One for all, all for One Health

Assessing the impact of installing joint human-animal disease surveillance on the reporting performance of Community Health Workers in Sierra Leone

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Abstract

The recent Ebola Virus Disease outbreak demonstrated that Sierra Leone is at risk for the spread of zoonotic diseases due to its weak health system. The existing network of Community Health Workers (CHWs), in charge of monitoring and reporting on human health events in their communities, was insufficient to prevent, detect or halt the outbreak. This master's thesis focusses on improving the reporting capacity of CHWs in the One Health project, a project implemented in cooperation with the Sierra Leonean Ministry of Agriculture, Forestry and Food Security and the Ministry of Health and Sanitation. The project elects, trains and installs Community Animal Health Workers (CAHWs) to provide basic animal health services to their communities, trains CHWs and CAHWs on joint disease surveillance and installs a community One Health committee. This thesis exploits the random assignment of communities to the One Health project to estimate the impact of the One Health program on the reporting behavior of 88 CHWs in two chiefdoms. We construct measures for timeliness and quality of surveillance reports and hypothesize that engaging CHWs in a One Health approach will improve their disease reporting performance. We find that CHWs in treatment communities submit significantly more reports compared to their counterparts in control communities, without compromising the quality of the submitted reports. Our results suggest that surveillance performance can be enhanced by a holistic approach, engaging all health actors in a community through training and increased coordination.

Keywords*: One Health, community-level disease surveillance, Community Health Workers, Community Animal Health Workers, disease reporting*

Table of contents

List of figures

List of tables

Abbreviations

CAHW	Community Animal Health Worker
CBS	Community-Based Surveillance
CHW	Community Health Worker
DHMT	District Health Management Team
EVD	Ebola virus disease
iCCM	Integrated Community Case Management
IRC	International Rescue Committee
MAFFS	Ministry of Agriculture, Forestry and Food Security
MoHS	Ministry of Health and Sanitation
PHU	Peripheral Health Unit

1. INTRODUCTION

Human and animal livelihoods and wellbeing are inextricably interlinked, especially in resource-constrained environments (FAO, 2002). This human-animal interface encourages the emergence of zoonoses, diseases that are transmitted from animals to humans. About 60% of all emerging infectious diseases are zoonotic and a significant share of these pathogens (71.8%) originate in wildlife species (Jones et al., 2008). The prevalence of zoonoses is predicted to increase due to population growth, climate change, deforestation and associated bush meat hunting (Mwangi, de Figueiredo, & Criscitiello, 2016; Wolfe, Daszak, Kilpatrick, & Burke, 2005). In addition to their impact on human morbidity and mortality, animal diseases negatively impact the livelihoods of communities depending on livestock as a source of nutrition, income or saving mechanism (Pieracci et al., 2016).

The Ebola virus disease (EVD) is one example of a zoonotic disease that is being transmitted from fruit bats to humans (Leroy et al., 2005). The 2013-2015 EVD epidemic in West Africa exposed the vulnerability of public health systems as the disease surveillance system in place was unable to timely identify and respond to the outbreak (Kieny & Dovlo, 2015; Mwangi et al., 2016; Nyatanyi et al., 2017; Woolhouse, Rambaut, & Kellam, 2015). Moreover, the lack of an effective disease surveillance system is identified as one of the factors that exacerbated the outbreak, causing a delayed detection and severe underreporting of cases (Tambo, Ugwu, & Ngogang, 2014; Woolhouse et al., 2015). The EVD crisis clearly demonstrated that innovations in the current approach to public health surveillance are much-needed (Kieny & Dovlo, 2015).

As part of their post-Ebola agenda, the Government of Sierra Leone has acknowledged the importance of a well-functioning disease surveillance system that monitors both human and animal health in their environmental context. To promptly detect, monitor and respond to future disease outbreaks, a One Health disease surveillance system is installed. One Health is a holistic system in which different disciplines, operating at different levels, collaborate for the health of all (Association AVM, 2008; Gibbs, 2014; The World Bank, 2012). One Health is high on the global health agenda, with initiatives involving disease surveillance, integrated research, disease control and health policies (Baum, Machalaba, Daszak, Salerno, & Karesh, 2017; Mwangi et al., 2016).

The former system of disease surveillance in Sierra Leone relies on Community Health Workers (CHW) to administer basic treatment of human diseases and to report health events at the community level. The One Health project trains and installs a Community Animal Health Worker (CAHW) to work alongside the CHW, including an animal component in the community health disease surveillance. Above that, the projects brings CHWs and CAHWs together for a workshop on joint disease surveillance and installs a One Health committee in the community. In developing countries, CAHWs are frequently used for service delivery and animal health surveillance at the community-level. There is evidence of CAHWs being beneficial to livestock health and mortality (Admassu et al., 2005; Catley et al., 2009; Peeling & Holden, 2004), rural livelihoods (Mugunieri, Irungu, & Omiti, 2004; Peeling & Holden, 2004) and animal disease reporting (Allport, Mosha, Bahari, Swai, & Catley, 2005; Stratton et al., 2017).

