Is the Phone Mightier than the Virus? Cell Phone Access and Epidemic Containment Efforts in Liberia

Robert Gonzalez* Elisa M. Maffioli†

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Abstract

This paper examines the impact of mobile phone access on the spread (or containment) of a disease during a health crisis. We study this question in the context of the 2014 Ebola Virus Disease (EVD) epidemic in Liberia. Combining proprietary data on cell phone towers and Ebola cases, we estimate a radio-wave propagation model that uses variations in terrain topography and the spatial distribution of cell phone towers to predict signal strength on the ground. We then employ a regression discontinuity design that compares villages at the margin of the signal strength threshold required for coverage. We find that having access to cell phone coverage leads to a 10.8 percentage point reduction in the likelihood that a village has an EVD case. We investigate whether this reduction is explained by mobile phones increasing access to *information* or facilitating the provision of *care* in affected areas. By means of novel survey data collected following the epidemic, we uncover that the results are likely explained by the *care* mechanism.

Keywords: Ebola Virus Disease, Mobile Phones, Technology, Information, Care

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*Department of Economics, Moore School of Business, University of South Carolina, Columbia, SC 29208 (e-mail: robert.gonzalez@moore.sc.edu)

†Health Management and Policy, University of Michigan School of Public Health, Ann Arbor, MI 48109 (e-mail: elisamaf@umich.edu)

1 Introduction

Infectious disease outbreaks are a major burden to low and middle-income countries (Holmes et al., 2017). For this reason, assessing the effectiveness of tools that can prevent or contain these outbreaks has become a first-order policy issue. Given their widespread availability, mobile phones have the potential to be one such tool. In fact, a growing literature shows that mobile phone technology can be used to improve the delivery of health care (Braun et al., 2013; Agarwal et al., 2015; Obasola et al., 2015), to predict the spread of infectious diseases by studying post-outbreak mobility patterns (Bengtsson et al., 2015; Wesolowski et al., 2015), to help diagnosing diseases (D'Ambrosio et al., 2015), and as a tool for information sharing, reporting, and disease surveillance (Yang et al., 2009; Freifeld et al., 2010; Sacks et al., 2015). While this literature offers guidance on the design and use of specific tools that can be deployed during outbreaks, the broader question of whether mobile phone access has an impact on the spread (or containment) of a disease during emergency situations remains largely unexplored.

Ex-ante, it is ambiguous whether living in an area with cell phone coverage, and thus having access to mobile phones, has a positive or negative impact on the spread of an infectious disease. On the one hand, cell phone coverage enables individuals to use mobile phones, and potentially, through this technology, to have a larger network of friends and family (Hampton et al., 2011, Pew Research Center, 2011, Pew Research Center, 2019). If these individuals interact with their social network in person, then having access to cell phone coverage might increase the probability of getting infected, and consequently increase the likelihood of spreading the disease along the network. We refer to this as the *network* channel. On the other hand, mobile phone technology can increase exposure to outbreak-related information (e.g., prevention education, hygiene practices), as well as facilitate access to health care resources (e.g., reporting sick and dead people, requesting ambulances). We refer to the former as the *information* channel, and the latter as the *care* channel. In such cases, the likelihood of transmitting a disease is expected to be lower in cell phone coverage areas, as mobile phones can potentially lead to changes in individual health behavior (*information* channel) and/or higher relief efforts (*care* channel). This paper explores the causal effect of mobile phone access –proxied by cell phone coverage– on the spread (or containment) of an infectious disease,

namely the Ebola Virus Disease (EVD, hereafter) in the context of the 2014 West Africa epidemic.

We investigate whether cell phone coverage affects the likelihood that a village reports an EVD case by employing two novel sources of data. First, proprietary data on EVD cases compiled by the authors from primary records obtained from the Liberia's Ministry of Health (MOH). This dataset encompasses the entire set of villages in the country for the whole duration of the epidemic. Second, data on the location of cell phone towers across Liberia in the year 2013 –just prior to the outbreak– obtained from the Liberia Telecommunications Authority (LTA). We measure cell phone coverage by estimating a radio-wave propagation model, widely used across regulatory agencies and businesses to model coverage and signal propagation, due to its high accuracy and ability to capture terrain topography (Crabtree and Kern, 2018). This model combines the cell tower footprint with information on terrain topography to provide a measure of signal strength at each point on the ground. We then employ a regression discontinuity (RD) design that uses the signal strength obtained from the propagation model as the forcing variable. To account for the selection into coverage, we limit our analysis to villages that are at the margin of cell phone coverage. At this margin, whether a village receives enough signal strength or not is mostly determined by minor exogenous variations in topography, which we control for. Furthermore, a careful assessment of a rich set of ex-ante village socioeconomic and demographic indicators suggests a smooth transition across the cell phone coverage cutoff, and thus little indication that the likelihood of having an EVD case is explained by these characteristics jumping at the cutoff.

In line with preliminary graphical analysis, the main estimates of the RD specification show a 10.8 percentage point reduction in the likelihood that a village with just enough coverage reports an EVD case, relative to villages that are just under the cutoff. Additional results, using a panel-RD specification that exploits monthly variation in EVD incidence, provide significant evidence of containment effects. Specifically, we find that the likelihood that a village reports an EVD case in a month, given other EVD cases within the district in the previous month, is reduced by 1.9 percentage points if the village has cell phone coverage. Villages without coverage are not as shielded, reporting instead a 1.6 percentage point increase in the likelihood of EVD given past exposure to EVD within the district. This

is consistent with the hypothesis that, overall, cell phone coverage helped contain the spread of the disease.

More importantly, we explore several channels underlying the relationship between cell phone coverage and the likelihood of being affected by the epidemic. As a first step, we take advantage of the introduction of a toll-free, nationwide phone alert system established for rapid notification and response (i.e., a hotline) to provide preliminary evidence on the network, information, and care channels defined above. We expect the network channel to be particularly relevant during the pre-hotline period as government-provided emergency resources were scarce, forcing individuals to rely on their network for support. Similarly, we expect the information and care channels to be more relevant after the introduction of the hotline given that they depend on the existence of a tool, such as a hotline, that can connect individuals to the appropriate agencies (ambulances, Ebola treatment units, NGOs providing educational material, etc.). We find that cell phone coverage leads to a large and significant drop in the likelihood of EVD in the period *after* the introduction of the hotline (August 2014), but not prior to this. Therefore, these results provide preliminary evidence that the network channel is either trivial or that the *information* and *care* channels dominate any detrimental effect cell phone access might have via the network channel.

We proceed by delving deeper into the *network* channel. First, we classify all villages across Liberia according to their clan, i.e., the third-tier administrative division in Liberia, by using the latest available census data pre-epidemic (2008). Clans are groups of villages that, although currently considered administrative units, correspond to historical tribal chiefdoms that were gradually fused into the state (Nyei, 2014). Thus, we consider clans to be a plausible measure of a village's closest social network. We explore the network channel by testing whether EVD spreads more easily if there is a "coverage match" between an affected village and other villages within the clan. In other words, we assess whether the likelihood of an EVD case in villages with cell phone access increases if an affected village within the clan also has coverage. Consistent with the preliminary results, we find that a "coverage match" does not lead to a higher likelihood of EVD spread within the network.

Instead, we explore the information and care channels using a novel survey conducted six months after the end of the epidemic on about 2,000 respondents across Liberia. First,

we test whether survey respondents in cell phone coverage areas are more likely to have access to EVD-related *information* during the epidemic, by asking individuals whether health workers, officials, and community task-forces came to their village to explain EVD, to hold hygiene meetings, to bring information or to teach safe burial procedures. We find weak evidence on this channel. Individuals in coverage areas are more likely to report that health workers, officials, and community task-forces came to their village to explain EVD and to bring information. However, the estimated coefficients are not always statistically significant. Second, we test whether survey respondents in coverage areas are more likely to receive *care* during the the epidemic. We find that the care channel plays a bigger role in explaining the effect of coverage on the likelihood of an EVD case. Survey respondents in cell phone coverage areas are more likely to report that someone came to take sick people, that ambulances arrived on time, and that care centers were placed near their villages. Putting together the information and care outcomes into a summary index measure for each channel (Kling et al., 2007), we uncover a statistically significant effect for the care index, but no statistically significant effects for the information one. Overall, these findings suggest that, while having access to mobile phones, on average, did not increase exposure to information, it did help respondents report their need for relief efforts and receive a higher response.

This paper fits into the literature in economics that investigates the economic impact of mobile phones and other information and communication technologies (ICTs) in developing economies (Aker and Mbiti, 2010). Among others, studies explored the effects on price dispersion (Jensen, 2007; Aker, 2010; Aker and Fafchamps, 2014), education (Aker et al., 2012; Aker and Ksoll, 2018), the role of mobile money in financial transactions (Jack and Suri, 2011, 2014), also at the time of disasters (Blumenstock et al., 2016).

More specifically, this paper contributes to past research exploring the role of mobile phone technology as a tool to improve a number of health-related outcomes. Some of the outcomes studied in this literature include the management of health records and health care utilization (Agarwal et al., 2015), maternal and child health indicators (Obasola et al., 2015), the remote diagnosing of diseases (D'Ambrosio et al., 2015), the quality of care provided, the efficiency of services, and the capacity for program monitoring (Braun et al., 2013). Our paper advances this literature in three areas. First, we present a way of measuring access to mobile

phone technology at a large, country-wide scale. Previous studies typically focus on limited settings where access is determined by whether individuals or health care providers employ study-specific tools and phone applications. Our approach of accurately measuring coverage over a large area allows for analyses that can assess the effect of mobile phone interventions at a much larger scale than previous work. Second, selection into the use of mobile technology is likely endogenous. Thus, when comparing health-related outcomes across users and non-users of the technology, as done in previous studies, it is difficult to disentangle the effect of the mobile phone interventions from the effect of other determinants of the technology such as education or attitudes towards new technology adoption. Our empirical design addresses this underlying issue. Third, while this literature focuses on studying the effect on health-related outcomes in regular, day-to-day settings, our paper explores whether the technology is effective during a health crisis–namely, a sudden-onset epidemic–in a setting characterized by general mistrust towards local and international institutions. Our paper shows that mobile-based interventions can be effective even in such settings.

This paper also contributes directly to the strand of the literature related to mobile technology and infectious diseases. Generally, studies within this area focus on how mobile technology can be used to prevent future outbreaks (e.g., using post-outbreak mobility patterns estimated from phone usage to predict the spread of the disease (Lu et al., 2012; Bengtsson et al., 2015; Wesolowski et al., 2015)), or evaluating phones as a "participatory epidemiology" tool (e.g. using phone technology for information sharing, reporting, and tracking of cases within communities (Yang et al., 2009; Freifeld et al., 2010; Sacks et al., 2015; Feng et al., 2018)).[1] While this literature evaluates specific tools that can be deployed during outbreaks, our paper answers a more general question: whether access to mobile phones among the general population can have an impact on spreading (or containing) outbreaks. More importantly, we go beyond the evaluation exercise by exploring mechanisms that can potentially explain the relationship between cell phone access and epidemic spread (or containment). Our findings show how something as simple and ubiquitous as a mobile phone can have positive externalities on economic development by allowing communities to access health care in

[1] Mobile phones were also used during the 2014 West Africa Ebola epidemic to collect and share data, to create and share digital maps of the diseases, to track contacts and the spread of the disease within a community (Sacks et al., 2015), and to track health seeking behavior (Feng et al., 2018).

times of crisis.

This paper proceeds as follows. Section 2 describes the context. Section 3 provides details on the dataset used in the analysis. Section 4 describes the empirical models and the results, Section 5 describes the channels of impact, while section 6 concludes.

2 Background on the 2014 EVD Outbreak in Liberia

The first case of EVD in West Africa occurred in Guinea near the border with Sierra Leone and Liberia in December 2013, but EVD was not confirmed in Liberia until March 2014. After the first case was recorded in the country on March 20, 2014, the Government of Liberia (GOL) started responding to the epidemic with social mobilization, case management, treatment and surveillance, water sanitation, and hygiene activities. The MOH took the lead in managing the relief efforts supported by several international institutions such as the World Health Organization (WHO), Medicines sans Frontiers, and Samaritan's Purse. The first wave of EVD was contained very quickly and, by April 9, the last EVD case for almost two months was confirmed.

However, on May 25 2014, a new EVD case was recorded in Lofa county near the border with Guinea. By the end of June, the disease had spread to the capital city, Monrovia. A second wave of the epidemic started, deteriorating quickly. By August 2014 the situation was out of control. The GOL urgently called on the international community for a massive response, by declaring a State of Emergency on August 6. Schools and Liberia's land borders were closed, and strict control measures, including quarantines of neighborhoods and a nightly nationwide curfew, were imposed. On August 8 the WHO declared the Ebola outbreak a "Public Health Emergency of International Concern", the highest level of international alert. By the end of that month, there was a growing awareness of the need for more decentralized control and involvement of local communities: The GOL created county-level taskforces to strengthen local coordination in the fight against EVD, and, then, an Incident Management System (IMS) devoted exclusively to the national management of the epidemic (Nyenswah et al., 2016, Hymowitz, 2017).

