# Community-based Crisis Response: Evidence from Sierra Leone's Ebola Outbreak

Darin Christensen, Oeindrila Dube, Johannes Haushofer,
Bilal Siddiqi, Maarten Voors\*

March 6, 2020 Forthcoming, *AEA Papers & Proceedings* 

In September 2014, the World Health Organization (WHO) described West Africa's Ebola epidemic as "the most severe acute public health emergency seen in modern times. Never before in recorded history has a biosafety level four pathogen infected so many people, so quickly, over such a broad geographic area, for so long." At that point, less than 7,000 individuals had been infected. By the end of the crisis in early 2016, the Centers for Disease Control and Prevention (CDC) estimate more than 28,000 confirmed, suspect, or probable cases; 11,300 deaths; 3.5 billion USD spent on response efforts; and 2 billion USD lost in economic activity. Sierra Leone accounts for roughly half of those cases and just under 4,000 deaths.

Ebola containment efforts emphasize early isolation and treatment. Yet, during the West Africa Epidemic the WHO assumed that many cases were never reported (Enserink 2014). Distrust deterred symptomatic individuals from visiting health facilities: "Local communities were suspicious of efforts to test, treat, and isolate patients with Ebola symptoms and engaged in practices of hiding sick family members, running away from local communities, or attempting to manage the course of Ebola within local households and communities" (Abramowitz et al. 2016, 24).

Post-mortems on the crisis stress that "robust community engagement" helps to build trust and encourage reporting (Kruk et al. 2015, e1910). To assess this oft-repeated claim, we evaluate a large-scale

<sup>\*</sup>Christensen: UCLA, Luskin School of Public Affairs, 337 Charles Young Drive East, Los Angeles, CA 90095, darinc@luskin.ucla.edu; Dube: University of Chicago, Harris School of Public Policy, 1307 E 60th St., Rm. 2015, Chicago, IL 60637, odube@uchicago.edu; Haushofer: Princeton University, 427 Peretsman-Scully Hall, Princeton, NJ 08540, haushofer@princeton.edu; Siddiqi: Center for Effective Global Action, 714B University Hall, Berkeley, CA 94720, bilal.siddiqi@berkeley.edu; Voors: Wageningen University and Research, 6700 EW Wageningen, The Netherlands, maarten.voors@wur.nl. Acknowledgements: We thank the Njala University Museum and Archive for sharing the de-identified data on Ebola cases. We thank Imran Rasul for comments. Moritz Poll, Kevin Grieco, Niccolo Meriggi, Afke de Jager and Mirella Schrijvers provided able research assistance. We gratefully acknowledge funding from NWO grant #451-14-001, ESRC grant #ES/J017620/1, the Royal Netherlands Embassy in Ghana and UCLA's California Center for Population Research.

<sup>&</sup>lt;sup>1</sup>https://www.who.int/mediacentre/news/ebola/26-september-2014/en/, accessed 2 January 2020.

<sup>&</sup>lt;sup>2</sup>https://www.cdc.gov/vhf/Ebola/outbreaks/2014-west-africa/cost-of-Ebola.html, accessed 2 January 2020.

policy effort that involved the construction of Community Care Centers (CCCs) across Sierra Leone in the midst of the country's Ebola outbreak. CCCs where designed to alleviate fears about western medicine and encourage reporting. Using a difference-in-differences research design, and geo-coded data on the number of reported cases (including individuals who test negative for Ebola) in a given week and section,<sup>3</sup> we find that CCCs roughly triple the increase in reported cases, relative to sections without CCCs. We find substantial increases in both the total number of cases, as well as the number of cases that eventually test positive for Ebola (i.e., confirmed cases). This suggests that CCCs increased the isolation of infected patients, a necessary step for containing the outbreak.

These results are consistent with Christensen et al. (2019), who evaluate two randomized accountability interventions that were implemented across government-run clinics in Sierra Leone roughly one year before the Ebola crisis. Their medium-run results from before the crisis show improvements in clinic utilization and the perceived quality of care; amid the subsequent Ebola crisis, these treated areas also saw a large increase in Ebola reporting.

More broadly, our findings contribute to recent work which finds that fear and distrust deter patients from utilizing health facilities (Alsan and Wanamaker 2017; Blair, Morse and Tsai 2017; Vinck et al. 2019; Lowes and Montero 2018).<sup>4</sup>

## 1. Community Care Centers (CCCs)

The initial response to the Ebola outbreak envisioned large-scale facilities, accommodating over 100 patients and capable of enforcing strict biosafety control procedures. Yet, would-be patients viewed these treatment centers with suspicion and refused to report, instead hiding their symptoms and potentially prolonging the epidemic (Mokuwa and Maat forthcoming).