Despite increasing attention for the One Health concept, there is still a large discrepancy between systematically documented outcomes of interventions and the perceived potential of a One Health approach (Baum et al., 2017; Hueston et al., 2013; Lapinski, Funk, & Moccia, 2015; Rostal et al., 2018). Luckily, efforts to generate empirical evidence are increasing. In the literature, several studies report outcomes of One Health disease surveillance and control on human and animal health outcomes, disease identification and health knowledge (Berrian et al., 2018; Häsler et al., 2014; Jean-Richard et al., 2014; Masthi, Narayana, Kulkarni, Gangaboraiah, & Belludi, 2014; Rostal et al., 2018; Roth et al., 2003; Sripa et al., 2015; The World Bank, 2012; Zinsstag & Tanner, 2008). This master's thesis adds to this growing body of evidence on the effectiveness of One Health disease surveillance by estimating the impact of a One Health project on CHW reporting performance. To the best of our knowledge, this study is the first to document the impact of a One Health approach on the performance of CHWs.

The Ministry of Health and Sanitation (MoHS), together with the Ministry of Agriculture, Forestry and Food Security (MAFFS) and partners from Wageningen University and Njala University are implementing a pilot One Health project in Kono district in Eastern Sierra Leone. The project trained and installed CAHWs in 287 communities that were randomly selected from a set of 363 communities with an existing CHW. 63 communities serve as a control group. The One Health intervention consists of CAHW selection, a 21-day training on basic animal health care for the selected CAHWs, a 2-day One Health workshop attended by the CHW and CAHW, installation of the CAHW in the community and the creation of a One Health community platform. The overall aim of the project is to improve disease surveillance and human and animal health outcomes.

One potential channel through which community health can be affected by the One Health program is by altering the performance of CHWs. In the literature, CHW characteristics, financial and non-financial incentives, training, peer relationships and community engagement are all identified channels influencing health workers' performance. This project can improve CHW performance by selecting and adding an additional health worker to the community, by training both health actors on joint disease surveillance and by installing a One Health platform in the community.

This thesis aims to provide a first assessment of the impact of the One Health project on CHW reporting performance in two chiefdoms. We assess the impact of the program on reporting timeliness, non-empty reports, coverage, completeness and coherence by exploiting the random assignment of treatment to communities. Above that, we provide an insight into the general characteristics related to CHW reporting performance.

CHWs file reports that guide health system priorities and help detect emerging diseases. Achieving high-quality data is essential. CHW data can suffer from over- or underreporting of community health issues and data aggregation at different levels could add to poor data quality. To date, only few studies have assessed the quality and factors affecting data collected and reported by CHWs. In order to assess the reporting behavior of these CHWs in a One Health project, we have been collecting and digitizing CHW registers in two chiefdoms that are part of the One Health pilot project. Monthly registers of 88 CHWs between May 2017 and April 2018 are included in this research.

We find that the One Health project significantly improves CHWs' reporting performance: CHWs in treatment communities are 9 percentage points more likely to submit a register compared to CHW that are not part of the One Health project. This corresponds to a 19% increase from the control group mean. We also find community size and residency of the CHW in the community to be positively and significantly correlated with the number of submissions. The number of CHWs per PHU and the distance between the community and PHU is negatively and significantly correlated with report submission. We also find that the quality of the submitted reports is not affected by treatment status. There is large scope for improving quality of the submitted reports.

This thesis contributes to two strands of literature. First, it contributes to the growing body of evidence on the impact of a One Health approach. To date, very few studies have assessed the impact of a One Health community-level approach to disease surveillance and to the best of our knowledge, no study assessed the impact of One Health on CHWs' reporting performance. Second, this thesis contributes to the literature on the effectiveness and usefulness of health workers operating at the community level. To date, very few studies provide evidence on factors affecting CHWs reporting behavior. Above that, this research is highly relevant for policy makers in Sierra Leone, as the government is working hard to improve the current disease surveillance system and this research could provide a first insight into the outcomes of the pilot project.

The remainder of this thesis is organized as follows. Chapter 2 introduces the literature on One Health and factors affecting CHWs' performance and outlines the research hypotheses of this thesis. Chapter 3 outlines the One Health intervention and dives deeper into the current disease surveillance system in Sierra Leone. Chapter 4 contains the methodology and results, followed by a conclusion and discussion in Chapter 5.

2. ONE HEALTH AND CHW PERFORMANCE

2.1 Literature

The realization that most emerging infectious diseases originate from animals has led to a radical paradigm shift amongst health practitioners. Worldwide, human and animal health experts are advocating a One Health approach to improve the health of humans, animals and the environment they share (Gibbs, 2014; Hueston et al., 2013; Lapinski et al., 2015; Stärk et al., 2015; Zinsstag et al., 2009; Zinsstag, Schelling, Waltner-Toews, & Tanner, 2011). One Health can be thought of as a holistic framework for "*interdisciplinary and trans-disciplinary thinking about complex systems* (Lapinski et al., 2015, p. 59)". It encompasses the collaborative effort of various disciplines working at the local, national and global level intending to reach optimal health for people, animals and the environment (Association AVM, 2008; Gibbs, 2014; The World Bank, 2012).