As the number of EVD cases continued to rise, international funding started being poured into Liberia. The United States government committed US$319 million for the response in

West Africa. Other institutions, such as the World Bank, approved an additional US$105 million, with US$52 million specifically for Liberia (World Bank, 2014). Overall, about 62 countries committed US$2.3 billion to respond to the epidemic in West Africa, including US$806 million to Liberia (White House, 2014). Over time, the GOL was able to open Community Care Centers (CCCs), Ebola Treatment Units (ETUs), and coordinate safe burials and the removal of dead bodies from communities, through teams of governmental health workers. Following an assessment of the major areas of intervention during the EVD outbreak, Kirsch et al. (2017) concluded that no single intervention stopped the epidemic, rather all interventions likely had reinforcing effects. In fact, the epidemic's turning point –September 2014– coincided with a reorganization of the response, the emergence of community leadership in control efforts, and changing beliefs and practices within the population. While in the following months the epidemic was rapidly slowing down, the GOL efforts kept securing additional funding, constructing the planned ETUs and coordinating the activities of the international partners involved. By early 2015, 31 ETUs were constructed and more than 70 CCCs opened.

In January 2015 there were fewer than 15 weekly confirmed cases with the last EVD case being reported in mid-March 2015. The country was initially declared EVD-free on May 9, 2015. However, a small number of other cases reported in July and December of the same year led to the official EVD-free declaration to take place on January 14, 2016. Along with Sierra Leone and Guinea, Liberia was among the most affected countries by EVD in West Africa. In Liberia, 10,675 confirmed, probable, or suspected cases were recorded, while the cumulative number of deaths reached 4,809–the highest number in West Africa (World Health Organization, 2016). Following the epidemic, the GOL's focus shifted from the emergency response to the strengthening of the health care system.

3 Data

3.1 Ebola Data

The data on EVD cases are primarily constructed from a proprietary patient database from the MOH containing more than 19,000 patients tested for EVD from March 2014 to July

2015. The data are widely considered to be the most comprehensive database to date, since every organization taking part in the response to the outbreak was required to report cases to the MOH (Liberian Ministry of Health, 2017). Furthermore, we supplement these data with a database from Global Community, a development organization that managed all the burials after July 2014. Since the database records the village where the person resided when suspected to have contracted EVD, we were able to manually code and match the data with the entire list of 9,686 villages in the 15 counties of Liberia.

For each village, we construct the main outcome of interest as an indicator equal to 1 if at least one (probable, confirmed, or death) case was recorded in the village during the period of study (January, 2014-July, 2015). We rely on this extensive margin measure because it is less likely to suffer from measurement error than an intensive margin measure such as the ultimate number of cases. We consider the total number months a village was affected by EVD on the intensive margin, and whether a village recorded a suspected EVD death on the extensive margin, as robustness checks. We also use the date when the blood tests were performed for individuals suspected of EVD to explore the effects across different stages of the epidemic.

3.2 Measure of Cell Phone Coverage

This paper uses a radio-wave propagation model to determine coverage strength across Liberia. Specifically, we employ the Irregular Terrain Model (ITM), which due to its high accuracy and ability to capture terrain topography, has become the primary model used across regulatory agencies and businesses to model coverage and signal propagation (Crabtree and Kern, 2018).[2] Broadly speaking, the transmission of high-frequency radio waves between cell phone towers (transmitters) and mobile devices (receivers) is what enables the transfer of information (e.g., voice calls, SMS, etc.) in a cell phone network. By combining the location and characteristics of the transmitter/cell phone tower and of the receiver/mobile device, and the topography of the terrain, the ITM then can assess the strength of cell phone coverage and provide a measure of received power or signal strength, at a given point on the ground.

[2]Refer to Crabtree and Kern (2018) for a detailed discussion of the ITM. In summary, predictions from this model have been extensively validated via on-the-ground measurements (Longley and Rice, 1968; Eppink and Kuebler, 1994; Seybold, 2005; Lazaridis et al., 2013).

We obtain the location of cell phone towers in the year 2013 for the two largest network providers in Liberia, MTN Lonestar and Cellcom, which accounted for 91% of all mobile subscribers in Liberia during the year of study (LTA, 2014).[3] Proprietary data are obtained from the Liberia Telecommunications Authority (LTA) and provide the footprint of towers by the end of 2013, just before the start of the outbreak. Appendix Figure A1 provides a map of the towers' footprint. We combine these data with the most precise global-scale elevation data model available, the 30-meter resolution ALOS Global Digital Surface Model (Open Topography, 2017). This allows us to accurately capture the effect of topography on signal propagation (JAXA, 2016).

Figure 1 presents the model output on a map of Liberia along with the location of cell phone towers. Note that the proportion of Liberia with no cell phone coverage in 2013 correspond to non-populated areas covered by forest.[4] Received power on the ground is measured in decibel-milliwatts (dBm). Received power typically ranges between -50 and -140dBm with values closer to zero representing higher signal strength. However, for ease of interpretation, our measure of coverage uses the absolute value of received power. Therefore, lower dBm levels should be interpreted as stronger coverage. When we explore the causal effect of cell phone coverage on the likelihood of EVD in a village, our analysis will use a dichotomous indicator for whether the village had coverage or not in 2013. See more details in Section 4 for how this measure is constructed.

3.3 Village Location and Census Data

We obtain GPS coordinates (latitude and longitude) of each village from the Liberia Institute of Statistics and Geo-Information Services (LISGIS). This allows matching the village location data with the spatial radio-wave propagation model in order to determine signal strength for each village in Liberia. We also obtain data on road networks across Liberia. We use this to construct other determinants of EVD such as distance by road (in kilometers) to the origin point of the epidemic, and the capital city, Monrovia.

In addition, we gather data from the 2008 National Population and Housing Census

[3] Note that Cellcom is currently Orange given its acquisition by Orange in 2016.

[4] Please see the location of villages in Liberia in Maffioli, 2020, Figure II; see map of Liberia on forest land at http://www.fda.gov.lr/wp-content/uploads/2014/10/forest_land2.jpg

(LISGIS, 2008). The census data include information on population characteristics, such as education, household size, working status, occupation, tribe, and religion. It also includes information on housing and asset ownership, which we use to create proxies of village wealth. We aggregate census data at the village level and match it to our village-level EVD and cell phone coverage measures. We use this dataset primarily as a source of covariates for the main analysis and to assess the validity of the empirical design. Finally, we access publicly available data on various measures of village exposure to relief efforts, such as the location of CCCs.[5]

4 The Effect of Cell Phone Coverage on EVD

4.1 Regression Discontinuity Design (RD)

This paper estimates the effect of cell phone coverage on the spread of EVD, by employing a regression discontinuity (RD) design that uses signal strength as the forcing variable and the receiver's sensitivity threshold as the treatment cutoff. A receiver's sensitivity threshold is essentially the minimum received power or signal strength required to be able to make a voice call or send an SMS. Broadly speaking, the received power is the underlying continuous measure of the "bars" displayed on a mobile phone screen, while the receiver sensitivity threshold is the point where one goes from a single "bar" to "no-service".[6] Figure 1 depicts the received power on the ground in Liberia estimated using the ITM. For GSM networks such as the ones in Liberia, the receiver sensitivity typically ranges between 95 to 105 dBm in absolute value, meaning that areas shaded in red are receiving sufficient cell phone coverage. With this in mind, our RD specification is given by the following equation:

$$EVD_i = \alpha + \beta D_i + f(\tilde{R}_i) + h(\mathbf{G}_i) + \epsilon_i \tag{1}$$

where EVD_i is an indicator for whether village i was affected by an EVD case (probable, confirmed, or death) within our period of study (January, 2014-July, 2015). $\tilde{R}_i = R_i - c$ is the received power (measured in dBm) in village i net of the receiver sensitivity cutoff c. Values

[5] See the Ebola crisis page at Humanitarian Data Exchange, https://data.humdata.org/ebola.

[6] Refer to Gonzalez (2019) for a detailed description and application of the ITM model in a regression discontinuity setting.

of $\tilde{R}_i$ greater than zero mean that cell phone coverage is available in village i, while negative values mean that the location is below the sensitivity threshold and thus no cell phone coverage is available. We use a sensitivity cutoff of 95 dBm for two reasons. First, this value is within the 95-105 dBm interval specified in the signal propagation literature (Farahani, 2008). Second, the graphical examination of the outcome variable in Figure 3 confirms a clear discontinuous change right at that value which provides empirical support for a discontinuous change in coverage at the theoretical cutoff.[7] $D_i = \mathbb{1}\{R_i \geq c\} = \mathbb{1}\{\tilde{R}_i \geq 0\}$ is an indicator for whether village i has coverage (i.e., received power is higher than the cutoff c). $f(\tilde{R}_i)$ is the RD polynomial. Our analysis uses a local linear specification with a bandwidth h around the cutoff c, optimally determined as in Calonico et al. (2014), and a triangular weighting kernel. $h(\mathbf{G}_i)$ is a flexible polynomial in topographic characteristics such as elevation and terrain slope. This ensures that the estimated effect is the result of coverage and it is not due to changes in topography captured by the radio-wave propagation model.

Coefficient β in Equation (1) identifies the causal effect of cell phone coverage under the assumption that potential outcome functions $E[EVD(1)|\tilde{R}]$ and $E[EVD(0)|\tilde{R}]$ are continuous at the coverage threshold c, where one and zero denote assignment and non-assignment into treatment, respectively. This entails that observable and unobservable characteristics must transition smoothly across the coverage cutoff, so that villages with received power just below the cutoff can serve as a valid counterfactual for villages where coverage is just available. This is a plausible assumption within a reasonable bandwidth of analysis, as we will be comparing villages that are at the margin of cell phone coverage. At this margin, whether a village receives just enough signal strength or not is mostly determined by exogenous variations in topography, which we control for.

Figure 2 provides a visual depiction of our empirical strategy. In panel (a), we provide a closer look at the estimated signal strength for three cell phone towers near one of the largest cities in Liberia, close to border with Sierra Leone and Guinea, i.e. Foya town, Lofa county, along with the surrounding villages. Panel (b) highlights villages that are part of a hypothetical regression discontinuity design that uses a bandwidth of 10 dBm around the coverage cutoff.[8] First, note that at the margin of coverage, there is rich spatial variation in

[7] Section 4.2 provides more details on Figure 3.

[8] This hypothetical bandwidth is actually quite close to the optimal bandwidth of 9 dBm used in our

treatment and control villages. Most importantly, note that at this margin, treatment status is determined by minor changes in topography that dictate whether enough signal reaches the ground, while there are not intrinsic differences across treated and control locations. We proceed by providing further evidence on the validity of our design.

In order to assess how village-level characteristics change with cell phone coverage, we further explore the validity of our design by assessing various determinants of selection into coverage. Table 1 presents results from a linear regression of signal strength, measured in dBm, on a rich set of ex-ante village-level covariates.[9] The goal is to show that ex-ante demographic and economic village characteristics (2008) do not predict the signal strength (2013) around the cell-phone coverage cut-off. Note in column (1) that there is evidence of significant selection into cell phone coverage when considering the entire sample of villages. Elevation, population size, and most economic indicators are strongly correlated with the signal strength. Furthermore, the set of topographic, demographic, and economic controls are all jointly statistically significant. However, as we restrict our analysis to villages that are within a close window of the coverage cutoff (column (3)), only the topographic controls remain jointly significant, while demographic and economic characteristics of the villages do not explain signal strength. Overall, our analysis suggests that, although there is significant selection into coverage when considering the entire sample, for villages at the margin what largely determines cell phone coverage availability are minor exogenous variations in topography, and not endogenous village characteristics.

Appendix Table A1 also provides summary statistics for the same village-level characteristics for several bandwidths around the cell phone coverage threshold. Columns (1) and (2) report the mean of these variables by coverage status for the entire sample. Columns (4) and (5) repeat the exercise for villages within 20 dBm on each side of the sensitivity cutoff. Columns (7) and (8) narrow the window of analysis to a 10 dBm bandwidth. Columns (3), (6), and (9) report the clustered standard errors of the difference in means between villages with and without cell phone coverage. Comparing columns (1) and (2) confirms that, among other things, villages in areas with coverage tend to be at lower elevation and on a smoother

baseline results (section 4.2).