To allay fears and encourage reporting, UNICEF and Sierra Leone's Ministry of Health and Sanitation (MoHS) started to implement the CCC model in mid-October 2014 and built facilities through January. Based on estimates from DFID, a typical CCC cost about 1 million GBP, which funds an eight-bed unit staffed by individuals, who were often recruited from nearby communities and then trained in infection prevention and control.<sup>5</sup> CCCs employed community liaisons and social mobilizers to raise awareness in surrounding areas, resolve misconceptions, and refer patients. According to Abramowitz et al. (2016, 16), the typical message from the liaisons and social mobilizers was "CCC is where you and your loved ones who are sick with Ebola symptoms can receive safe care closer to your home and community."

Ebola prevalence fell from early 2015 in areas outside of the capital, Freetown. The decommissioning

<sup>&</sup>lt;sup>3</sup>Sections are small administrative units in Sierra Leone with a median area of 40 square kilometers. Figure A.1 maps total reported cases in the Viral Hemorrhagic Fever (VHF) database by section.

<sup>&</sup>lt;sup>4</sup>They also relate to Bandiera et al. (2019) which finds that an empowerment program for young women in Sierra Leone increases their capacity to cope with disruptions caused by the Ebola crisis.

<sup>&</sup>lt;sup>5</sup>CCC staff received three days of classroom and practical training in infection prevention and control, onsite training, and two weeks of 24-hour mentorship after the CCC opened. CCCs were then monitored three times per week. Cost estimates drawn from https://devtracker.dfid.gov.uk/projects/GB-1-204896.

of CCCs started in March 2015.

In case studies and field reports, CCCs have been heralded as a success. Michaels-Strasser et al. (2015, 361) conduct an early "rapid cross-sectional [qualitative] assessment" of 11 CCCs in December 2014, and report that CCCs were very quickly established, delivered the expected services, and maintained essential safety measures. Abramowitz et al. (2016) assess CCC's toward the end of the crisis and conclude "CCCs were an effective community-based mechanism to screen for Ebola, triage persons exhibiting signs of illness, and isolate Ebola suspects." (p10) And they specifically address the issue of reporting, writing "By making Ebola care available at the community-level, fear was reduced and communities were more likely to seek care" (p11). This finding is echoed in interviews conducted by Pronyk et al. (2016) and Mokuwa and Maat (forthcoming).

### 2. Data and Research Design

We employ two sources of data. First, data on the locations of 41 CCCs from the UN Mission for Ebola Emergency Response (UNMEER) (see Figure A.1).

Second, we construct panel data on the number of reported cases — including cases that will return both positive and negative lab tests for Ebola — in every week and section from August 2014 through February 2015. These case counts are derived from the Epi Info Viral Hemorrhagic Fever (VHF) database, which comprised the primary data management system for case and contact tracing during the outbreak, implemented and maintained by the Ministry of Health and Sanitation, with support from the CDC. Officers employed (even prior to the crisis) by the MoHS oversaw teams of case investigators charged with following up on suspected cases. Investigators learned about cases through walk-ins at health centers, active surveillance (e.g., contact tracing), and outreach to communities (Owada et al. 2016). For each reported case, they completed a Case Investigation Form (CIF), which included demographic (including district, chiefdom, and village) and health information. Completed CIFs were brought back to District Ebola Response Centers and entered by data managers in the local VHF database. Each observation in our data represents one of these CIFs.

We geocode cases using information on individuals' residence included in the VHF database (typically, district, chiefdom, section and village or parish). We use a fuzzy matching algorithm (to permit alternative spellings) to search gazetteer files of placenames in Sierra Leone, using Open Street Map (OSM, see full geocoding protocol in the online appendix). Below we use data from 1,316 sections over 30 weeks. Our main dependent variables are the count reported cases, either all cases or confirmed cases that test positive for Ebola.

Exploiting this panel data, we employ a difference-in-differences design, estimating the differential change in reported cases in sections that do and do not host CCCs, before and after the start of CCC imple-

<sup>&</sup>lt;sup>6</sup>We use de-identified data (where patient names and characteristics have been redacted) from the Njala University Ebola Museum and Archive.