Integrating human and animal health is not a novel phenomenon. In the 19th century, universities introduced comparative medicine after discovering similar disease processes in humans and animals (Zinsstag et al., 2011). A century later, Schwabe (1984) introduced the concept of "One Medicine" to capture the equality between human and animal sciences in terms of anatomy, physiology, pathology and disease origin. "One Medicine" was later extended to "One Health" by linking ecosystem health to human and animal health and wellbeing (Lapinski et al., 2015; Zinsstag et al., 2011).

In recent decades, "One Health" is in the center of attention, with a multitude of initiatives like stakeholder conferences and scientific debates promoting a transdisciplinary approach to research, surveillance, disease control and policy making (Baum et al., 2017; Hueston et al., 2013; Zinsstag et al., 2009). For example, One Health has been institutionalized in ministries (Ministry of Health and Sanitation, 2017), international organizations (Food and Agriculture Organisation/World Animal Health Organisation/World Health Organisation, 2008), academic curricula (Muma et al., 2012), journals (Osterhaus & MacKenzie, 2016) and research platforms (Jansen et al., 2016). Academics are advocating the extension of the One Health concept by introducing social sciences in One Health (Binot et al., 2015; Lapinski et al., 2015) and deeper involvement of Environmental Health Practitioners (Musoke, Ndejjo, Atusingwize, & Halage, 2016; Zinsstag et al., 2011). So far, the concept of One Health has primarily been used to stimulate interaction in research at the highest levels (Davis et al., 2017; Lebov et al., 2017). However, a combined approach to human and animal health can also be extended to the work of local health workers operating at the community level.

Given the wide array of One Health initiatives undertaken in recent decades, some success stories have been achieved, both globally and regionally. The majority of the established One Health initiatives focusses on treating infectious diseases in the human-animal interface (Hueston et al., 2013). Examples are the 2006 international response to Avian Influenza, the eradication of rinderpest worldwide and the local eradication of swine fever and foot and mouth disease (Gibbs, 2014; Rushton, Häsler, De Haan, & Rushton, 2012). Next to effectively responding to zoonoses, One Health is expected to be an efficient approach to disease prevention and control. The World Bank estimated that a global One Health approach to pandemic prevention could potentially lead to costs savings of up to US$30 billion per year, a number that far exceeds investment costs (The World Bank, 2012).

Despite increasing attention for the One Health concept, there is still a large discrepancy between systematically documented outcomes of interventions and the perceived potential of the approach (Baum et al., 2017; Hueston et al., 2013; Lapinski et al., 2015; Rostal et al., 2018). Luckily, efforts to generate empirical evidence on the impact of One Health projects are increasing. Broadly speaking, One Health interventions can be categorized in interventions with a focus on disease control and interventions with a focus on disease prevention. The former has the potential to reduce the costs of diseases by reducing the overlap between different sectors (Baum et al., 2017; The World Bank, 2012), while the latter avoids losses ex ante by avoiding outbreaks or decreasing the time to detect the disease (Narrod, Zinsstag, & Tiongco, 2012; Rushton et al., 2012; Zinsstag & Tanner, 2008).

One Health projects aiming at disease control are implemented and assessed in a diverse range of situations. In some cases, health interventions focusing on animals led to better control of human health risks. In Mongolia, for example, a large-scale livestock vaccination campaign to control Brucellosis proved to be a highly cost-effective strategy to improve human health (Roth et al., 2003). In other cases, a collaboration of human and animal health services led to more efficient disease control. For example, in Sri Lanka, an interdisciplinary rabies control program led to a significant reduction in rabid dogs, large gains in Disability-Adjusted Life Years due to avoiding human rabies deaths and increasing social acceptance of dogs, compared to the baseline scenario (Häsler et al., 2014). In India, increasing awareness and introducing free pre- and post-exposure rabies vaccines led to a 30% decrease in animal bite/exposure cases, compared to a control group (Masthi et al., 2014). In Thailand, A One Health intervention consisting of anthelmintic treatments, health education in communities and schools, environmental monitoring and community participation led to a 33% decline of Human Liver Fluke (Sripa et al., 2015). A final set of studies consist of cases where close cooperation between different sectors led to an improved diagnosis of diseases. In Mauritania, closer cooperation between human and animal health agents led to a shift from improper identification of Yellow Fever to the correct diagnosis of Rift Valley Fever (Zinsstag & Tanner, 2008). In Sub Saharan Africa, seroprevalence simulations demonstrated that an integrated collaboration improved the probability of detecting Rift Valley Fever, compared to two separate approaches (Rostal et al., 2018). In Madagascar, a multi-ministry approach enhanced the prognosis and mapping of Rift Valley Fever Outbreak (The World Bank, 2012).