[9]The demographic and economic controls are obtained from the 2008 National Population and Housing Census LISGIS (2008) and thus predate the cell phone coverage outcome used.

terrain, households in those villages have a smaller average household size, higher levels of primary and secondary education, higher asset ownership and quality housing, and they live much closer to the capital Monrovia and to the closest main city. As we restrict our analysis to villages at the margin of cell phone coverage, however, most statistically significant differences disappear (columns (6) and (9)). Overall, the results presented in Appendix Table A1 provide support for the continuity assumption discussed above.[10]

4.2 Graphical Analysis

Figure 3 presents regression discontinuity plots for the outcome variable EVD_i in Equation (1). Specifically, we let the main outcome of interest be an indicator equal to 1 if at least one EVD case (probable, confirmed, or death) was recorded in the village. The solid vertical line refers to the cell phone coverage cutoff. Signal strength is normalized so that negative (positive) dBm values represent no coverage (coverage). Solid dots refer to the averages of the outcome variable for 1 dBm signal strength bin. We focus on villages within 20 dBm of the coverage cutoff.[11] Note that, overall, the likelihood of an EVD case increases with more coverage. This is reasonable considering that urban areas with higher cell phone coverage were the areas most affected by the epidemic. More importantly, however, note that there is a clear drop in the likelihood of an EVD case as soon as a village receives enough signal strength to allow cell phone use. Specifically, there is close to a 10 percentage point decrease in the likelihood of an EVD case in villages with just enough coverage relative to villages that are just under the coverage cutoff.

4.3 Regression Discontinuity (RD) Estimates

Table 2 presents estimates of the RD coefficient β in Equation (1). Given the relationship between signal strength and topography (see Table 1), all specifications include controls for terrain elevation and slope. In column (1), we document a reduction of about 10.8 percentage points in the likelihood that a village has an EVD case relative to villages that are just under the coverage cutoff. The optimal bandwidth used in this empirical specification is

[10] For a graphical depiction of the continuity of time-invariant covariates across the coverage cutoff, refer to Appendix Figure A3. Unfortunately, we do not have baseline covariates in 2013 as for cell phone coverage. We refer to Table 1 for the main predictors (in 2008) of coverage (in 2013).

[11] Refer to Appendix Figure A2 for regression discontinuity plot using a wider 40-dBm window.

about 9 dBm. The estimates remain very similar after including a set of socio-economic and demographic characteristics (column (2)), confirming that the estimated drop in the likelihood of EVD at the cell phone coverage cutoff is not explained by these covariates.

Columns (3)-(6) show that the results are robust to a set of alternative specifications. Column (3) includes a flexible polynomial in elevation and slope to capture whether the effect on EVD is simply driven by changes in topography captured by the ITM. The effect remains robust (at 10.1 percentage points) suggesting that this is unlikely. Column (4) estimates a parametric RD specification that uses almost the entire sample of villages (50 dBm bandwidth) and a flexible third degree polynomial in the signal strength. The results are consistent with the optimal bandwidth estimates in columns (1)-(3), although there is a gain in precision given the larger number of observations. Column (5) confirms that the estimated effect is robust to the choice of kernel. Given our binary outcome variable, column (6) estimates a Probit model within a specified bandwidth around the coverage cutoff. The marginal effect (at about 7 percentage points) is not far from our previous estimates. We also probe the sensitivity of our baseline results to the choice of bandwidth. Appendix Figure A4 confirms that the coverage effect on EVD remains negative and statistically significant for a wide set of bandwidths. Appendix Tables A3 and A4 also show that the findings are robust to alternative measures of EVD, defined as whether a suspected death from EVD was recorded in the village, and the total number of months the village was affected by the epidemic.[12] A final robustness check takes into account the fact that we see few jumps on some religion and tribe covariates, which we usually control for in the main empirical models (Appendix Figure A3). Appendix Table A5 presents results, dropping six counties from the analysis. We drop Grand Bassa, where the Bassa tribe lives (mostly Christian); Grand Cape Mount where Vai tribe lives (mostly Muslim); Lofa, where Lorma tribe lives (mostly from a traditional African religion); in addition, we also drop three other counties (Bong, Margibi, Montserrado) where Kpelle tribe (the most common tribe in Liberia) mainly lives. By implementing a similar analysis on this sub-sample, the jumps on religion and tribe covariates at the cut-off are reduced (Appendix Figure **??**, and results are statistically significant stronger and of bigger

[12]Unfortunately, the Ebola data do not allow us to distinguish between EVD and non-EVD deaths since all cases reported in the patient database from the MOH were suspected with EVD and not every case was tested before dying.

magnitude (Appendix Table A5). However, consider that the sample is much smaller. Lastly, it is important to highlight that if access to cell phone coverage arbitrarily led to more reporting of cases in coverage villages relative to non-coverage villages, then our estimates would be a lower bound on the actual magnitude of the drop in EVD cases due to coverage.

4.4 Panel-Regression Discontinuity Design (RD)

This section explores whether cell phone coverage helped contain the spread of the disease by exploiting the (monthly) time variation of the EVD epidemic. Specifically, we disaggregate our EVD measure in Equation (1) and create a village-by-month panel database. We are interested in learning whether the likelihood that EVD spreads into a village from surrounding affected villages diminishes with cell phone coverage. Our empirical specification is the following:

$$EVD_{ijt} = \alpha + \beta D_{ij} + \gamma EVD_{j(i),t-1} + \delta D_{ij} \times EVD_{j(i),t-1} + f(\tilde{R}_{ij}) + \lambda_j + \nu_t + \epsilon_{ijt} \quad (2)$$

where EVD_{ijt} is an indicator for whether village i in district j was affected by EVD in month t, i.e., whether a (probable, confirmed, or death) EVD case was ever recorded in the village that month. $\tilde{R}_{ij}$, $\tilde{R}_{ij}$, and D_{ij} are defined as in Equation (1) since these variables do not vary by month. $\text{EVD}_{j(i),t-1}$ is an indicator for whether district j, where village i is located, was affected by EVD in the previous month $t-1$. λ_j and ν_t are district and month fixed effects, respectively. The district fixed effects account for any time-invariant unobservables that may lead to endogenous selection into EVD within a village's district.

To account for endogenous selection into cell phone coverage, we integrate into our panel study an RD design that uses a linear specification in $\tilde{R}_{ij}$, while restricting our analysis to the same bandwidth as the baseline specification in Table 2.[13] Equation (2) estimates the likelihood of an EVD case in village i given that there was at least one EVD case within that village's district in the last month. Coefficients γ and δ estimate how this contagion effect varies by whether village i has coverage or not.

Columns (1) and (2) in Table 3 present panel-RD estimates of the effect of cell phone coverage on the likelihood that a village has an EVD case. Column (3) presents estimates of

[13] Specifically, we let $f(\tilde{R}_{ij}) = \theta_1 \tilde{R}_{ij} + \theta_2 D_{ij} \times \tilde{R}_{ij} + \theta_3 EVD_{j(i),t-1} \times \tilde{R}_{ij} + \theta_4 D_{ij} \times EVD_{j(i),t-1} \times \tilde{R}_{ij}$.

the contagion effect, namely the association between a village's district having an EVD case in the last month and the likelihood that that village subsequently has an EVD case in month t. Columns (4) and (5) present estimates on how this contagion effect varies by whether village i has cell phone coverage or not. Columns (1) and (2) present the panel equivalent of the results presented in columns (1) and (2) of Table 2. In line with previous findings, we find that cell phone coverage leads to a 0.69 percentage point drop in the likelihood of an EVD case in any given month. Column (3) provides strong evidence of contagion effects within districts. In fact, the likelihood of a village reporting an EVD case in a given month increases by 0.56 percentage points if there was at least one EVD case in the previous month within that village's district. Column (4) disaggregates this contagion effect by whether a village has cell phone coverage or not. The results provide evidence that the spread of the disease is considerably undermined by the presence of cell phone coverage. In fact, the likelihood of reporting an EVD case given past EVD cases within the district increases by about 1.6 percentage points in villages without coverage, while it significantly decreases by about 1.9 percentage points if a village has coverage. The estimates are quantitatively similar after adding controls (column (5)).

5 Channels of Impact

This section explores several potential channels underlying the relationship between cell phone coverage and the likelihood of a village being affected by the epidemic. On the one hand, cell phone coverage enables individuals to use mobile phones, and potentially, through this technology, to have a larger network of friends and family (Hampton et al., 2011, Pew Research Center, 2011, Pew Research Center, 2019). Thanks to this larger social network, individuals have a larger probability of interacting with friends and family, especially during emergencies (Blumenstock et al., 2016). For example, individuals living in a cell phone coverage area can more easily tap into their network if they need care or if they want to gather family for events such as funerals, one of the main factors contributing to how quickly EVD was transmitted (Alexander et al., 2015, Fallah et al., 2015). If these individuals interact with their larger network in person, a potentially unintended consequence of this access is that the disease can spread more easily along this larger, more accessible network. We refer to this mechanism as

the *network* channel.

On the other hand, cell phone access can also better connect individuals to outbreak-related information (e.g., prevention education, hygiene practices), as well as facilitate access to health care resources (e.g., reporting sick and dead people, requesting ambulances). We refer to the former as the *information* channel and the latter as the *care* channel.

With this in mind, we expect the network channel to increase the likelihood of EVD (spread) in cell phone coverage areas, while the information and/or care channels to decrease it (containment).

5.1 Preliminary Evidence

Recall that we document a negative effect of cell phone coverage on the likelihood that a village reports an EVD case (Tables 2 and 3, column (1)). These results then suggest that the network channel is either trivial, or that the information and care channels dominate whatever detrimental effect cell phone access might have –via the network channel– on the spread of the disease. In other words, in the presence of a non-trivial network channel, our estimates would have a downward bias.

We proceed by using the introduction of a hotline set up during the epidemic in Liberia as a first step in disentangling the relative importance of the network, information, and care channels. Specifically, the hotline was a toll-free, nationwide phone alert system established for rapid notification and response, in collaboration with private cellular telephone companies (Kirsch et al., 2017). The GOL General Service Agency opened a call center on August 7, 2014 with the goal of answering callers' questions about EVD, and to enter requests to dispatch ambulances to take sick individuals to treatment centers, or to dispatch a dead body management team to pick up suspected corpses–which would still be contagious for days after death–for safe disposal. The overall goal was to create a vital link between the public and the government-provided relief efforts.[14]

The success of the information and care channels likely depends on the existence of this tool (e.g., a hotline) that can connect individuals to the appropriate agencies (ambulances,

[14]While the center received queries from nearly 1,000 people within its first two days (Kirsch et al., 2017), pranksters' calls were also common especially at the beginning (Baker, 2014). The number of ambulances to be dispatched to collect suspected cases was also limited compared to the volume of calls received. It took few months to be fully effective.

Ebola Treatment Units, NGOs providing educational material, etc.). Therefore, we argue that these two channels are relevant *after* the introduction of the hotline. Consequently, any effect of cell phone coverage during the pre-hotline period is likely attributed to the network channel, given that alternative, government-provided emergency resources were scarce and inefficient at that point in time and individuals were likely relying on their network for relief during this period. With this in mind, we should expect the effect of cell phone coverage to be much larger after the introduction of the hotline.

Figure 4 confirms our hypothesis. In panel (a) we find that there is no change in the likelihood of having an EVD case at the coverage cutoff in the pre-hotline period. Instead, in panel (b) we find that the likelihood of having an EVD case significantly responds to cell phone coverage only after the introduction of the hotline. This graphical evidence is confirmed in Table 4, which provides estimates of Equation (1) separating the analysis by whether the hotline was in place or not. Consistent with the graphical evidence, the effect of coverage in the pre-hotline period is indistinguishable from zero. After the introduction of the hotline, we document a consistent and robust drop in the likelihood that a village has an EVD case. It is important to highlight that if the hotline arbitrarily led to more reporting of cases in coverage villages then the results in Table 4 would underestimate the magnitude of the drop in EVD cases in the post-hotline period.

Note that the percentage of villages with any EVD case in the period pre-hotline is much smaller than the percentage of villages with any EVD case in the period post-hotline, so we cannot fully exclude that the lack of statistically significant results pre-hotline might be partially explained by the limited variation in the data. Despite this caveat these preliminary findings point to two main takeaways. First, we find suggestive evidence that the network channel is less important in the pre-hotline period. Second, we find suggestive evidence of information and care channels likely at play given how EVD responds following the introduction of the primary tool (hotline) used to implement these channels. We proceed with a more detailed analysis of these two latter channels.

5.2 Network Channel

We are unable to directly test whether there is evidence of a network channel as this would entail observing an individual's or village's social network. However, we provide suggestive evidence that the network channel is trivial in our context.

