRA-specific activities. This effect is mainly driven by a reduction in the number of attacks committed by the LRA.

Table 9: 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 4 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 activity 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 of 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 show that the higher intensity of defection messaging is not picking up the effects of higher mobile phone coverage. Mobile phone coverage can affect 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, 2016). To rule out the possibility that we are picking up the effects of mobile phone coverage rather than radio, we estimate our main specification by controlling for the share of the cell covered by the GSM mobile phone network. Estimates are presented in the odd numbered columns of Table 10.

As an additional robustness check we also control for self-reported coverage (*circular coverage*) which is not corrected for topography. In the even numbered columns of 10 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.

We do not control for these variables in our main specification due to their 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 is likely to be endogenous since it is not corrected for topography. We therefore avoid estimating our main specification with these "bad" controls (Angrist and Pischke, 2008).

From Table 10 we see that 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.[28] The circular coverage variable on the other hand is associated with increases in violence, suggesting that radio coverage was probably targeted at areas with higher levels of violence.

6.4 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 examine 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.[29]

The effect of defection messaging with random antennas is on average zero for all the variables we have used in this analysis.[30] 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

[28] 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.

[29] 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.

[30] In the Appendix Table D13 we see that the 5^{th}-95^{th} percentiles interval always include zero.

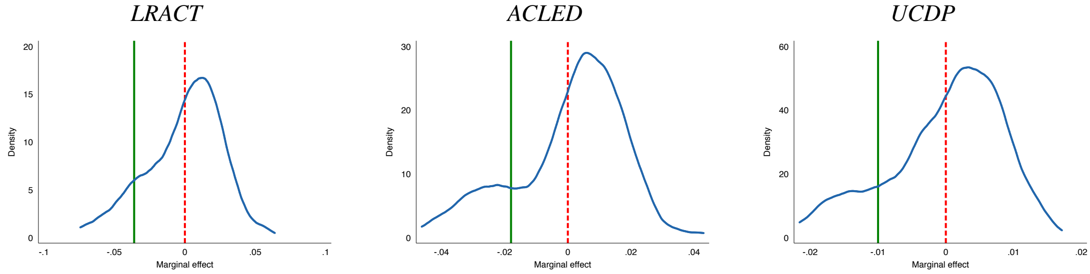
Table 10: Defection messaging and alternative coverage

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 4 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.

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.

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

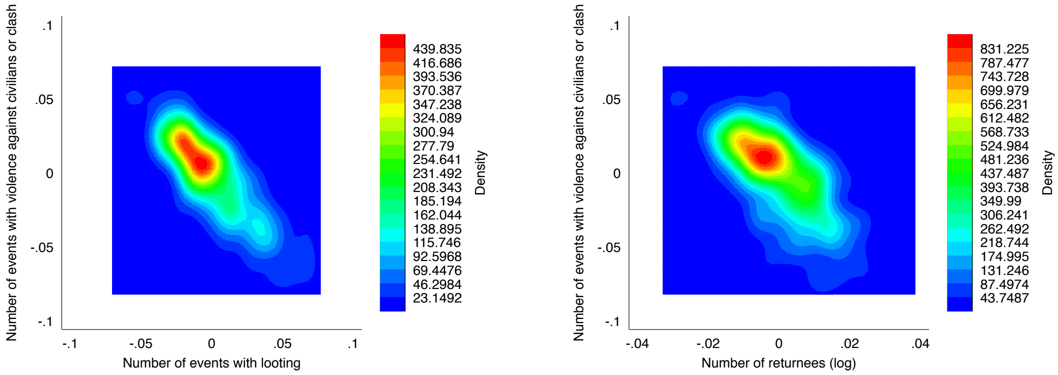


Note. The figures show the distribution of the coefficient on intensity of defection messaging in the placebo samples. Outcome variables are events characterized by violence against civilians or clashes with security forces as defined by the LRACT database (left figure), and the number of violent events 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 9).

The results from the placebo test suggest that the effect captured using the real intensity of defection messaging is 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 each outcome variable 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 marginal effects 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 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.

7 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 difficult to fight with conventional military operations. This is particularly true in the phases of the conflict characterized by a dispersion of the group over a large area spanning different countries. In such settings, FM radio defection messaging has the potential of encouraging defections among rebels, and reducing overall violence.