The second set of studies focusses on One Health surveillance systems to improve human and animal health. One Health disease surveillance is defined as "*the systematic collection, validation, analysis, interpretation of data and dissemination of information collected on humans, animals and the environment to inform decisions for more effective, evidence- and system-based health interventions* (Stärk et al., 2015, p. 125)". An effective, resilient and holistic One Health surveillance system has the potential to timely predict, prevent and control disease outbreaks. However, a well-functioning disease surveillance system should bridge the gap between the communities and the local health system (World Health Organization, 2014). Community-based surveillance allows villagers to actively contribute to the monitoring, detection, reporting and treatment of health events in the community (World Health Organization, 2014). Communities can and should play a key role in disease surveillance in low-resource settings for several reasons. First of all, community members are often outstanding observers of the health and wellbeing of animal and humans within the local context (Dickmann, Kitua, Apfel, & Lightfoot, 2018; Zinsstag et al., 2009). Secondly, enhancing community participation can be a useful strategy to deal with the often insufficient state capacity and the lack of human resources that prohibit qualified human and animal health personnel to operate at the lowest level (Goutard et al., 2015; Zinsstag et al., 2009). Third, Reshaping the role of communities and putting them at the center of disease response makes them active managers of the issues affecting their well-being, rather than victims (Dickmann et al., 2018). Mobilizing communities for disease surveillance in a One Health approach has been documented in a limited number of cases. A mobile phone surveillance system for Chadian pastoralist households and their livestock proved to be a promising and cost-effective strategy to improve human and animal health among nomadic populations (Jean-Richard et al., 2014). In South-Africa, a community-engaging One health approach trained local facilitators to hold community workshops on infectious disease risk assessment and mitigation skills. After the intervention, test scores amongst facilitators and participants increased significantly and 98% of the workshop participants implemented at least one risk mitigation strategy (Berrian et al., 2018).

Theoretically, community-based surveillance is a promising strategy to prevent, detect and treat diseases at the village level and consequently minimize the economic impact and public health hazards resulting from epidemics (Goutard et al., 2015). However, effective systems for disease surveillance at the community level are very often not in place. Assessments of existing community-based disease surveillance systems in West-Africa demonstrate that these systems are not ready to deal with severe disease outbreaks like the EVD outbreak for several reasons (Adokiya, Awoonor-williams, Beiersmann, & Müller, 2015; Stone et al., 2016). First, current disease surveillance systems often produce data of poor quality and reliability. Research shows that community-level health data are often of sub-optimal quality and that delayed, incomplete or biased reporting impedes the usefulness of community-level data for program management (Goutard et al., 2015; Mitsunaga et al., 2013; Ratnayake et al., 2016). Secondly, there is no system in place to monitor animal health. In order to empower communities to engage in effective surveillance and response activities, local health workers need to be trained in a One Health approach (World Health Organization, 2014).

The government of Sierra Leone recognized these deficiencies and is now setting up a One Health community-based surveillance system. In this pilot project, CAHWs are trained to work alongside CHWs with the aim to have a system in place that can both prevent and treat human and animal diseases. The project includes multiple components: CAHW selection, a 21-day CAHW training, a 2-day One Health workshop attended by the CHW and CAHW, installation of the CAHW in the community and the creation of a One Health community platform. The overall aim of the project is to improve disease surveillance and human and animal health outcomes. This research aims to evaluate the effect of the One Health approach on Community Health Workers' reporting quality and quantity.

For decades now, CHWs have played a crucial part in delivering health services to the community and, that way, addressing the shortage of health staff in developing countries. Despite large differences in CHWs' demographics all over the world, they are often characterized as low-educated community members that are trained to provide health services to the communities they reside in (The Lancet Global Health, 2017). Their tasks and required skillset depend on the specific program but very often involve health education, community mobilization, and disease prevention, reporting and treatment. CHW's reporting performance is of crucial importance for several reasons. First, reporting performance can give a general idea about CHWs' overall performance. Second, for reports to be useful for monitoring, management and evaluation of CHW programs, they need to be of reasonable quality. Third, good quality community-level data can aid to detect priorities for care provision and identify emerging health issues, which is crucial in the context of emerging infectious diseases.

To date, only few studies have assessed the quality of, and the factors affecting data collected and reported by health workers (Mitsunaga et al., 2013). Studies assessing the performance of village health workers in providing frequent and high-quality data for disease surveillance provide mixed evidence. Stratton et al. (2017) find that Village Animal Health Workers in Cambodia have high rates of disease reporting. About 70% of surveyed Village Animal Health Workers report to have contacted the district or provincial officer at least once a month. On the contrary, a study in Uganda revealed worrisome discrepancies between the accuracy of data generated by CAHWs and serological results (Jost, Stem, Ramushwa, Twinamasiko, Mariner, 1998).