We use historic Liberian clans as a way to define a village's closest social network. Officially, clans in Liberia are a third-tier administrative division.[15] However, clans also correspond to historical tribal chiefdoms that were merged into the state, throughout Liberian history, with chiefs simply assuming the role of agents of the central government (Nyei, 2014). Therefore, villages within the same clan are more likely to be socially interconnected than villages within another administrative unit. Based on the Census data (LISGIS, 2008), there are 619 clans in Liberia with an average of about 38 villages within each clan. We expect that, if a network channel exists, the likelihood that a village has EVD increases if that village and other EVD-affected villages within the same clan, have cell phone coverage. To assess this, we estimate the following empirical model using the same panel structure described in Section 4.4:

$$EVD_{ijt} = \alpha + \beta Match_{i,j(i)} + \gamma EVD_{j(i),t-1} + \delta Match_{i,j(i)} \times EVD_{j(i),t-1} + \lambda_j + \nu_t + \epsilon_{ijt} \quad (3)$$

where j indexes a clan. $EVD_{j(i),t-1}$ is an indicator for whether there is one or more EVD cases in at least one village within village i's clan in the past month. We define $Match_{i,j(i)}$ as a "coverage match" between village i and any of the affected villages in the past month within village i's clan, i.e., $Match_{i,j(i)}$ equals 1 if village i has cell phone coverage and at least one of the villages within village i's clan having an EVD case in the past month also has coverage. The remaining terms are defined as in Equation (2). The clan fixed effects λ_j account for any time-invariant unobservables that may lead to endogenous selection into EVD within a village's clan.

In the presence of a network channel, we should expect the likelihood of an EVD case in village i at time t to increase if there is a "coverage match" between village i and a village within i's clan with an EVD case at time $t-1$. Thus, we should expect coefficient δ to be positive if the network channel is non-trivial. We restrict the analysis to the pre-hotline/early-

[15] Administrative divisions in Liberia are county, district, clan, and village in this order.

outbreak period when access to centralized relief efforts was limited and individuals likely relied on their network for relief efforts. This allows us to better isolate any network channel from information and care channels that more likely rely on the existence of the hotline.

Table 5 presents estimates of Equation (3). Consistent with our preliminary evidence, we find no evidence of a network channel in the pre-hotline period (columns (1) and (2)). Although a "coverage match" with an affected village slightly increases the likelihood of an EVD case, this effect is not statistically significant. To better account for the endogenous selection into EVD exposure within the clan, columns (3)-(5) restrict the analysis to the first three months of the epidemic. During this period, the spatial distribution of cases was largely dependent on the distance to the outbreak origin in Guinea and not to intrinsic differences across villages. This result is also robust restricting the sample to villages within the pre-hotline bandwidth from Table 4 (column (5)). Again, with the caveat in mind that the percentage of villages with any EVD case in the period pre-hotline is small, we do not find additional suggestive evidence of a network channel.

5.3 Information and Care Channels

In order to explore the information and care channels, we use a novel survey data conducted about six months after the end of the epidemic (Maffioli, 2019). Phone numbers from 2,265 respondents in 571 villages across all of Liberia were selected through random dialing of phone numbers. These respondents were then interviewed through a combination of an Interactive Voice Response (IVR) survey to find out about their location before the beginning of the outbreak and a mobile phone survey conducted by a local NGO. About 30% of the individuals surveyed were living in areas that did not have coverage just prior to the outbreak in 2013. This allows us to perform analyses that compare outcomes across the pre-outbreak coverage cutoff.

Note, however, that the survey sample is not representative of the national population, instead it is biased towards respondents with access to a mobile phone during the time of the survey, i.e. male and educated individuals from urban areas.[16] However, once we restrict the

[16] We refer to Maffioli 2019 for more details on the methodology used to sample and screen respondents and to gather data, and for more details on the sample characteristics and how it compares to a nationally representative sample.

analysis to a small bandwidth around the cell phone coverage cutoff to assess the continuity of a number of individual-level characteristics in the survey, we find that most differences disappear (Appendix Table A2). This gives us confidence to implement a RD design similar to the one used in our main results.[17]

Using the survey data, we construct self-reported measures of access to *information* and *care*. Consider that we do not directly observe hotline-specific call behavior. However, we can use a set of outcomes that capture whether cell phone access allowed communities to be more exposed to information and/or care efforts. This can happen if, for instance, cell phone access improves coordination between communities and teams in charge of delivering information and/or care. The survey asked whether during the Ebola crisis anyone from government health workers, NGO, or international organizations came to the community, and if yes, to conduct which activity. Respondents were asked about whether anyone came to explain what EVD was, held hygiene meetings, distribute prevention material, do contact tracing, to explain how to conduct safe burials, to take sick people or dead bodies. Respondents were also asked directly whether a taskforce came to their villages as the taskforce was directly set-up to bring information about EVD. In addition, we asked respondents whether they knew anyone sick with Ebola symptoms for which hot-line was called, but the ambulance came very late or never came, and on average how long did the ambulance took to come to their community. Finally, we use publicly available data on the location of CCCs to construct a variable equal to 1 if the village had a CCC within a 10km radius.

Specifically, for the *information* channel (Table 6), we study whether individuals, among those who report any response during the Ebola crisis, report that someone (from government, health workers, local or international NGOs) came to their village to explain what EVD was (column (1)), to teach EVD-related hygiene practices (column (2)), whether a community taskforce came to share information on EVD and how to prevent it (column (3)), or someone came to explain how to conduct safe burials (column (4)). For the *care* channel (Table 7), we explore indicators for whether someone came to bring prevention material (chlorine, buckets, etc.), to do contact tracing, to take sick people or dead bodies (columns (1)-(4)). We further

[17]Note that using a bandwidth of 10 dBm (columns (7)-(9)) there is still a slight difference in education levels and in Kpelle tribe. Given this, we make sure to include these two variables in our set of covariates in all the analysis implemented using the survey data.

examine if individuals report that ambulances arrived within 4 hours after being requested through the hotline (column (5)), and whether a CCC was built within 10 kilometers of the village (column (6)).[18] We replicate the RD design and estimate Equation (1) using each of the information and care measures as our outcomes of interest. [19]

Table 6 presents results for the *information* channel. Respondents in coverage areas are 12.3 percentage points more likely to report that someone came to their village to explain what EVD was (column (1)), 13.5 percentage points more likely to report that the community taskforce came to teach preventive measures (column (3)), and 9 percentage points more likely to report that someone came to explain how to conduct safe burials (column (4)). Instead, respondents in coverage areas are less likely to report that hygiene meetings were held in their villages (column (2)). This might be consistent with the fact that in areas with cell phone coverage simple information on hygiene practices, such as washing or not shaking hands, can be channeled through mobile phones or radio, instead of using and sending already limited personnel. On the other hand, even in areas with cell phone coverage, it might still be necessary to send health workers to explain and show how to conduct safe burials or to gain the trust of individuals with limited knowledge on EVD. Overall, we find that, while the signs of the coefficients are, generally, in the right direction, the results lack statistical power.

Table 7 explores the *care* channel. We find evidence that survey respondents in coverage areas are 7.9 percentage points more likely to report that someone came to bring prevention material (column (1)). They are 10.2 and 22.3 percentage points more likely to report that someone came to trace contacts (column (2)) and to take sick people (column (3)), respectively. They are also 20.6 percentage points more likely to report that when they called an ambulance, it arrived on time (column (5)), and significantly more likely to report that a CCC was placed near their village (column (6)).[20] We find a null effect on the likelihood of someone coming to take dead bodies. Some outcomes are statistically significant (columns (3), (5), and (6)), while we find a lack of statistically significant effects on other coefficients, despite being in the right direction and of sizable magnitude.

[18] In the survey data, 4 hours is the median time taken from an ambulance to reach the village of destination from the dispatch.

[19] The analysis uses village clustered standard errors given that the sample selection in the survey data was done at the individual level, and outcomes could be correlated for individuals within the same village.

[20] Appendix Tables A6 and A7 present results that only include controls for topographic characteristics (elevation and slope). The results are qualitatively similar.

Combining the results in Tables 6 and 7, we conclude that the care channel seems to play a bigger role in explaining the effect of coverage on the likelihood of an EVD case. In the case of the information outcomes, while the signs of the cell phone coverage effect are generally reasonable, the results lack precision. This is further corroborated when we explore summary indexes of each of the two channels constructed following Kling et al. (2007). The index of all information outcomes results in a null coverage effect (Table 6, column (5)), while we find a positive and statistically significant effect in the case of the combined care outcomes (Table 7, column (6)).[21] Overall, these results are quite plausible given our setting. In the midst of a crisis, an additional ambulance or a CCC near a village is likely more impactful and immediately observed, compared to an additional information session on prevention. The effects of increasing information may take longer to materialize as they essentially entail a change in health behavior.

The survey also asked respondents who they thought it was responsible to bring Ebola to Liberia.[22] They were also asked about how well or badly they would say the GOL (President Hellen Sirleaf) handled the Ebola crisis in the previous year, and why. Table 8 presents additional results related to the channels at play. First, columns (1) and (2) provide further evidence that individuals in cell phone coverage areas are not necessarily more informed than their non-coverage counterparts. Specifically, when we examine whether individuals are more informed about the origin of the outbreak, we do not find any significant differences across coverage status. Specifically, the share of individuals who correctly answer, after the epidemic ended, that the EVD originated in Guinea (Table 8, column (1)) or who do not know where the outbreak originated (Table 8, column (2)) is similar across cell phone coverage and non-coverage areas. Again, this is plausible given our setting, since basic information on the disease, such as where it originated, can be delivered using alternative communication methods such as radio, which does not depend on whether an individual has cell phone access. Second, individuals in coverage areas perceive the government's response to the crisis to be significantly better. Among those who reported that government responded well

[21] Note in Appendix Table A6 that, although we find that the share of individuals reporting that they received EVD information and that a community taskforce visited the village are statistically significant, the overall information index remains statistically insignificant.

[22] Whether white people, UNMIL, the GOL, Fula, Mandingo, Kissi, people from Guinea, from Sierra Leone, foreign NGOs, god, witchcraft, other or do not know).

to the epidemic, when asked about the reasons why, respondents with cell phone coverage are 12 percentage points more likely to respond that the government's reaction time was "quick" (column (3)), and 16 percentage points more likely to respond that the health services provided were "good" (column (4)).[23] These results are only suggestive, given that they relate to subjective perceptions, rather than the actual individuals' level of knowledge about the origin of the outbreak and actual measures of government performance. However, when taken together with the results in columns (1) and (2), they provide further evidence that care measures (e.g., reaction time, quality of services) are more relevant in explaining the effect of coverage on the likelihood of EVD.

6 Conclusion

Combining proprietary data on cell phone tower locations and Ebola cases in Liberia, we show that cell phone coverage contains the spread of the Ebola Virus Disease (EVD). Specifically, comparing villages at the margin of the signal strength threshold, we find that having access to cell phone coverage leads to a 10.8 percentage point reduction in the likelihood that a village has an EVD case. There is some indication that most of the effect is accrued to the introduction of a cell phone hotline designed to provide information about the disease and ease the provision of care. Using novel survey data collected after the epidemic, we assess the relative importance of several channels that may explain the observed relationship between cell phone coverage and epidemic containment. Specifically, we focus on an *information* channel (facilitation of access to information on the disease and actions to take) and a *care* channel (facilitation of access to relief efforts). We provide suggestive evidence that the cell phone coverage-EVD relationship is likely explained by facilitating access to health care, rather than improving access to information. This result is quite plausible as, in the short run, the returns to an additional ambulance or a care center in the midst of a health crisis are likely higher and immediately realized. On the other hand, the effects of increasing information may take longer to materialize as they essentially entail a change in health behavior.

Infectious disease outbreaks are still a major burden to low and middle-income countries

[23] Refer to Appendix Table A8 for estimates presented in Table 8 that only include controls for topographic characteristics (elevation and slope).

(Holmes et al., 2017), and extreme events, such as health epidemics, are expected to remain a worldwide threat (United Nations Office for Disaster Risk Reduction, 2015). Even though they might be unpredictable, the ultimate human and economic costs could be mitigated through appropriate governmental actions. Our findings show how something as simple and ubiquitous as a mobile phone can have positive externalities on economic development by allowing communities to access health care in times of crisis. From a policy perspective, it is fundamental for governmental stakeholders to know the relative effectiveness of potential tools, such as mobile phones, in mitigating the negative consequences of infectious diseases. In normal times, this can guide policymakers towards facilitating investments in increasing cell phone coverage to the most remote areas. At the time of crisis, instead, policy makers should more efficiently allocate the limited funds, by taking advantage of the cell phone coverage and technology to set-up interventions (such as a hotline number) to enhance access to care and thus improve the effectiveness of the response. Further research should explore specific interventions to take advantage of this technology and the effects of these tools in the context of other health epidemics.