<sup>&</sup>lt;sup>7</sup>We use the date when a case first appears in the VHF database to determine the week interval. Data excludes Waterloo Rural in the Western Area, a peri-urban section that received three larger CCCs with over 50 total beds.

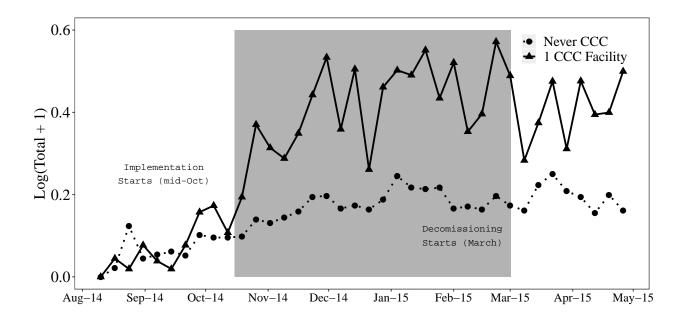


Figure 1: Trends in Total Cases by CCC Presence

*Note:* Using UNMEER data, we identify those sections that eventually contain one CCC. We then compute the average number of total cases (logged) in sections that do and do not receive a CCC in each week from 10 August 2014 to 1 May 2015. The grey area starts with CCC implementation in mid-October 2014 and ends with their initial decommissioning in March 2015

mentation. Specifically, we estimate two models:

$$y_{st} = \alpha + \kappa CCC_s + \delta Post_t + \beta D_{st} + \varepsilon_{st}$$
 (1)

$$y_{st} = \alpha_s + \gamma_t + \beta D_{st} + \varepsilon_{st} \tag{2}$$

where  $s \in \{1,2,...,1316\}$  indexes sections,  $t \in \{1,2,...30\}$  weeks, and  $D_{st}$  ( $CCC \times Post_t$ ) is an indicator for whether a section contains a CCC after 15 October 2014, which we use to approximate the start of implementation in "mid-October." Equation (1) is a simple two-group-two-period model; in Equation (2) we include section fixed effects ( $\alpha_s$ ) and week fixed effects ( $\gamma_t$ ). We employ several functional forms as a robustness check, logging the counts (adding one to avoid dropping section-weeks with no cases), using a inverse-hyperbolic sine transformation, and running a linear probability model for whether any cases were reported (see Table B.1). Across models, we cluster our standard errors at the section level.

The key identifying assumption is that trends in the sections that do and do not host CCCs would have remained parallel absent implementation. We bolster this assumption through a series of placebo tests that employ data prior to implementation and look for differential pre-treatment trends in reporting (see Table B.2).

	Total	Cases	Confirmed Cases		
	(1)	(2)	(3)	(4)	
Cases					
$CCC \times Post(D_{st})$	0.544 (0.173)***	0.544 (0.176)***	0.129 (0.058)**	0.129 (0.06)**	
Log(Cases + 1)					
$CCC \times Post(D_{st})$	0.237 (0.056)***	0.237 (0.057)***	0.041 (0.02)**	0.041 (0.02)**	
Section FEs Week FEs		1,316 30		1,316 30	
Observations	39,480	39,480	39,480	39,480	

Table 1: Effect of CCC on Confirmed and Total Cases

*Note:* Standard errors clustered on section shown in parentheses. Models 1 and 3 estimate Equation (1) using OLS; models 2 and 4 estimate Equation (2), which includes section and week fixed effects. Each row corresponds to a different transformation of the dependent variable: raw case counts and logged case counts (plus one). Significance: \*p < 0.10, \*\*p < 0.05, and \*\*\*p < 0.01.

### 3. Results

Our main result is apparent in Figure 1: while trends are parallel prior to CCC implementation, we see a large uptick in reported cases (logged) in sections hosting CCCs relative to control. Prior to implementation, the average number of cases in sections that eventually hosted a CCC was 0.14, compared to 0.28 in control. Between 15 October 2014 and the end of February 2015, the average jumps to 0.94 in sections hosting CCCs but increases to only 0.54 in control. That represents over a close to seven-fold increase in sections with CCCs, compared to just a doubling in control sections. When we focus attention on confirmed cases — which are of special interest for containment — we find the same divergent increase following the implementation of CCCs (see Figure A.2). Yet, there is a fall off in confirmed cases across all sections in early 2015, as Ebola prevalence fell across rural Sierra Leone and concentrated in the capital, Freetown.