In Rwanda, assessed reports generated by CHWs were of variable quality with the main pitfall being erroneous data aggregation (Mitsunaga, 2014). In Pakistan, less than half of the revised monthly Lady Health Worker reports were scored as accurate; moreover, 35% of the reports contained erroneous information. There is severe over- and underreporting of immunization status of children (in 40% of reports), maternal (12,5%) and infant deaths (10%) (Mahmood & Ayub, 2010). In Kenya, a test/retest method revealed that reliability of the data collected by CHWs is conditional on the type of indicator; for example, data on maternal and environmental health were more reliable than data on child health or the use of bed nets (Otieno, Kaseje, Ochieng, & Githae, 2012). According to Mahmood & Ayub (2010), several factors obstruct good quality data. A first obstacle are inappropriate instruments, a variety of different registers and hand-written forms. A second factor that could induce overreporting, is the belief among health workers that repercussions would follow, if a certain standard is not obtained. A possible third barrier are weak supervision and a lack of incentives. A final barrier consists of the large work load resulting in time pressure.

In the literature, evidence is provided on several factors that affect the performance of health workers. The treatment, consisting of multiple components, was implemented as one entity. Therefore, there is no possibility to identify the treatment effects of every separate component – CAHW selection and training, One Health workshop, installation in the community and the creation of a One Health committee. It is likely that the treatment may have changed CHW performance through several plausible channels, which we outline below. Identified channels are often interrelated.

First, both financial and non-financial incentives are found to impact public service provision in a variety of contexts (Finan, Olken, & Pande, 2015). There are papers documenting that wage deduction, a pay-for-performance scheme or financial rewards were able to improve performance in the delivery of health care (Banerjee, Duflo, & Glennerster, 2008; Basinga et al., 2011; G. Miller et al., 2012). Non-financial incentives, such as provision of career prospects, intrinsic motivation or improved self-esteem are found to affect service provision (Finan et al., 2015).

Prospects of a future career can affect the type of workers self-selecting in for the job. For example, Ashraf, Bandiera, & Lee (2016) found that advertising different characteristics (social impact or career opportunities) for the job position of Community Health Assistant, attracted different types of workers which affected workers' performance and eventually health outcomes in the communities. They found that applicants motivated by career advancement and job promotion were equally motivated, but more qualified compared to applicants motivated by the social dimension of the job. In terms of delivering health services, agents attracted by career incentives largely outperformed the group attracted by "doing good" (Ashraf et al., 2016). Evidence on the effect of career prospects on performance is documented in other sectors too. For example, among Indian civil servants, promotion prospects and career incentives positively influenced effectiveness and performance (Bertrand, Burgess, Chawla, & Xu, 2016).

Next to career prospects, intrinsic motivation is found to affect an agent's performance. Intrinsically motivated workers typically work better. In a field experiment among public health promotors in Zambia, intrinsic rewards work as a motivating factor (Ashraf, Bandiera, & Jack, 2014). In this study, hair dressers and barbers are recruited to promotive HIV prevention by selling condoms. Clusters are randomly assigned to one of two financial incentive schemes (a 10% or 90% margin on condom sales), a non-financial reward scheme (a publicly displayed chart showing their sales performance using stars), or a control group. The evidence for the non-financial reward schema is overwhelming as agents in the star-treatment are found to sell double the amount agents in other treatment arms sell. The One Health intervention could change the perception over the contribution to a public good (and consequently motivation for the bigger cause) by adding an additional health worker to the community.

Another factor that is found to influence CHW performance is self-esteem (Kok et al., 2015). For example, in India, about a third of the Accredited Social Health Activists reported improvements in self-esteem as a major motivating factor (Srivastava et al., 2009). In Ghana and Uganda, community volunteers reported to be motivated by the respect from the community and a sense of pride for their work (Dil, Strachan, Cairncross, Korkor, & Hill, 2012; Jack, Kirton, Birakurataki, & Merriman, 2012). The One Health intervention could affect CHWs' self-esteem by assigning an additional Health Worker to their community. Job satisfaction, for example as a consequence of increased recognition or self-confidence in skills, could also affect performance (Dieleman & Harnmeijer, 2006).

Second, employee development through training is an important determinant of motivation, job satisfaction and performance amongst CHWs (Kok et al., 2015). In organizations, training can affect performance by improving skills and capabilities, but also employee motivation and commitment (Elnaga & Imran, 2013). Several studies identified the importance of training modules for CHW performance. For example, in Pakistan, Traditional Birth Attendants receiving an 8-day training significantly outperformed untrained Attendants (Miller, Rashida, Tasneem, & Haque, 2012). In Madagascar, the performance of Community Health Volunteers working on reproductive health and family planning was correlated with refresher training, while no significant correlation was found among Volunteers working on community case management of childhood illnesses (Smith et al., 2013). In the One Health intervention, CHWs and CAHWs are invited to attend a two-day workshop on joint human-animal disease surveillance, which could affect their performance.