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Figures and Tables

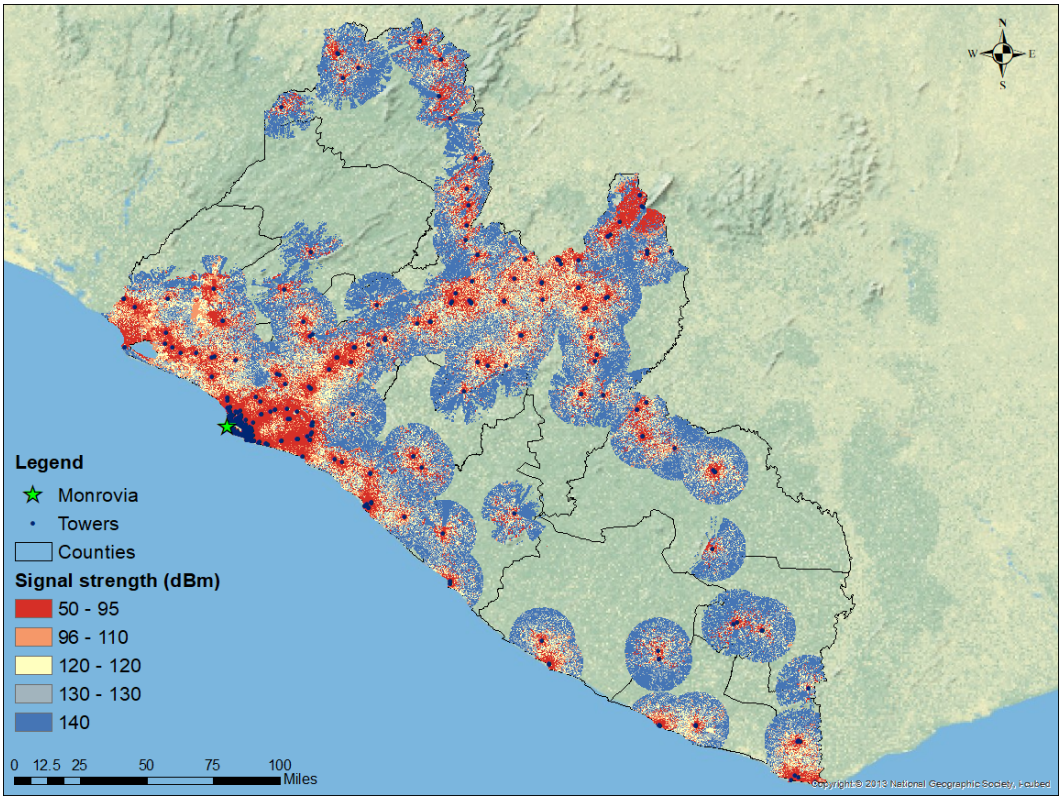
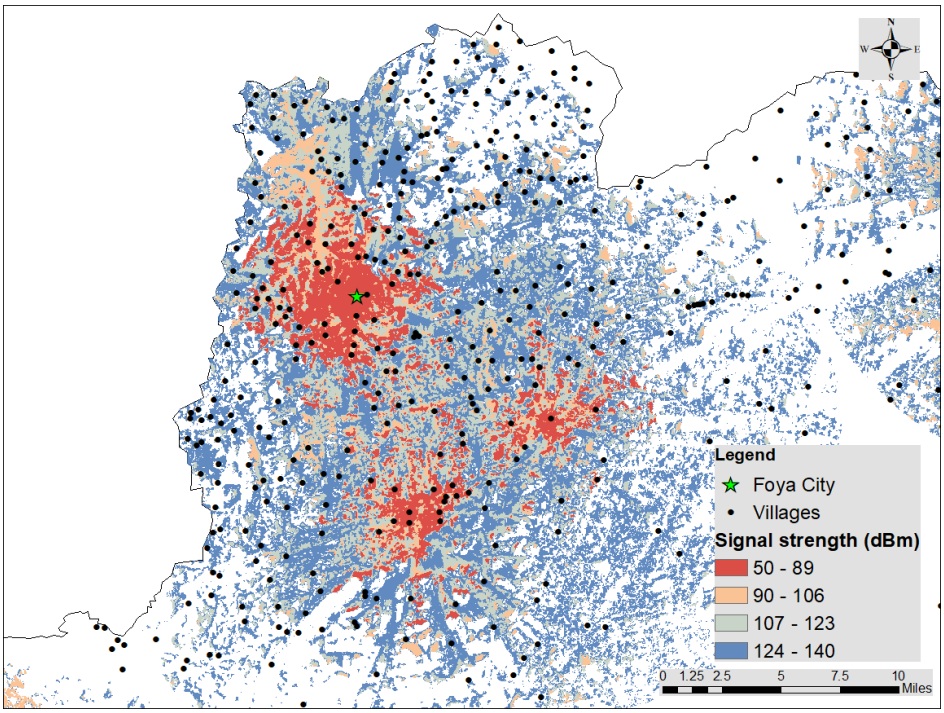
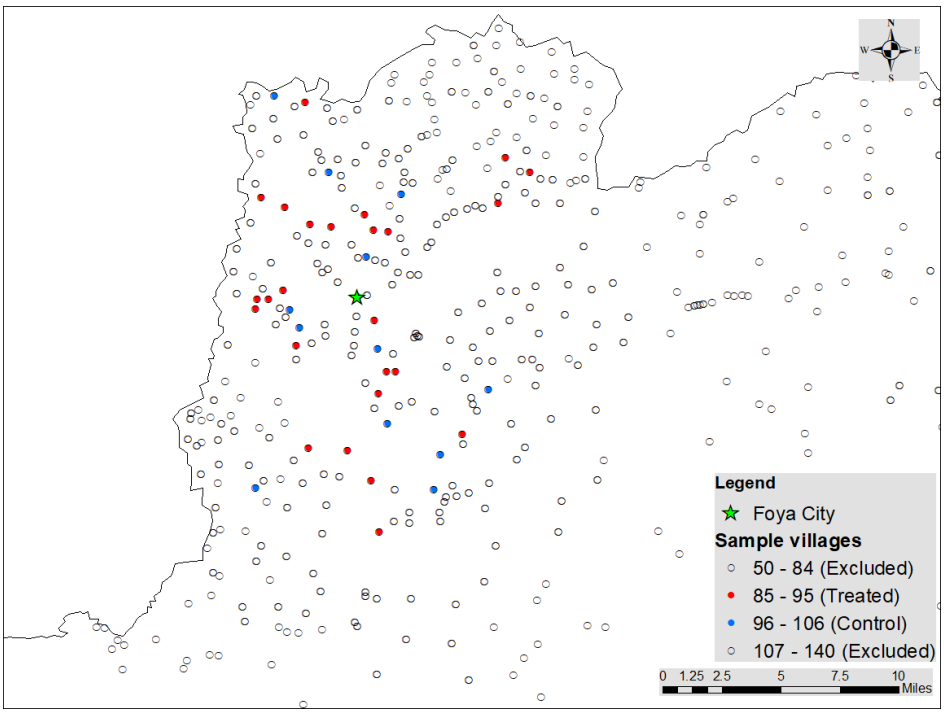


Figure 1: Irregular Terrain Model, Liberia (2013)

Notes: Cell phone towers' location obtained from the Liberia Telecommunications Authority (LTA). Estimates of the ITM model described in Section 3.2. Lower dBm values mean higher signal strength (i.e., more coverage).



(a) ITM detailed



(b) Villages within 10dBm Bandwidth of Cutoff

Figure 2: Irregular Terrain Model with Village Sample

Notes: Cell phone towers' location obtained from the Liberia Telecommunications Authority (LTA). Estimates of the ITM model described in Section 3.2. Lower dBm values mean higher signal strength (i.e., more coverage). Dots indicate the location of villages.

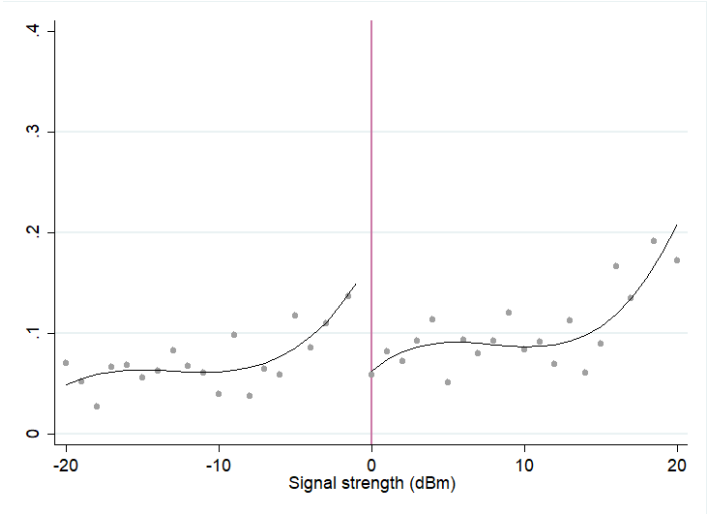
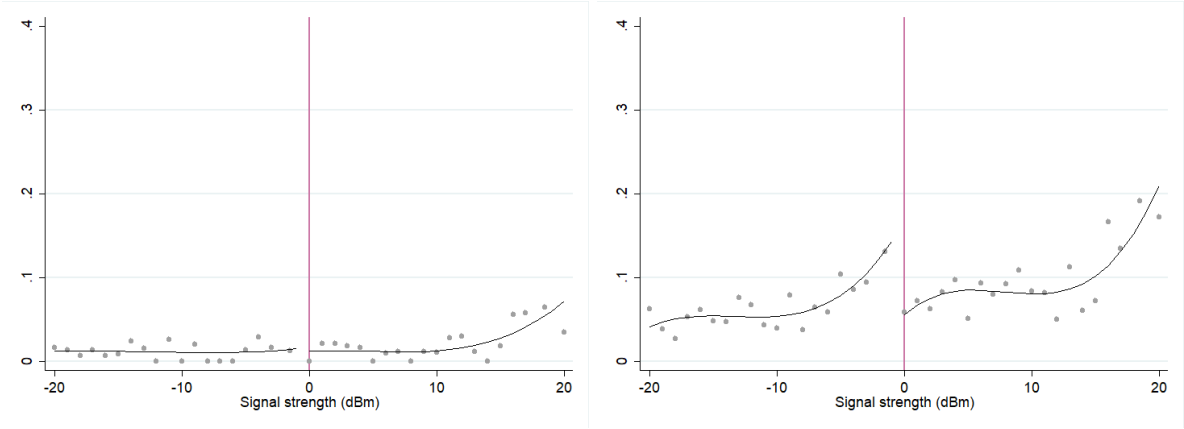


Figure 3: Regression Discontinuity (RD) Plot for Likelihood of EVD

Notes: Solid dots give the average of the specified variable for each bin of signal strength (dBm). "Signal strength (dBm)" refers to the received power or signal strength, measured in decibel milliwatts, at the village level. Signal strength is normalized so that negative values mean no coverage (i.e., not enough signal strength). The solid line trends give the predicted values from a regression of the outcome variable on a fourth degree polynomial in distance to the boundary that uses a triangular kernel.



(a) Pre-hotline

(b) Post-hotline

Figure 4: Regression Discontinuity (RD) Plots for Likelihood of EVD Case and by Timing of Hotline

Notes: Solid dots give the average of the specified variable for each bin of signal strength (dBm). "Signal strength (dBm)" refers to the received power or signal strength, measured in decibel milliwatts, at the village level. Signal strength is normalized so that negative values mean no coverage (i.e., not enough signal strength). The solid line trends give the predicted values from a regression of the outcome variable on a fourth degree polynomial in distance to the boundary that uses a triangular kernel.

Table 1: Determinants of Coverage

	Dep. variable: Signal strength (dBm)		
	Full sample (1)	Within 20 dBm (2)	Within 10 dBm (3)
Topographic controls			
Elevation (m)	-0.082***	-0.032**	0.005
	(0.024)	(0.014)	(0.009)
Slope (%)	-0.283	1.129***	0.828***
	(0.455)	(0.379)	(0.256)
Demographic controls			
Household size	-0.194	0.014	0.118
	(0.171)	(0.131)	(0.087)
Population (log)	0.880***	0.225	-0.013
	(0.166)	(0.162)	(0.117)
Female (%)	-0.367	1.805	1.474
	(2.456)	(3.029)	(1.775)
Married (%)	-4.267*	-1.750	1.236
	(2.170)	(1.679)	(1.481)
Christian (%)	1.974	3.553**	-0.340
	(2.593)	(1.543)	(1.603)
Muslim (%)	1.655	-0.263	-1.721
	(3.180)	(2.473)	(1.982)
African religion (%)	6.102	6.790	-0.579
	(5.602)	(6.518)	(7.128)
Kpelle (%)	-0.040	-1.410	-1.190
	(1.159)	(1.430)	(0.946)
Bassa (%)	3.648	1.031	0.497
	(2.229)	(1.771)	(1.163)
Economic controls			
Primary education (%)	-0.347	0.142	-1.199
	(1.665)	(1.269)	(1.200)
Secondary education (%)	5.027**	2.097*	0.925
	(2.091)	(1.107)	(1.137)
Owns house (%)	1.084	-0.498	-0.403
	(1.189)	(0.858)	(0.568)
House condition: Good (%)	9.476***	4.908***	0.858
	(2.175)	(1.332)	(0.941)
Assets ownership (%)	2.350	1.413	0.505
	(3.844)	(2.828)	(1.621)
Distance to Monrovia (km)	-0.098**	-0.013	-0.020
	(0.047)	(0.049)	(0.024)
Distance to closest city (km)	-0.306***	-0.064	-0.035
	(0.113)	(0.088)	(0.049)
Observations	7,014	3,839	1,913
P-value for F-test for joint significance:			
Topographic controls	0.00	0.00	0.00
Demographic controls	0.00	0.01	0.35
Economic controls	0.00	0.00	0.79
Demographic and economic controls	0.00	0.00	0.15

Notes: Standard errors clustered at district level. All specification include district fixed effects. *, **, and *** indicate 10, 5, and 1 percent significance, respectively.