Table 1 presents our estimates from Equations (1) and (2) using both total and confirmed cases as outcome measures. We find that CCCs substantially increase reported cases, both total and confirmed cases. This holds for both outcomes, across equations, and using different functional forms. In raw numbers, while the number of confirmed cases actually falls by 13 percent in control sections, reports of confirmed cases increase by over 140 percent in sections with CCCs.

We run a series of placebo tests to assess whether trends in the two groups of sections are parallel prior to treatment (see Table B.2). These tests are consistently small in magnitude: our actual estimate is four times larger than the maximum placebo coefficient. Field reports indicate that CCCs were not sites of nosocomial transmission; the increase in cases reflects greater reporting, not a heightened incidence of Ebola. Pronyk et al. (2016) argue that CCCs reduced the reproduction rate of the virus by between 13 and 32 percent.

<sup>&</sup>lt;sup>8</sup>CCCs are not co-located with other specialized treatment facilities (e.g., Ebola Treatment Units) in the UNMEER data. Our results are robust to dropping the one section in our sample that contains a CCC and another type of facility.

### 4. Discussion

A recent report by the Lancet Global Health Commission argues that patients' trust in providers contributes to the resiliency of health systems. "Trust is essential for maximizing outcomes because it can motivate active participation in care — i.e., adherence to recommendations and uptake of services, including in emergencies" (Kruk et al. 2018, e1201). Effectively responding to public health crises requires not just international coordination of humanitarian resources, but also localized efforts to engage and build confidence in the communities most directly affected by crisis.

While this claim has featured among "lessons learned" from the West African Ebola Crisis, it has not been rigorously evaluated. To help fill that gap, we evaluate the impacts of Community Care Centers — a new model of crisis response that stressed community engagement, recognizing the need to overcome fears and build trust. CCCs did not boast the equipment or specialized personnel of larger treatment centers; the model, instead, employed local staff and community liaisons to close the physical and social distance between patients and providers.

While CCCs have been heralded as a success, existing qualitative work and field reports do not consider or attempt to estimate how the outbreak might have progressed absent the intervention. Employing new panel data on reported cases and a difference-in-differences design, we find that CCCs dramatically increased reporting, including by infected patients.

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# **Supporting Information**

Community-based Crisis Response: Evidence from Sierra Leone's Ebola Outbreak

Following text to be published online.

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# A. Appendix Figures

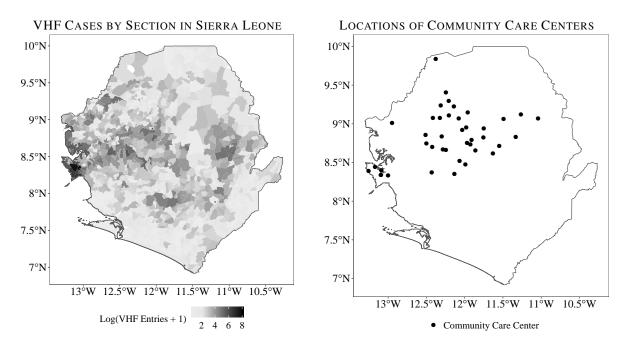


Figure A.1: Map of Reported Cases and Community Care Centers

*Note:* Left: the number of cases (logged) by section in the Viral Hemorrhagic Fever (VHF) database maintained by the CDC during the Ebola crisis. Right: the locations of Community Care Centers using data from UNMEER accessed through Humanitarian Data Exchange.

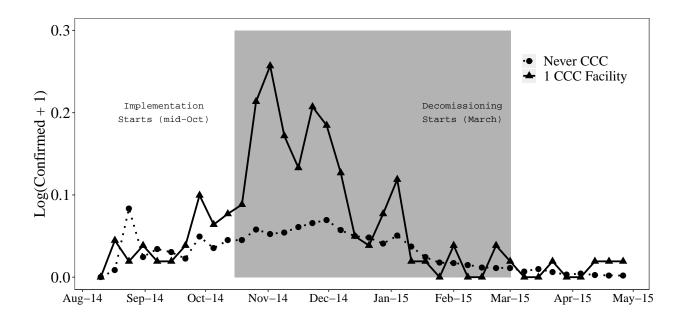


Figure A.2: Trends in Confirmed Cases by CCC Presence

*Note:* Using UNMEER data, we identify those sections that eventually contain one CCC. We then compute the average number of confirmed cases (logged) in sections that do and do not receive a CCC in each week from 10 August 2014 to 1 May 2015. The grey area starts with CCC implementation in mid-October 2014 and ends with their initial decommissioning in March 2015