Third, peer relations affect performance. The CAHW is expected to form a One Health team together with the CHW(s) in his community. Introducing an additional health worker to the community could lead to collaboration, imitation, social comparison or competition, which could affect performance. Forming an interdisciplinary team of health workers does not guarantee good performance. Successful teams need clear goals, mutual commitment, coordination, communication and coaching (Dieleman & Harnmeijer, 2006; Stephen & Stemshorn, 2016). Several field studies in different contexts document the gains from convening workers into team. Overall, the evidence suggests that peers successfully pressure each other into better performance (Lazear & Oyer, 2009). In a steel mill, Boning, Ichniowski, & Shaw (2007) find that firms organizing in teams and providing group-based financial incentives are much more productive. In supermarkets, the introduction of highly productive employees is found to spillover to the effort of peers. The highest gains in productivity are obtained when clerks see each other working, pointing to the importance of social pressure (Mas & Moretti, 2009). In the health sector, English nurses working in interdisciplinary teams, were found to have higher job satisfaction, exert higher quality of care, and have higher autonomy and decision making (Rafferty, Ball, & Aiken, 2001).

Fourth, enhancing the relationship with service beneficiaries could affect CHW performance. CHWs have a close bond with the community they serve; not only are they inhabitants of the same village as their patients, they are also responsible for the health status of their fellow community members (Druetz, Kadio, Haddad, Kouanda, & Ridde, 2015). Adding a second health worker to the community could revitalize this sense of responsibility and increase community recognition. Above that, by involving communities in a One Health system, beneficiaries can feel empowered to pressure their local health providers into better health care delivery as the intervention encourages community members to set up an action plan and think about strategies to improves service provision. Bottom-up community pressure is expected to affect CHW performance (Kok et al., 2015). In a randomized field experiment in rural Uganda, communities were able improve the quality and quantity of local health care provision by pressuring their primary health care providers into better performance. Treatment communities received report cards on health units' performance, which allowed beneficiaries to confront their health care providers during a series of public meetings and the joint draft of an action plan (Björkman & Svensson, 2009).

Fifth, several CHW characteristics are found to influence their overall performance. In a systematic review by Kok et al. (2015), 10 characteristics were identified to be correlated with overall CHW performance. These characteristics are age, gender, level of education, years of experience, social class, wealth, marital status, community of origin, household duties and personal experience with the health condition (Kok et al., 2015). There are only few studies diving deeper into the characteristics related to the quality of CHW data. In previous studies, the following factors were found to be correlated with the quality of data collected. In Kenya, CHW characteristics such as gender, level of education and age were associated with the quality of record-keeping. Males and higher educated CHWs were significantly more likely to keep better records. The optimal record keeping occurred with CHW aged between 30 and 40 years, with suboptimal reporting found for CHWs falling outside that age group (Crispin et al., 2012). In the ART program in Malawi, supervision, presence of a data entry clerk, greater program experience and patient volume were found to be correlated with completeness and accuracy of the facility-level reported data (Makombe et al., 2008). In Rwanda, no significant correlation was found between CHW data quality and sociodemographic characteristics, training and supervision. The authors attribute this to homogeneity among CHWs and resulting small sample sizes (Mitsunaga, 2014). In this thesis, we will assess which CHW characteristics are correlated with their reporting performance and whether some characteristics interact with the treatment.

2.2 Hypotheses

Using a subsample of the Sierra Leonean One Health pilot project, this research primarily aims to assess the impact of the One Health project on the timeliness, non-emptiness, coverage, completeness and coherence of CHW reports. Introducing structures for both animal and human health is only desired when the gains for both are higher in comparison to two separate structures and if there are no compromises made regarding the quality of surveillance on either side. We use CHW surveillance reports as a first indicator of the overall performance of CHWs. We hypothesize that a Community One Health program improves the quality and quantity of CHWs' surveillance reports.

Above that, this research sheds a light onto the characteristics related to the quantity and quality of reports generated by CHWs. These characteristics are split up in CHW, community and program characteristics. From a policy perspective, it is important to understand the factors related to CHW performance in order to be able to improve it, and to be more confident using the reports for program management.

3. ONE HEALTH IN SIERRA LEONE

3.1 Health and disease surveillance

Access to quality health care is a major public challenge today. Despite substantial investments made over the past decades, Sierra Leone's health indicators are among the poorest in the world. The country suffers from high infant and under-five mortality rates (92 and 156 deaths per 1,000 live births respectively), with a majority of deaths occurring due to easily preventable diseases such as diarrhea or malaria (Ministry of Health and Sanitation, 2017). Maternal mortality is a wide-spread phenomenon (12 deaths per 1,000 live births) and only half of all births are accompanied by a skilled worker (Ministry of Health and Sanitation, 2017).

The EVD outbreak crippled an already weak health system by, amongst others, reducing the number of health staff available and by imposing a stigma on health centers (Evans, 2015; Unicef, 2014). The crisis directly took the lives of nearly 4,000 Sierra Leoneans, while another estimated 2,800 indirect deaths followed as the outbreak impeded access to any medical care (Ministry of Health and Sanitation, 2017). The epidemic painfully exposed the weaknesses in the public health system. The national surveillance system failed to timely trace infected persons, increasing the risk of contamination (Ratnayake et al., 2016). Above that, a lack of reliable and timely data aggravated the outbreak (Glennerster, M'Cleod, & Suri, 2015). The existing network of CHWs was utilized to detect infected cases, to act as a burial team or to engage in social mobilization. However, a severe lack of supplies and supervision, further affected their work during the outbreak (Ministry of Health and Sanitation, 2016). Lessons were learnt, and building an efficient, strong and resilient system for public health that provides easily accessible, high-quality health care and that is prepared to respond to future outbreaks of emerging infectious diseases is central to the government's post-Ebola policy agenda (Devlin, Farnham Egan, & Pandit-Rajani, 2017).