While little was known about whether and when defection programs are most successful, we provide evidence on the conditions for this approach to be effectively replicated. Firstly, defection programs should focus on the economic incentives of fighters to continue fighting. We found that economic incentives measured by commodity price shocks directly affect LRA activity, and are also important determinants for the effectiveness 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 conflict intensity and violence, other actions of armed groups, such as looting, can also be violent and costly for the communities. We saw that a higher intensity of defection messaging caused increases in looting in the same areas where it reduced fatalities and other forms of violence. This suggests that defection messaging operations should be complemented by interventions reducing the incentives of fighters to loot.

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.[31] Hence, the focus now has to shift to other non-military strategies to end the insurgency and bring back the remaining members out of the bush. Clearly defection messaging can be a low cost but highly effective policy under these circumstances.

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[31] http://www.bbc.com/news/world-africa-39643914, https://www.nytimes.com/2017/04/20/world/africa/uganda-joseph-kony-lra.html.

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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 geo-located 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)																			

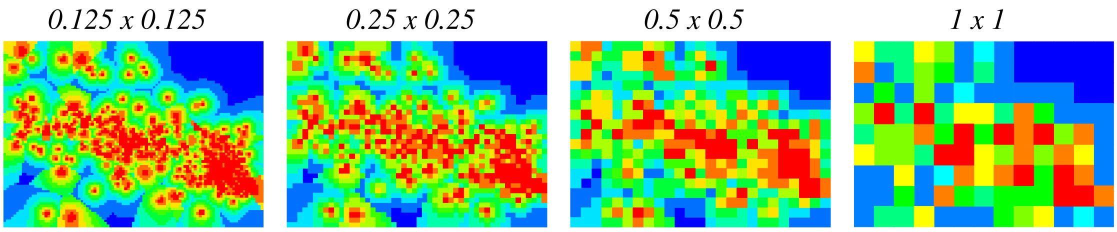
Q12	Please describe any relevant aspects of the station's history and the context where it has/does operate(d):
Q13	If you feel any part of Question 9 or 10 (Q9/Q10) needs further explanation please describe here with reference to the year and month:
Q14	Any further reflections on the station, its operators,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



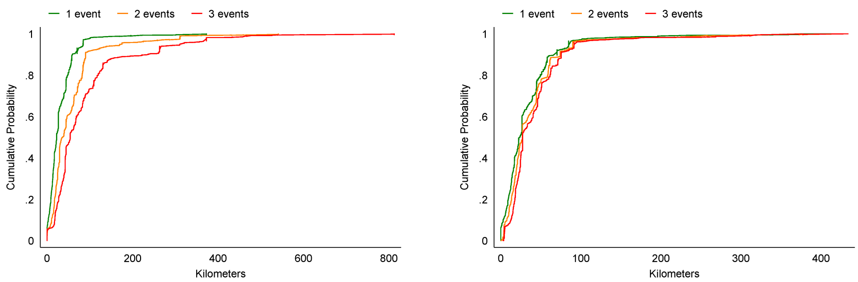
Note. Cell resolution is expressed in degrees per side. Results are produced using Stata command *spkde*. Kernel is estimated using a quartic distribution and assuming as bandwidth the minimum number of data points method (k = 1). We use ACLED database for the period 1996-2015 to compute these statistics.

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 taking place in the same location, the 0.5 probability distance of finding one neighbor is at about 22 km, and the 1.0 probability distance of finding one neighbor is 373 km. When we exclude events taking place in the same location, these are equal to 25 km and 431 km.

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

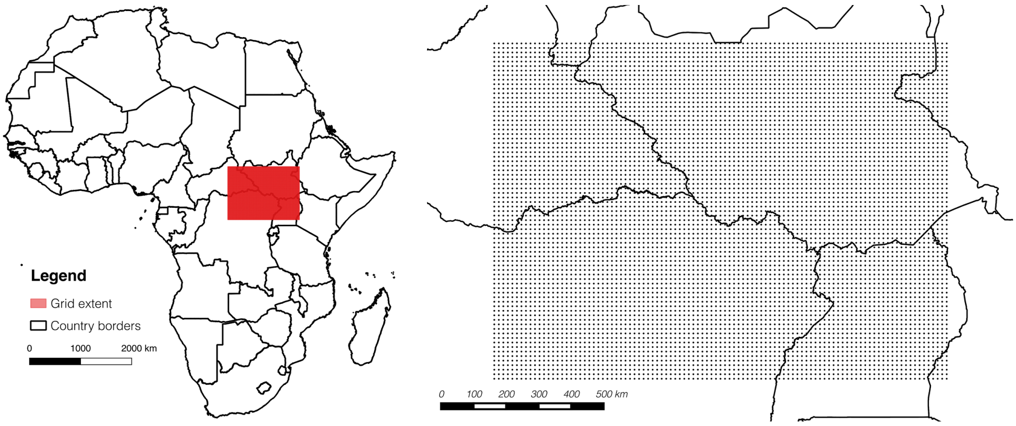
Includes same-location points *Excludes same-location points*