# **B.** Appendix Tables

	Total Cases		Confirmed Cases		
	(1)	(2)	(3)	(4)	
Inverse-hyperbolic Sine(Ca	uses)				
$\operatorname{CCC} \times \operatorname{Post}(D_{st})$	0.307 (0.072)***	0.307 (0.074)***	0.053 (0.026)**	0.053 (0.026)**	
1(Cases > 0)					
$\operatorname{CCC} \times \operatorname{Post}(D_{st})$	0.201 (0.041)***	0.201 (0.041)***	0.038 (0.017)**	0.038 (0.018)**	
Section FEs Week FEs Observations	39,480	1,316 30 39,480	39,480	1,316 30 39,480	

Table B.1: Effect of CCC on Total Cases: Alternative Specifications

Note: Standard errors clustered on section shown in parentheses. Models 1 and 3 estimate Equation (1) using OLS; models 2 and 4 estimate Equation (2), which includes section and week fixed effects. Each row corresponds to a different transformation of the dependent variable: inverse-hyperbolic sine and a linear probability model. Significance: \*p < 0.10, \*p < 0.05, and \*p < 0.01.

		Log(Total Cases + 1)								
Placebo Dates:	Start	Aug-17	Aug-24	Aug-31	Sep-07	Sep-14	Sep-21	Sep-28	Oct-05	Actual Oct-15
CCC × Placebo Date	Start	0.007 (0.029)	-0.006 (0.022)	0.048 (0.026)*	0.031 (0.029)	0.038 (0.033)	0.060 (0.041)	0.060 (0.050)	0.048 (0.050)	0.237 (0.057)***
Section Fl Week FEs Observation		1,316 10 13,160	1,316 30 39,480							

Table B.2: Placebo Tests for CCC Analysis

Note: Standard errors clustered on section shown in parentheses. Significance: \* p < 0.1, \*\* p < 0.05, \*\*\* p < 0.01. Table displays estimates of Equation (2) using OLS, where the placebo CCC starting date is indicated in each column.

# C. Geo-coding Procedure

The VHF data includes information on individuals' residences, including their district, chiefdom, and village or parish. We use this information to place observations within sections. Our geo-location protocol involves several steps. First, a human coder inspected and cleaned all district and chiefdom names that did not exactly match the conventional spelling. Of 85,410 entries in the case data, we can code the chiefdom of residence for 97% of observations.

Second, we employ fuzzy string matching to match the available village or parish names to gazetteer files of placenames from Sierra Leone. Fortunately, in the chiefdoms that include our sample, only 14 confirmed, suspected, or probable Ebola cases do not include village or parish information. We employ the gazetteer file from Open Street Map (www.openstreetmap.org/), which includes 9,975 entries, ranging from hamlets to cities. We prefer this list to the 2004 census data from Sierra Leone, which only provides names for around 5,000 localities. Moreover, during the Ebola epidemic, Open Street Map mounted a humanitarian effort aimed at updating and verifying information on the locations of villages and roads in Sierra Leone. 10

Ten sample entries from OSM gazetteer file:

	osm_id	name	C	pordinates
1	27565056	Freetown	(-13.26802	8.479002)
2	314001434	Во	(-11.73665	7.962065)
3	314005602	Kenema	(-11.18639	7.885936)
4	314007819	Koidu	(-10.97163	8.642281)
5	320058940	Kambia	(-12.91934	9.125073)
6	320060481	Kamakwie	(-12.24125	9.496301)
7	320060535	Pujehun	(-11.72124	7.356632)
8	320060540	Zimmi	(-11.31032	7.312338)
9	370327499	Goderich	(-13.28887	8.432966)
10	370495828	Murray Town	(-13.26534	8.491613)

Fuzzy string matching calculates the string distance between each village or parish name in the VHF data and each placename in the gazetteer file that falls within the exact same district and chiefdom. An exact match returns a distance of zero; "FREE TOWN" and "FREETOWN," for example, would return a distance of 1. We do not match any entries with a string distance that exceeds 2.

<sup>&</sup>lt;sup>9</sup>Of all entries in the case data that fall within the chiefdoms the include our sample, only 0.07 percent are missing an entry for village or parish of residence.

<sup>10</sup>http://wiki.openstreetmap.org/wiki/2014\_West\_Africa\_Ebola\_Response

<sup>&</sup>lt;sup>11</sup>We use optimal string alignment distance, a variant of the Levenshtein distance, which is commonly employed in geo-coding algorithms.