The current village-level disease surveillance system in Sierra Leone relies on CHWs to monitor and report human health events in every community throughout the country. The CHW program, operating under MoHS, has been incorporated in the national health system since 2012 (Devlin et al., 2017). In every urban, rural and peri-urban community, one or more CHWs are trained and installed to provide local access to primary health care. CHWs are tasked with visiting households, administering basic treatments and generating reports with a special focus on women and children. In areas further than 3 km from a health facility, one CHW is responsible for 250 people on average (Devlin et al., 2017). Their services and treatment are provided free-of-charge. Cases of severe or infectious illnesses should be referred to local health units. The CHW is recruited by community structures (in coordination with the Peripheral Health Unit (PHU) and the District Health Management Team (DHMT)) and should meet certain selection standards, such as permanent residency in the community (mandatory), basic literacy and numeracy (preferred) and aged above 18 years (mandatory) (Ministry of Health and Sanitation, 2016). The CHW's ideal skill set consists of both medical and social skills and a preference is given to women (Ministry of Health and Sanitation, 2016). CHWs are officially recognized by MoHS and trained in a national CHW training program, consisting of three different modules, each lasting seven to ten days. CHWs receive a monthly salary of about US$13, a fee for logistical support and financial incentives based on their performance (Devlin et al., 2017).

A structure of monitoring and accountability is set up (see Figure 1). In first instance, a Peer Supervisor is appointed to supervise and mentor every CHW within their catchment area. The peer supervisor has served as a CHW for at least one year with a history of excellent performance. Peer supervisors report to the PHU-in-charge. In our study district, one PHU consists of 12 communities on average. At the district level, DHMT is responsible for implementation and monitoring of the program. Their tasks consist of certifying, registering and supporting CHWs in their operations, through the PHUs. DHMTs are often assisted by local or international NGOs, called Implementing Partners, who assist them logistically and facilitate the practical implementation of the program. The CHW program is coordinated by the national CHW Hub, operating under MoHS.

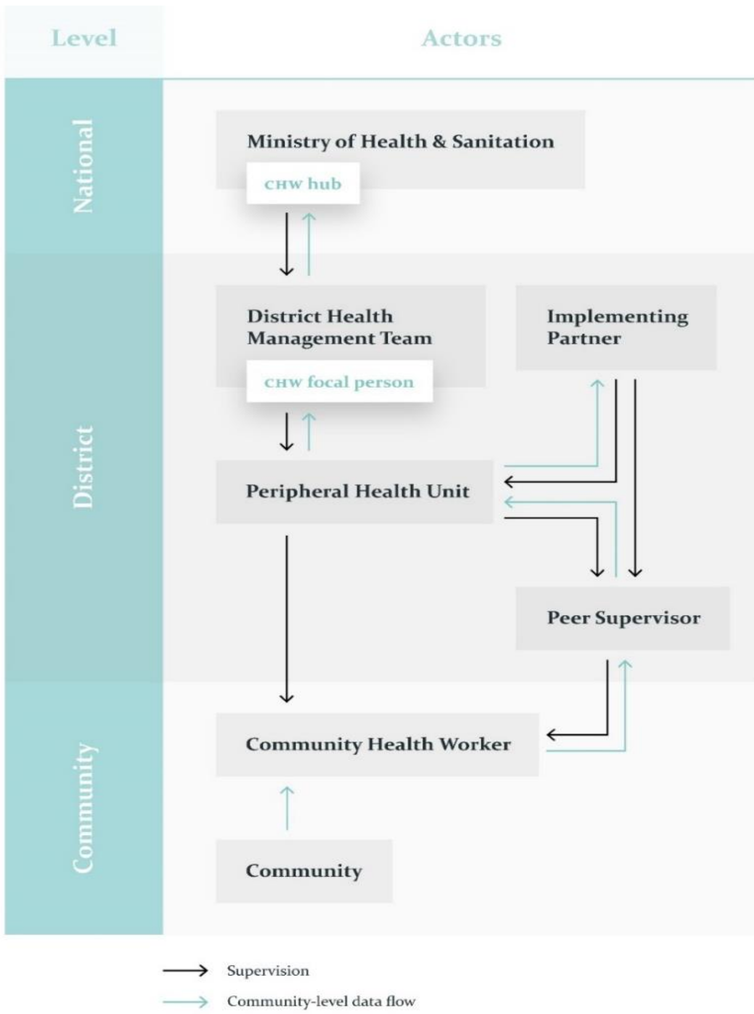

Figure 1: Organogram CHW reporting structure

Notes. This figure shows the CHW supervision structure and data flow. Throughout the country, CHWs have been active since 2012. The systems aims to facilitate flows of information from the community to the national level. Data flows are represented by the blue arrows, running from community level up to the national level. The supervision runs in opposite direction and is depicted by the black arrows. This figure is an own drawing, based on conversations with DHMT and IRC (implementing partner in Kono district) and policy documents (Ministry of Health and Sanitation (2016) and Devlin et al (2017)).