Table 2: Effect of Coverage on Likelihood of EVD Case

	Dep. Variable = $\mathbb{1}\{\text{Number of Reported EVD cases} > 0\}$					
	Baseline	Controls	Topography Poly	Polynomial RD	Kernel choice	Probit model
	(1)	(2)	(3)	(4)	(5)	(6)
Coverage	-0.108**	-0.101**	-0.110**	-0.096***	-0.105***	-0.429**
	(0.048)	(0.042)	(0.048)	(0.035)	(0.041)	(0.204)
Mean outside coverage	0.09	0.09	0.09	0.06	0.09	0.09
Bandwidth (dBm)	8.99	8.13	9.09	50.00	8.24	8.24
Observations	1547	1547	1741	7014	1547	1547
Districts	83	83	84	115	83	83
Marginal Effect	-	-	-	-	-	-0.07

Notes: Columns (1) and (2) present estimates of β using a local linear regression specification of Equation (1). All specification include controls for elevation and slope. Column (2) adds controls for average household size, population, female, married, Christian, Muslim, African religion, Kpelle, Bassa, primary education, literacy, house ownership and quality, an index of asset ownership, distance to Monrovia, and distance to closest main city. Optimal bandwidth chosen as in Calonico et al. (2014). Column (3) uses topography polynomial: $h(\mathbf{G}_i) = \rho_1 elev_i + \rho_2 elev_i^2 + \rho_3 slope_i + \rho_4 elev_i \times slope_i + \rho_5 elev_i^2 \times slope_i + \rho_6 slope_i^2 + \rho_7 elev_i \times slope_i^2 + \rho_8 elev_i^2 \times slope_i^2$. Column (4) uses a wider bandwidth of 50 dBm and a third degree polynomial specification for $f(\tilde{R}_i)$. Column (5) uses a rectangular kernel. Column (6) estimates a probit specification of Equation (1). Optimal bandwidths chosen as in Calonico et al. (2014) except for column (4) which uses a fixed, wider bandwidth. Standard errors clustered at district level. *, **, and *** indicate 10, 5, and 1 percent significance, respectively.

Table 3: Effect of Coverage on Likelihood of EVD, by Past EVD Exposure

	Dep. Variable = $\mathbb{1}\{\text{Number of Reported EVD cases} > 0\}$				
	(1)	(2)	(3)	(4)	(5)
Coverage_i	-0.0069**	-0.0059**		0.0005	0.0014
	(0.003)	(0.002)		(0.002)	(0.002)
$\text{EVD}_{j(i),t-1}$			0.0056**	0.0167**	0.0160**
			(0.002)	(0.007)	(0.007)
$\text{Coverage}_i \times \text{EVD}_{j(i),t-1}$				-0.0191***	-0.0186***
				(0.006)	(0.006)
Mean outside coverage	0.007	0.007	0.006	0.007	0.007
Observations	33079	33079	31338	31338	31338
Bandwidth (dBm)	9.00	9.00	9.00	9.00	9.00
Districts	84	84	84	84	84
District FE	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	Yes	No	Yes

Notes: Coverage_i equal 1 if village i has coverage. $\text{EVD}_{j(i),t-1}$ equals 1 if there is one or more EVD cases in at least one village within village i's district in the past month. Standard errors clustered at district level. Columns (2), (3), and (5) include controls for average household size, population, female, married, Christian, Muslim, African religion, Kpelle, Bassa, primary education, literacy, house ownership and quality, an index of asset ownership, distance to Monrovia, and distance to closest main city. *, **, and *** indicate 10, 5, and 1 percent significance, respectively.

Table 4: Effect of Coverage on Likelihood of EVD: Before and After Hotline Introduction

	Dep. Variable = $\mathbb{1}\{\text{Number of Reported EVD cases} > 0\}$											
	Pre-Hotline						Post-Hotline					
	Baseline	Controls	Topography Poly	Poly RD	Kernel choice	Probit model	Baseline	Controls	Topography Poly	Poly RD	Kernel choice	Probit model
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Coverage	-0.01	-0.00	-0.01	-0.00	-0.01	-0.01	-0.11**	-0.10***	-0.11**	-0.10***	-0.09***	-0.44***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.44)	(0.04)	(0.04)	(0.04)	(0.03)	(0.03)	(0.15)
Mean outside coverage	0.01	0.01	0.01	0.01	0.01	0.01	0.09	0.09	0.09	0.06	0.09	0.09
Bandwidth (dBm)	10.33	11.23	10.68	50.00	8.81	8.81	9.00	8.31	9.17	50.00	9.40	9.40
Observations	1913	2139	1913	7014	1547	1547	1741	1547	1741	7014	1741	1741
Districts	86	87	86	115	83	83	84	83	84	115	84	84
Marginal Effect	-	-	-	-	-	-0.00	-	-	-	-	-	-0.07

Notes: Columns (1), (2), (7), and (8) present estimates of β using a local linear regression specification of Equation (1). All specification include controls for elevation and slope. Columns (2) and (8) add controls for average household size, population, female, married, Christian, Muslim, African religion, Kpelle, Bassa, primary education, literacy, house ownership and quality, an index of asset ownership, distance to Monrovia, and distance to closest main city. Columns (3) and (9) use topography polynomial: $h(\mathbf{G}_i) = \rho_1 elev_i + \rho_2 elev_i^2 + \rho_3 slope_i + \rho_4 elev_i \times slope_i + \rho_5 elev_i^2 \times slope_i + \rho_6 slope_i^2 + \rho_7 elev_i \times slope_i^2 + \rho_8 elev_i^2 \times slope_i^2$. Columns (4) and (10) use a wider bandwidth of 50 dBm and a third degree polynomial specification for $f(\tilde{R}_i)$. Columns (5) and (11) use a rectangular kernel. Columns (6) and (12) use a probit specification of Equation (1). Optimal bandwidths chosen as in Calonico et al. (2014) except for columns (4) and (10) which use a fixed, wider bandwidth. Standard errors clustered at district level in all specifications. *, **, and *** indicate 10, 5, and 1 percent significance, respectively.

Table 5: Likelihood of EVD within Connected Villages of the Same Clan

	Dep. Variable = $\mathbb{1}\{$Number of Reported EVD cases $> 0\}$				
	Pre-Hotline		Within 3 months of Outbreak		
	(1)	(2)	(3)	(4)	(5)
$\text{EVD}_{j(i),t-1}$	0.0228***	0.0229***	0.0259***	0.0260***	0.0022
	(0.007)	(0.007)	(0.007)	(0.007)	(0.003)
$\text{Match}_{i,j(i)} \times \text{EVD}_{j(i),t-1}$	0.0017	0.0015	0.0006	0.0004	0.0144
	(0.013)	(0.013)	(0.022)	(0.022)	(0.030)
Mean outside coverage	0.002	0.002	0.001	0.001	0.001
Observations	56112	56112	49098	49098	13391
Bandwidth (dBm)	-	-	-	-	10.33
Clans	619	619	619	619	254
Clan FE	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes	Yes

Notes: $\text{EVD}_{j(i),t-1}$ equals 1 if there is one or more EVD cases in at least one village within village i's clan in the past month. $\text{Match}_{i,j(i)}$ equals 1 if there is a cell phone coverage match between village i and any of the affected villages in the past month within village i's clan (i.e., village i has coverage and at least one of the villages within village i's clan having an EVD case in the past month also has coverage). Standard errors clustered at the clan level. Columns (2), (4), and (5) include controls for average household size, population, female, married, Christian, Muslim, African religion, Kpelle, Bassa, primary education, literacy, house ownership and quality, an index of asset ownership, distance to Monrovia, and distance to closest main city. *, **, and *** indicate 10, 5, and 1 percent significance, respectively.

Table 6: Effect of Coverage on Information Outcomes

	Someone came to:				
	Explain EVD (1)	Hygiene meetings (2)	Bring info (Taskforce) (3)	Explain burials (4)	Information index (5)
Coverage	0.123	-0.173	0.135	0.090	0.213
	(0.086)	(0.110)	(0.088)	(0.092)	(0.141)
Mean outside coverage	0.897	0.465	0.282	0.174	0.094
Bandwidth (dBm)	14.89	17.12	8.94	11.77	11.89
Observations	434	551	296	328	328
Villages	166	203	86	122	122

Notes: Results present estimates of β using a local linear regression specification of Equation (1) on information variables. The observations are respondents in the survey sample (2016). Optimal bandwidth chosen as in Calonico et al. (2014). The information index is constructed following Kling et al. (2007). Results include controls for elevation, slope, sex, age, urban, secondary education level, and categories for Kpelle, Bassa, and other tribes. Standard errors clustered at the village level. *, **, and *** indicate 10, 5, and 1 percent significance, respectively.

Table 7: Effect of Coverage on Care Outcomes

	Prevention material	Contact tracing	Take sick	Take dead	Ambulance on-time	CCCs within 10km	Care index
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Coverage	0.079	0.102	0.223***	-0.006	0.206***	0.416*	0.344**
	(0.111)	(0.084)	(0.036)	(0.044)	(0.076)	(0.235)	(0.153)
Mean outside coverage	0.779	0.200	0.123	0.070	0.835	0.455	0.027
Bandwidth (dBm)	16.46	8.80	8.13	11.17	12.35	9.40	8.66
Observations	518	268	268	328	385	317	268
Villages	189	86	86	122	139	100	86

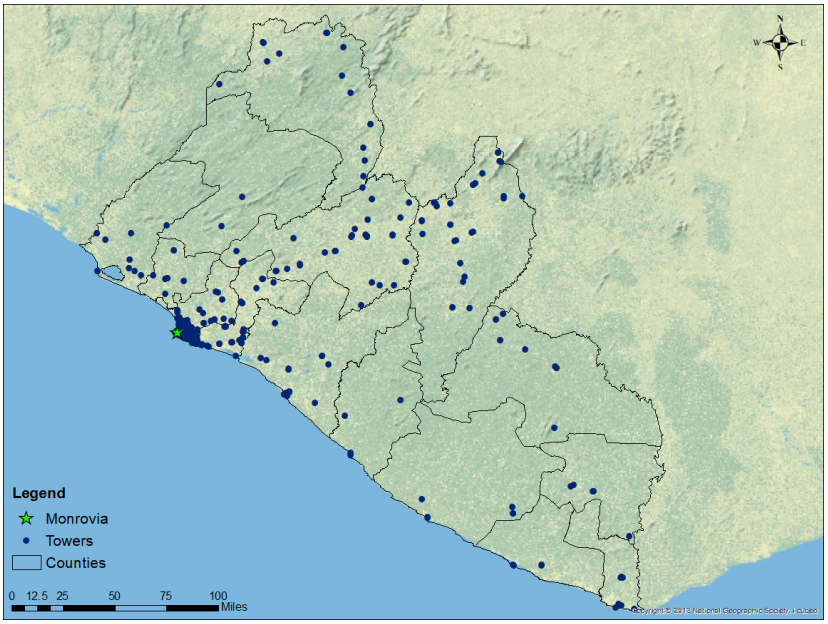
Notes: Results present estimates of β using a local linear regression specification of Equation (1) on care variables. The observations are respondents in the survey sample (2016). Optimal bandwidth chosen as in Calonico et al. (2014). The care index is constructed following Kling et al. (2007). Results include controls for elevation, slope, sex, age, urban, and education level, and categories for Kpelle, Bassa, and other tribes. Standard errors clustered at the village level. *, **, and *** indicate 10, 5, and 1 percent significance, respectively.