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



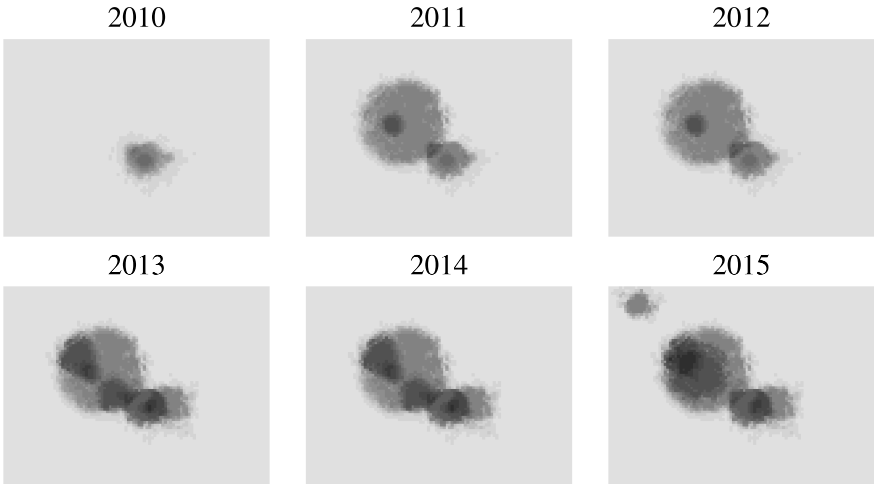
Note. The left panel shows the area covered by the selected grid. The right panel shows its resolution. Each dot represents the centroid of a 0.125x0.125 degrees cell.

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.

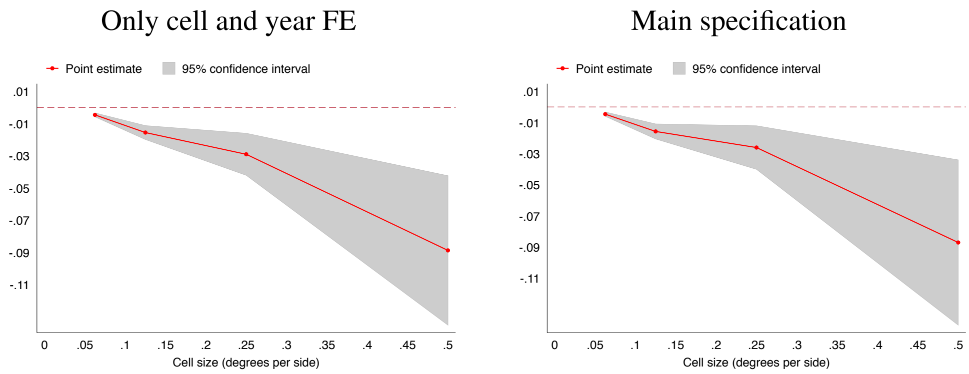
The direction of the effect is not affected by the size of each cell. However, the coefficients

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]

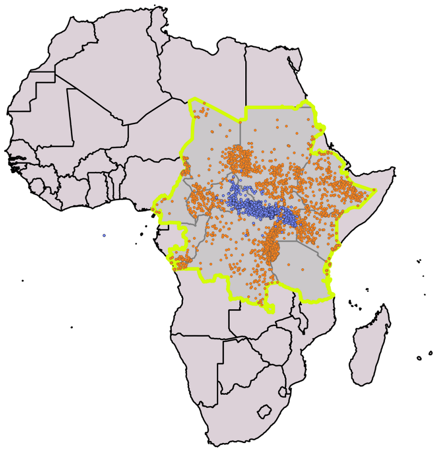
C.2 Geographical extent of study

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 use a rule based on the latitudinal and longitudinal distribution of events from 1989-2015.

[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.