Table 8: Effect of Coverage on Other Outcomes

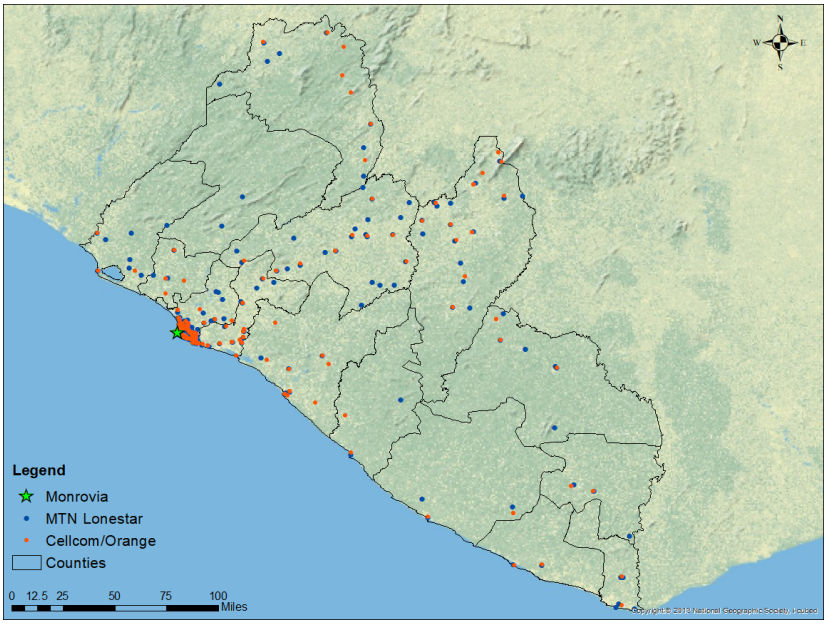
	Origin of EVD		Evaluate government response		
	Guinea	Don't know	Quick reaction time	Good health services	Other
	(1)	(2)	(3)	(4)	(5)
	(1)	(2)	(3)	(4)	(5)
Coverage	0.009	0.011	0.120	0.155*	0.035
	(0.12)	(0.14)	(0.08)	(0.09)	(0.06)
Mean outside coverage	0.74	0.76	0.74	0.78	0.76
Bandwidth (dBm)	13.30	12.75	13.64	16.62	10.27
Observations	445	385	358	459	269
Villages	146	139	146	189	111

Notes: Results present estimates of β using a local linear regression specification of Equation (1) on care variables. The observations are respondents in the survey sample (2016). Optimal bandwidth chosen as in Calonico et al. (2014). Results include controls for elevation, slope, sex, age, urban, and education level, and categories for Kpelle, Bassa, and other tribes. Standard errors clustered at the village level. *, **, and *** indicate 10, 5, and 1 percent significance, respectively.

Appendix A Additional Figures and Tables



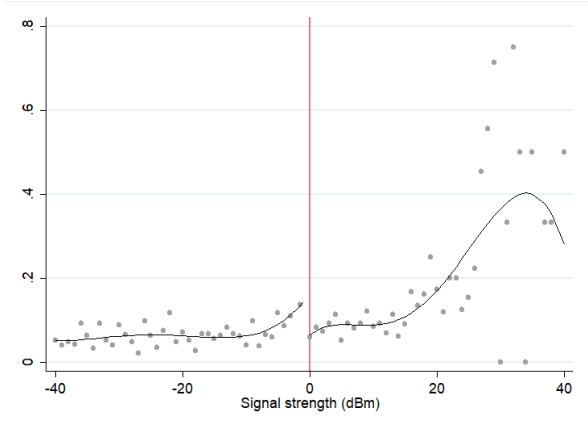
(a) All Towers



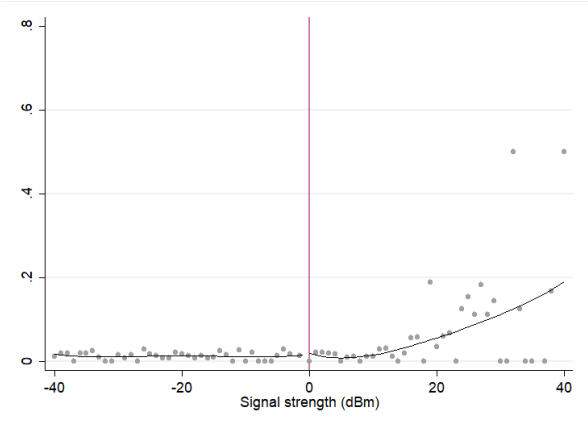
(b) By Network Operator

Figure A1: Cell Phone Towers, Liberia (2013)

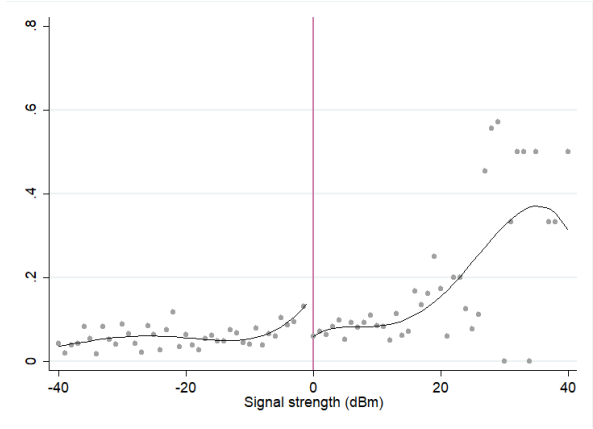
Notes: Cell towers' location obtained from the Liberia Telecommunications Authority (LTA).



(a) All



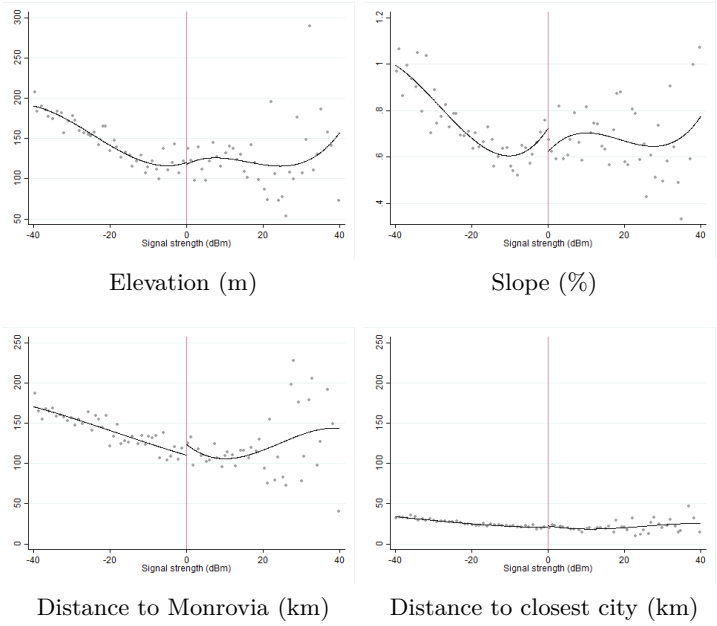
(b) Pre-hotline



(c) Post-hotline

Figure A2: Regression Discontinuity (RD) Plots

Notes: Solid dots give the average of the specified variable for each bin of signal strength (dBm). "Signal strength (dBm)" refers to the received power or signal strength, measured in decibel milliwatts, at the village level. Signal strength is normalized so that negative values mean no coverage (i.e., not enough signal strength). The solid line trends give the predicted values from a regression of the outcome variable on a fourth degree polynomial in distance to the boundary that uses a triangular kernel.



Elevation (m) Slope (%)

Distance to Monrovia (km) Distance to closest city (km)

Figure A3: Regression Discontinuity Plots, Covariates

Notes: Solid dots give the average of the specified variable for each bin of signal strength (dBm). "Signal strength (dBm)" refers to the received power or signal strength, measured in decibel milliwatts, at the village level. Signal strength is normalized so that negative values mean no coverage (i.e., not enough signal strength). The solid line trends give the predicted values from a regression of the outcome variable on a fourth degree polynomial in distance to the boundary that uses a triangular kernel.

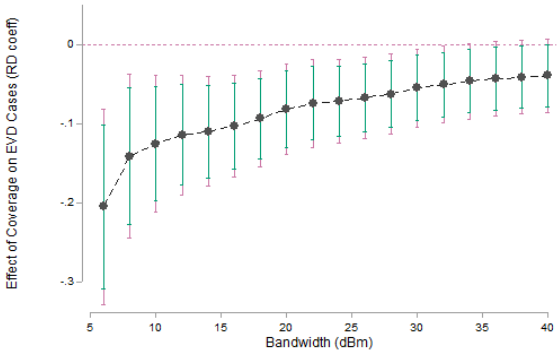
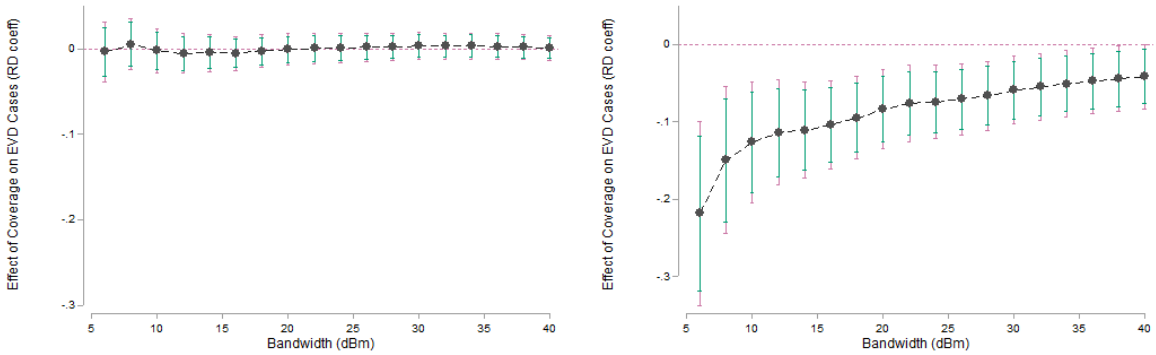


Figure A4: Bandwidth Sensitivity

Notes: Solid dots indicate the RD estimate from Equation (1) using the specified bandwidth. Range spikes indicate 95% and 90% confidence intervals of the estimates.



(a) Pre-hotline

(b) Post-hotline

Figure A5: Bandwidth Sensitivity, by Hotline Timing

Notes: Solid dots indicate the RD estimates from Equation (1) using the specified bandwidth. Range spikes indicate 95% and 90% confidence intervals of the estimates.

Table A1: Summary Statistics by Coverage Status (Villages)

	Full sample			Within 20 dBm			Within 10 dBm		
	Inside (1)	Outside (2)	S.E. (3)	Inside (4)	Outside (5)	S.E. (6)	Inside (7)	Outside (8)	S.E. (9)
Topographic characteristics:									
Elevation (m)	122.8	165.3	(14.69)***	123.5	124.6	(12.26)	122.3	117.7	(11.69)
Slope (%)	0.68	0.89	(0.05)***	0.68	0.64	(0.04)	0.67	0.62	(0.04)
Demographic characteristics:									
Household size	4.68	5.02	(0.10)***	4.66	4.58	(0.07)	4.64	4.52	(0.08)
Population (log)	4.38	4.32	(0.07)	4.25	4.17	(0.06)	4.16	4.19	(0.08)
Female (%)	0.48	0.48	(0.00)	0.48	0.48	(0.00)	0.48	0.48	(0.01)
Married (%)	0.37	0.38	(0.01)	0.37	0.39	(0.01)**	0.38	0.39	(0.01)
Christian (%)	0.85	0.87	(0.03)	0.85	0.85	(0.02)	0.83	0.85	(0.02)
Muslim (%)	0.11	0.10	(0.03)	0.11	0.13	(0.02)	0.13	0.13	(0.02)
African religion (%)	0.01	0.01	(0.00)	0.01	0.00	(0.00)	0.00	0.00	(0.00)
Kpelle (%)	0.31	0.28	(0.04)	0.31	0.33	(0.03)	0.31	0.36	(0.03)*
Bassa (%)	0.25	0.24	(0.06)	0.26	0.24	(0.04)	0.26	0.21	(0.04)
Other ethnic group (%)	0.43	0.48	(0.05)	0.42	0.42	(0.03)	0.42	0.42	(0.03)
Economic characteristics:									
Primary education (%)	0.28	0.25	(0.01)**	0.28	0.26	(0.01)**	0.26	0.26	(0.01)
Secondary education (%)	0.38	0.33	(0.02)***	0.37	0.34	(0.01)**	0.35	0.35	(0.01)
Owns house (%)	0.80	0.87	(0.02)***	0.81	0.84	(0.01)***	0.82	0.82	(0.01)
House condition: Good (%)	0.26	0.14	(0.02)***	0.25	0.20	(0.01)***	0.22	0.21	(0.01)
Asset ownership (%)	0.13	0.11	(0.01)***	0.13	0.12	(0.01)*	0.12	0.12	(0.01)
Distance to Monrovia (km)	112.3	166.9	(12.51)***	111.1	126.1	(10.08)	111.3	119.9	(9.11)
Distance to closest city (km)	19.82	33.72	(2.15)***	19.67	22.52	(1.36)**	19.58	21.06	(1.24)
Observations	1,856	7,830		1,698	2,141		1,112	801	

Notes: Columns (1), (2), (4), (5), (7) and (8) give the means of the corresponding variable. Columns (3), (6) and (9) give the clustered standard errors for the difference in means in parenthesis. Clustered standard errors at the district level. *, **, and *** indicate 10, 5, and 1 percent significance, respectively.

Table A2: Summary Statistics by Coverage Status (Survey Sample)

	Full sample			Within 20 dBm			Within 10 dBm		
	Inside (1)	Outside (2)	S.E. (3)	Inside (4)	Outside (5)	S.E. (6)	Inside (7)	Outside (8)	S.E. (9)
Topographic characteristics:									
Elevation (m)	191.1	227.2	(42.99)	189.8	157.9	(50.68)	195.8	124.7	(77.05)
Slope (%)	0.70	0.88	(0.17)	0.61	0.74	(0.11)	0.65	0.62	(0.13)
Demographic characteristics:									
Household size	4.79	4.98	(0.19)	4.64	4.75	(0.32)	4.40	4.99	(0.52)
Christian	0.86	0.87	(0.02)	0.86	0.83	(0.04)	0.87	0.83	(0.06)
Muslim	0.10	0.09	(0.02)	0.10	0.12	(0.04)	0.07	0.13	(0.05)
Female	0.37	0.32	(0.03)*	0.32	0.34	(0.04)	0.28	0.28	(0.06)
Age	32.02	33.91	(0.54)***	33.45	34.69	(0.94)	33.82	34.33	(1.37)
Married	0.44	0.57	(0.03)***	0.53	0.58	(0.05)	0.57	0.53	(0.08)
Kpelle	0.25	0.33	(0.08)	0.17	0.35	(0.06)***	0.15	0.34	(0.09)**
Bassa	0.09	0.13	(0.03)	0.17	0.16	(0.08)	0.23	0.15	(0.13)
Mano	0.16	0.09	(0.06)	0.19	0.09	(0.07)	0.24	0.10	(0.10)
Other tribe	0.50	0.44	(0.06)	0.47	0.40	(0.07)	0.38	0.41	(0.08)
Urban	0.80	0.50	(0.05)***	0.63	0.46	(0.08)**	0.62	0.50	(0.13)
Economic characteristics:									
Secondary education	0.62	0.58	(0.03)	0.62	0.57	(0.04)	0.67	0.57	(0.06)*
Works for wage	0.17	0.19	(0.02)	0.17	0.20	(0.03)	0.20	0.20	(0.06)
Lost job (2013)	0.15	0.16	(0.02)	0.17	0.22	(0.03)	0.17	0.24	(0.06)
Not working	0.28	0.18	(0.02)***	0.26	0.17	(0.03)***	0.25	0.19	(0.05)
Self-employed	0.40	0.48	(0.03)***	0.42	0.47	(0.05)	0.42	0.48	(0.09)
Wealth index (<20th percentile)	0.18	0.34	(0.03)***	0.20	0.35	(0.05)***	0.24	0.27	(0.07)
Wealth index (20-40th percentile)	0.28	0.23	(0.02)*	0.26	0.21	(0.03)	0.25	0.29	(0.06)
Wealth index (40-60th percentile)	0.12	0.10	(0.01)*	0.14	0.09	(0.02)*	0.14	0.09	(0.04)
Wealth index (60-80th percentile)	0.20	0.19	(0.02)	0.17	0.20	(0.03)	0.17	0.14	(0.04)
Wealth index (>80th percentile)	0.22	0.14	(0.03)***	0.24	0.15	(0.04)**	0.19	0.21	(0.06)
Distance to Monrovia (km)	145.03	172.26	(31.81)	157.44	130.70	(26.38)	175.02	116.62	(40.31)
Distance to closest city (km)	6.57	29.82	(2.69)***	15.86	23.09	(5.08)	11.61	22.34	(4.53)**
Observations	1,495	648		516	202		245	86	

Notes: Columns (1), (2), (4), (5), (7) and (8) give the means of the corresponding variable. Columns (3), (6) and (9) give the clustered standard errors for the difference in means in parenthesis. Clustered standard errors at the village level. *, **, and *** indicate 10, 5, and 1 percent significance, respectively.

Table A3: Effect of Coverage on Likelihood of EVD Suspected Death

	Dep. Variable = $\mathbb{1}\{\text{Number of Suspected EVD Deaths} > 0\}$					
	Baseline	Controls	Topography Poly	Polynomial RD	Kernel choice	Probit model
	(1)	(2)	(3)	(4)	(5)	(6)
Coverage	-0.069*	-0.074**	-0.069*	-0.058	-0.067*	-0.243*
	(0.037)	(0.030)	(0.036)	(0.036)	(0.035)	(0.129)
Mean outside coverage	0.111	0.111	0.109	0.091	0.106	0.087
Bandwidth (dBm)	10.64	10.26	11.10	50.00	9.02	.
Observations	1913	1913	2139	7014	1741	1741
Districts	86	86	87	115	84	84
Marginal Effect						-0.048

Notes: Columns (1) and (2) present estimates of β using a local linear regression specification of Equation (1). All specification include controls for elevation and slope. Column (2) adds controls for average household size, population, female, married, Christian, Muslim, African religion, Kpelle, Bassa, primary education, literacy, house ownership and quality, an index of asset ownership, distance to Monrovia, and distance to closest main city. Optimal bandwidth chosen as in Calonico et al. (2014). Column (3) uses topography polynomial: $h(\mathbf{G}_i) = \rho_1 elev_i + \rho_2 elev_i^2 + \rho_3 slope_i + \rho_4 elev_i \times slope_i + \rho_5 elev_i^2 \times slope_i + \rho_6 slope_i^2 + \rho_7 elev_i \times slope_i^2 + \rho_8 elev_i^2 \times slope_i^2$. Column (4) uses a wider bandwidth of 50 dBm and a third degree polynomial specification for $f(\tilde{R}_i)$. Column (5) uses a rectangular kernel. Column (6) estimates a probit specification of Equation (1). Optimal bandwidths chosen as in Calonico et al. (2014) except for column (4) which uses a fixed, wider bandwidth. Standard errors clustered at district level. *, **, and *** indicate 10, 5, and 1 percent significance, respectively.

Table A4: Effect of Coverage on Number of Months Affected by EVD

	Number of Months Affected by EVD				
	Baseline	Controls	Topography Poly	Polynomial RD	Kernel choice
	(1)	(2)	(3)	(4)	(5)
Coverage	-0.209**	-0.188**	-0.220**	-0.158**	-0.199**
	(0.096)	(0.084)	(0.099)	(0.074)	(0.087)
Mean outside coverage	0.128	0.128	0.128	0.090	0.142
Bandwidth (dBm)	8.72	8.97	8.59	50.00	7.10
Observations	1547	1547	1547	7014	1369
Districts	83	83	83	115	81

Notes: Columns (1) and (2) present estimates of β using a local linear regression specification of Equation (1). All specification include controls for elevation and slope. Column (2) adds controls for average household size, population, female, married, Christian, Muslim, African religion, Kpelle, Bassa, primary education, literacy, house ownership and quality, an index of asset ownership, distance to Monrovia, and distance to closest main city. Optimal bandwidth chosen as in Calonico et al. (2014). Column (3) uses topography polynomial: $h(\mathbf{G}_i) = \rho_1 elev_i + \rho_2 elev_i^2 + \rho_3 slope_i + \rho_4 elev_i \times slope_i + \rho_5 elev_i^2 \times slope_i + \rho_6 slope_i^2 + \rho_7 elev_i \times slope_i^2 + \rho_8 elev_i^2 \times slope_i^2$. Column (4) uses a wider bandwidth of 50 dBm and a third degree polynomial specification for $f(\tilde{R}_i)$. Column (5) uses a rectangular kernel. Optimal bandwidths chosen as in Calonico et al. (2014) except for column (4) which uses a fixed, wider bandwidth. Standard errors clustered at district level. *, **, and *** indicate 10, 5, and 1 percent significance, respectively.

Table A5: Effect of Coverage on Likelihood of EVD Case (sub-sample)

	Dep. Variable = $\mathbb{1}\{$Number of Reported EVD cases $> 0\}$					
	Baseline	Controls	Topography Poly	Polynomial RD	Kernel choice	Probit model
	(1)	(2)	(3)	(4)	(5)	(6)
	(1)	(2)	(3)	(4)	(5)	(6)
Coverage	-0.220**	-0.173**	-0.165**	-0.112*	-0.254***	-0.975**
	(0.088)	(0.072)	(0.070)	(0.057)	(0.095)	(0.486)
Mean outside coverage	0.080	0.080	0.086	0.058	0.101	0.051
Bandwidth (dBm)	6.70	6.63	7.95	50.00	4.63	.
Observations	276	276	322	1943	201	201
Districts	39	39	42	76	33	33
Marginal Effect						-0.188

Notes: Columns (1) and (2) present estimates of β using a local linear regression specification of Equation (1). All specification include controls for elevation and slope. Column (2) adds controls for average household size, population, female, married, Christian, Muslim, African religion, Kpelle, Bassa, primary education, literacy, house ownership and quality, an index of asset ownership, distance to Monrovia, and distance to closest main city. The analysis drop six counties (Grand Bassa, Grand Cape Mount, Lofa, Bong, Margibi, Montserrado). Optimal bandwidth chosen as in Calonico et al. (2014). Column (3) uses topography polynomial: $h(\mathbf{G}_i) = \rho_1 elev_i + \rho_2 elev_i^2 + \rho_3 slope_i + \rho_4 elev_i \times slope_i + \rho_5 elev_i^2 \times slope_i + \rho_6 slope_i^2 + \rho_7 elev_i \times slope_i^2 + \rho_8 elev_i^2 \times slope_i^2$. Column (4) uses a wider bandwidth of 50 dBm and a third degree polynomial specification for $f(\tilde{R}_i)$. Column (5) uses a rectangular kernel. Column (6) estimates a probit specification of Equation (1). Optimal bandwidths chosen as in Calonico et al. (2014) except for column (4) which uses a fixed, wider bandwidth. Standard errors clustered at district level. *, **, and *** indicate 10, 5, and 1 percent significance, respectively.

Table A6: Effect of Coverage on Information Outcomes

	Someone came to:				
	Explain EVD	Hygiene meetings	Bring info (Taskforce)	Explain burials	Information index
	(1)	(2)	(3)	(4)	(5)
Coverage	0.187*	-0.172	0.212**	0.122	0.168
	(0.112)	(0.110)	(0.090)	(0.097)	(0.142)
Control mean	0.874	0.472	0.282	0.174	0.053
Bandwidth (dBm)	12.25	19.18	8.68	11.69	14.19
Observations	346	589	296	328	434
Villages	139	228	86	122	166

Notes: Results present estimates of β using a local linear regression specification of Equation (1) on information variables. The observations are respondents in the survey sample (2016). Optimal bandwidth chosen as in Calonico et al. (2014). The information index is constructed following Kling et al. (2007). Results include controls for elevation and slope. Standard errors clustered at the village level. *, **, and *** indicate 10, 5, and 1 percent significance, respectively.

Table A7: Effect of Coverage on Care Outcomes

	Prevention material	Contact tracing	Take sick	Take dead	Ambulance on-time	CCCs within 10km	Care index
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Coverage	0.054	0.127	0.123***	-0.022	0.217**	0.494**	0.336**
	(0.145)	(0.082)	(0.038)	(0.051)	(0.087)	(0.223)	(0.163)
Control mean	0.745	0.194	0.100	0.070	0.802	0.477	0.027
Bandwidth (dBm)	13.58	7.99	10.76	11.59	10.75	10.43	8.95
Observations	404	251	300	328	331	331	268
Villages	146	77	111	122	111	111	86

Notes: Results present estimates of β using a local linear regression specification of Equation (1) on care variables. The observations are respondents in the survey sample (2016). Optimal bandwidth chosen as in Calonico et al. (2014). The care index is constructed following Kling et al. (2007). Results include controls for elevation and slope. Standard errors clustered at the village level. *, **, and *** indicate 10, 5, and 1 percent significance, respectively.

Table A8: Effect of Coverage on Other Outcomes

	Origin of EVD		Evaluate government response		
	Guinea	Don't know	Quick reaction time	Good health services	Other
	(1)	(2)	(3)	(4)	(5)
Coverage	0.025	0.010	0.205**	0.156	0.064
	(0.10)	(0.13)	(0.08)	(0.11)	(0.06)
Mean outside coverage	0.78	0.78	0.76	0.79	0.77
Bandwidth (dBm)	17.69	16.19	10.52	15.50	7.76
Observations	609	570	269	400	225
Villages	203	189	111	175	77

Notes: Results present estimates of β using a local linear regression specification of Equation (1) on care variables. The observations are respondents in the survey sample (2016). Optimal bandwidth chosen as in Calonico et al. (2014). Results include controls for elevation, slope. Standard errors clustered at the village level. *, **, and *** indicate 10, 5, and 1 percent significance, respectively.