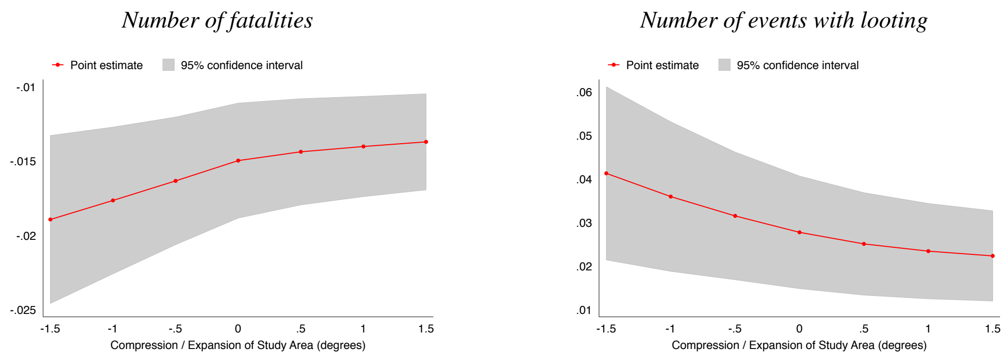
Figure C7: Extent of LRA violence in the region (1989-2015)



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.

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



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 Violence and looting

Columns (1)-(2) of Table C3 shows the effect of defection messaging on the number of events where LRA is the perpetrator that are characterized by either zero killings or at least one killing. Intensity of messaging decreases violent events characterized by at least one death and increases the number of events that do not produce a fatality. Columns (3)-(6) show instead whether the number of events characterized by looting are 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 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 C3: Effect of defection messaging on violent looting

Dependent variable:	**Number of LRA events...**		**Number of events characterized by looting and...**			
	without death	**with death**	**no death**	**at least one death**	**at least one injury**	**at least one abduction**
	(1)	(2)	(3)	(4)	(5)	(6)
	FE	FE	FE	FE	FE	FE
Intensity of messaging	0.026**	-0.039***	0.048***	-0.002***	0.002	0.014***
	(0.011)	(0.007)	(0.010)	(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). In columns (1) and (2), the dependent variable is the number of events where LRA is the perpetrator, depending on the number of fatalities associated with the event. In columns (3)-(6), 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 4 for a detailed description). The time period is restricted to 2008-2015.

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 C4: 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 4 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 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 4 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 4 for a detailed description). The time period is restricted to 2008-2015.

C.6 Robustness to alternative measures of intensity of messaging

Our measure of intensity of messaging might be picking up the expansion in the number of radio stations. Consider a situation where a particular cell receives radio messaging from two radio stations for 2 hours daily. Assume that the signals from both the stations cover the cell under consideration fully. Then according to our intensity measure defined by equation 3, our cell under consideration gets 4 hours of messaging. Now consider another cell which receives messaging from only one radio station but for a period of 4 hours daily. Our intensity variable then takes the value 4 in this case as well. However, if we use an average measure where we normalize by the number of stations emitting messages, then in the first case the average intensity is 2, while in the second case it is 4. There are advantages and disadvantages in using both these measures.

In this case, an increase in absolute messaging might not correspond a true increase in its actual visibility. To check this possibility and control for the role of absolute versus relative intensity, we focus on the average intensity of messaging in a cell, by normalizing our measure of intensity by the number of radio stations covering a cell. Table C7 presents estimates using this variable as main source of variation in exposure to messaging. Our conclusions are robust to this normalization.

Table C7: Defection messaging and average intensity of messaging

Dependent variable:	Number of fatalities (log)	Number of individuals...		Number of events involving...	
		Returning	Being abducted	Clashes/Violence against civilians	Looting
	(1)	(2)	(3)	(4)	(5)
	FE	FE	FE	FE	FE
Average intensity of messaging	-0.008***	0.004***	-0.001	-0.012***	0.012***
	(0.002)	(0.001)	(0.002)	(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	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). Average intensity of defection messaging is defined as the intensity of defection messaging (see equation 3) divided by the number of radio stations covering the cell. The variable is then standardized for ease of interpretation. 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 4 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.

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 C8 presents the results.

Table C8: Defection messaging and lagged intensity of messaging

Dependent variable:	Number of fatalities (log)	Number of individuals...		Number of events involving...	
		Returning	Being abducted	Clashes/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), the number of individuals returning or being abducted (columns 2-3) and the number of violent events involving different LRA activities (columns 4-5). 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 4 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.

C.7 Robustness to alternative specifications for fatalities

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 different normalizations of the number of fatalities. Table C9 presents the results. In columns (2) and (4), we normalize the number of fatalities by the population living in the cell. This allows estimating the effect of the intensity of messaging on the number of fatalities per thousand inhabitants. 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). In columns (3) and (6), we instead normalize by the amount of available land in the cell. This is define as the amount of land (in squared kilometers) that is not covered by forest. This allows estimating the effect of intensity of messaging per squared kilometer of available land. To show robustness to the exclusion of areas that had no defection messaging coverage, in columns (4)-(6), we restrict the sample to cells that had a positive coverage of defection messaging for at least one year during the period 2008-2015.

Table C9: Effect of defection messaging on fatalities, robustness to specification

Dependent variable:	**Number of fatalities (log)**					
Normalization of dependent variable:	**-**	**Population**	**Land**	**-**	**Population**	**Land**
Sub-sample:	All	All	All	Cells ever covered by messaging		
	(1)	(2)	(3)	(4)	(5)	(6)
	FE	FE	FE	FE	FE	FE
Intensity of messaging	-0.033***	-0.032***	-0.002***	-0.055***	-0.048***	-0.002***
	(0.004)	(0.004)	(0.000)	(0.008)	(0.007)	(0.000)
Observations	60600	60600	60600	13404	13404	13404
Number of Years	8	8	8	6	6	6
Number of Cells	7575	7575	7575	2908	2908	2908
Cell and Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Distance polynomial	Yes	Yes	Yes	Yes	Yes	Yes
Additional controls	No	Yes	Yes	Yes	Yes	Yes
Year x Macro-Region FE	No	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 total number of fatalities (in logs) in each cell at time t. Normalization by "*Population*" is made by dividing the number of fatalities with the population living in the cell (in thousands). Normalization by "*Land*" is made by dividing the number of fatalities with the available land in a cell (in squared kilometers). In both cases, we then compute the log of normalized fatalities plus one unit. 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 4 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.

C.8 Commodities and Income shocks

Table C10 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 geolocation. 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.

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

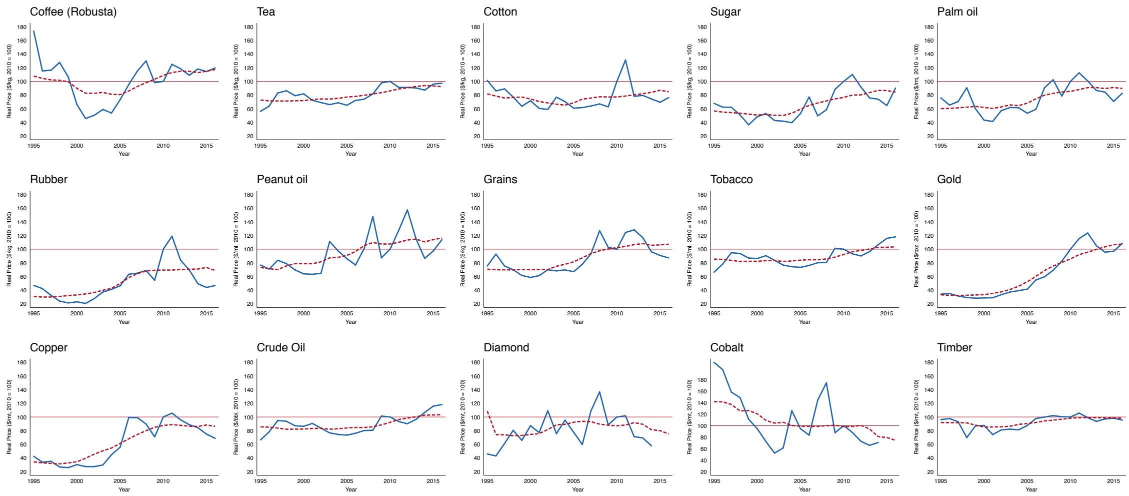
$$y_{irt} = \alpha_0 + \sum_{k=1}^{K} \phi_k \omega_{ik} p_{kt} + \mathbf{X}'_{it}\beta + d_t + d_t m_r + \gamma_i + u_{it} \quad (5)$$

Table C10: Main exported crops and natural resources present in LRA-affected countries

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

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.

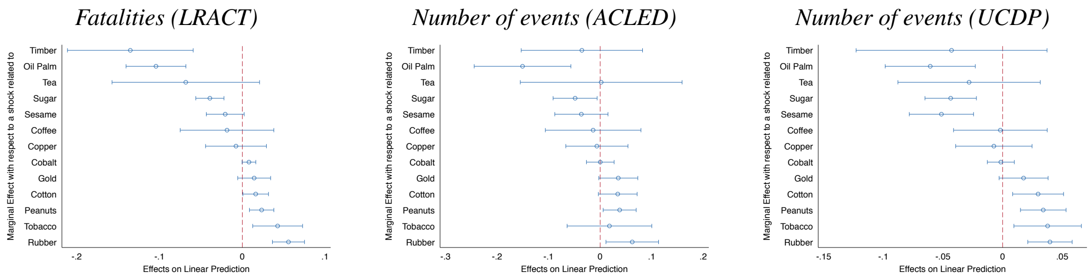
Figure C9: Price series of commodities present in LRA-affected areas



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.

where y_{irt} is the number of LRA fatalities in cell i of macro-region r at time t, 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 dummy variables, γ_i are cell fixed effects and u_{it} are idiosyncratic error terms. We include macro-region time fixed effects by 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 commodity if $\phi_k > 0$ 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



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.

C.9 Treatment spillover

In the main text we focused on the treatment effect at cell-level on violence in the same cell. We focus here of spatial spillover effects. We follow a spatial Durbin model (Anselin, 2013). Our indicator of LRA violence or activity in each cell depends on the observable characteristics of the cell and on the same characteristics of neighbouring cells. We estimate the following model:

$$y_{it} = \alpha_0 + \alpha_1 dm_{it} + \alpha_2 W dm_t + W\mathbf{X}_{it}\beta + \sum_{t=2}^{T}\gamma_t d_t + \sum_{t=2}^{T}\sum_{r=2}^{R}\psi_{tr} d_t m_r + c_i + u_{it} \quad (6)$$

where the structure of spatial dependence between observations is defined through a symmetric weighting matrix W. Our benchmark weighting matrix is a binary contiguity matrix in which a weight of 1 is assigned to cells surrounding the cell of interest within a 0.5 degrees distance cutoff, and a weight of 0 to other cells. Table C11 presents the results.

C.10 Spillovers across fighters

Table C12 presents estimates of the effect of intensity of messaging on the number of events characterized by returnees, distinguishing by the number of returnees in each event. We look at events motivated by atomostic behavior by looking at the number of events where the number of returnees is 1 or 2 individuals. While we look at events characterized by a larger number of returnees as being motivated by a social interaction argument. Table C12 shows that intensity of messaging increased returnees of both types, suggesting also heterogeneity in the type of mechanism, but effectiveness for both situations.

Table C11: Defection messaging and treatment spillover

Dependent variable:	Number of fatalities (log)			
Sub-sample:	All cells		Cells ever treated	
	(1)	(2)	(3)	(4)
	FE	FE	FE	FE
Intensity of messaging (distance from centroid)				
within 0.25 degrees	-0.023***		-0.020**	
	0.007		0.010	
0.25-1.5 degrees	-0.005		-0.028**	
	0.007		0.012	
within 0.5 degrees		-0.030***		-0.035***
		0.006		0.009
0.5-1.5 degrees		0.004		-0.010
		0.006		0.010
Observations	60600	60600	18448	18448
Number of Years	8	8	8	8
Number of Cells	7575	7575	2306	2306
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 fatalities linked to 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 4 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 C12: Effect of defection messaging on the type of returnee event

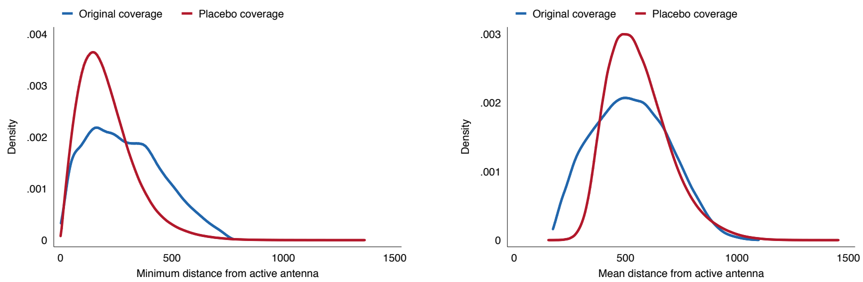
Dependent variable:	Number of events characterized by returnees with...				
	Any number of returnees	1-2 returnees	3-5 returnees	6-10 returnees	More than 10 returnees
	(1)	(2)	(3)	(4)	(5)
	FE	FE	FE	FE	FE
Intensity of messaging	0.010***	0.007***	0.002	0.001	0.001***
	(0.004)	(0.003)	(0.001)	(0.001)	(0.000)
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 variable is the number of events characterized by returnees, distinguishing by the number of returnees per event. 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 4 for a detailed description). The time period is restricted to 2008-2015.

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 D13: 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.

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.*