Flows of information run in opposite directions (see Figure 1). Community-level data regarding births, deaths and symptoms related to a specified set of diseases are gathered by CHWs. CHWs are provided with uniform registers to record data on their household visits. They are expected to submit these registers on a monthly basis to their peer supervisor, who is obliged to store these paper forms at the PHU. The peer supervisor, together with the PHU-in-charge, compile the reported data and incorporate it in consolidated monthly reports. These reports are then submitted to and reviewed by DHMT and the implementing partners, and incorporated into the digital district health information system. The CHW focal person at DHMT reviews severe cases when necessary. Data are used for decision-making at the community, district or national level.

One major impediment to the current disease surveillance system is the absence of animal health. MoHS, together with MAFFS and partners from Wageningen University and Njala University, are partnering to pilot a community One Health Surveillance System in 363 communities across seven chiefdoms in Eastern Sierra Leone. In this approach, a Community Animal Health Worker (CAHW) is added to work alongside the Community Health Worker. The overall purpose of this RCT is to evaluate the effectiveness of a Community One Health approach in preventing future outbreaks and improving community health.

The intervention consists of several components. First, CAHW candidates are elected by the community and the Paramount Chief. During the community selection meeting, the CHW is expected to be present. Parallel to CHWs, a CAHW must fulfill several eligibility requirements such as English literacy, basic numeracy skills, animal rearing experience and residency in the community. After election, CAHW nominees are tested on these requirements and when multiple candidates per community are qualified, a lottery determines which candidate is invited to training. Next, one selected CAHW per community is taught basic animal husbandry skills, disease prevention, treatment techniques, record keeping and reporting during a 21-day training program. At the end of the CAHW training, the CHW and the CAHW participate in a 2-day One Health Workshop on the concept and importance of One Health, One Health disease surveillance and reporting protocol. The workshop explores situations in which the health workers can work together and develops action plans for collaboration within the community. The goal of this workshop is to sensitize health workers into joint thinking about human and animal health in their community. Making use of each other's skills and knowledge in a One Health Platform can benefit the quality of health care as a whole. After the CAHW training and One Health workshop, CAHWs are installed in their communities during a community meeting. Community members are introduced to the importance of One Health disease surveillance and together with the health agents, they establish an Action Plan where every actor's responsibilities and actions are outlined. During the installation ceremony, led by MAFFS facilitators, the One Health platform is introduced to the community. Once installed, the CAHWs provide basic animal health services to their communities and report to MAFFS on animal disease symptoms.

3.2 Experimental design

The pilot project is implemented in Kono district in Eastern Sierra Leone. Kono district is home to an estimated 506,100 individuals, amongst which 75,4% live in rural areas (Statistics Sierra Leone, 2015). The district is an agricultural and mining district, divided into 14 chiefdoms. The district is served by a government-led district hospital and a clinic, 79 PHU's and 904 CHWs. Each health unit has a catchment area that draws from one to 37 CHWs, with 24 bigger communities being served by two CHWs.

The One Health project is implemented across the seven chiefdoms in Kono district where households are most involved in livestock rearing. Within these seven chiefdoms, MAFFS selected 375 communities with an existing CHW to participate in the pilot project. In this sample, households reported to own around seven animals on average, with a majority being chicken, goat or sheep. Animal deaths occur frequently: for example, during the rainy season in 2017, 56.60% of the households lost at least one animal.

From the 375 communities selected by MAFSS, five were used to as pilot communities, and seven did not exist, bringing the number of eligible communities to 363. Randomization of the One Health Project happened at the community level and is blocked on chiefdom to retain balance. Out of these 363 communities, 300 were randomly selected to nominate a CAHW. In these 300 communities, candidates were nominated by two different procedures. Both the Paramount Chief and the community members each selected up to three candidates. Following election, candidates were tested over a two-week period in central locations. Here, the candidates' level of English and numeracy was assessed. If both PC and community candidates passed the tests, a lottery decided which candidate would be invited to be trained as the CAHW. 11 communities failed to select a suited candidate. Consequently, 289 candidates were selected to be trained. 287 CAHWs finished the training. Two were sent home after discovering impostor situations. The 63 control communities have a trained CHW but did not receive the One Health intervention.

To analyze the impact of the One Health project on CHW reporting performance, we digitized CHW reports in Gbense and Fiama chiefdom. Due to logistical constraints, we restrict our sample to two out of the seven chiefdoms in which the intervention has been implemented. A map of the study chiefdoms can be found in Appendix (Figure A.4).

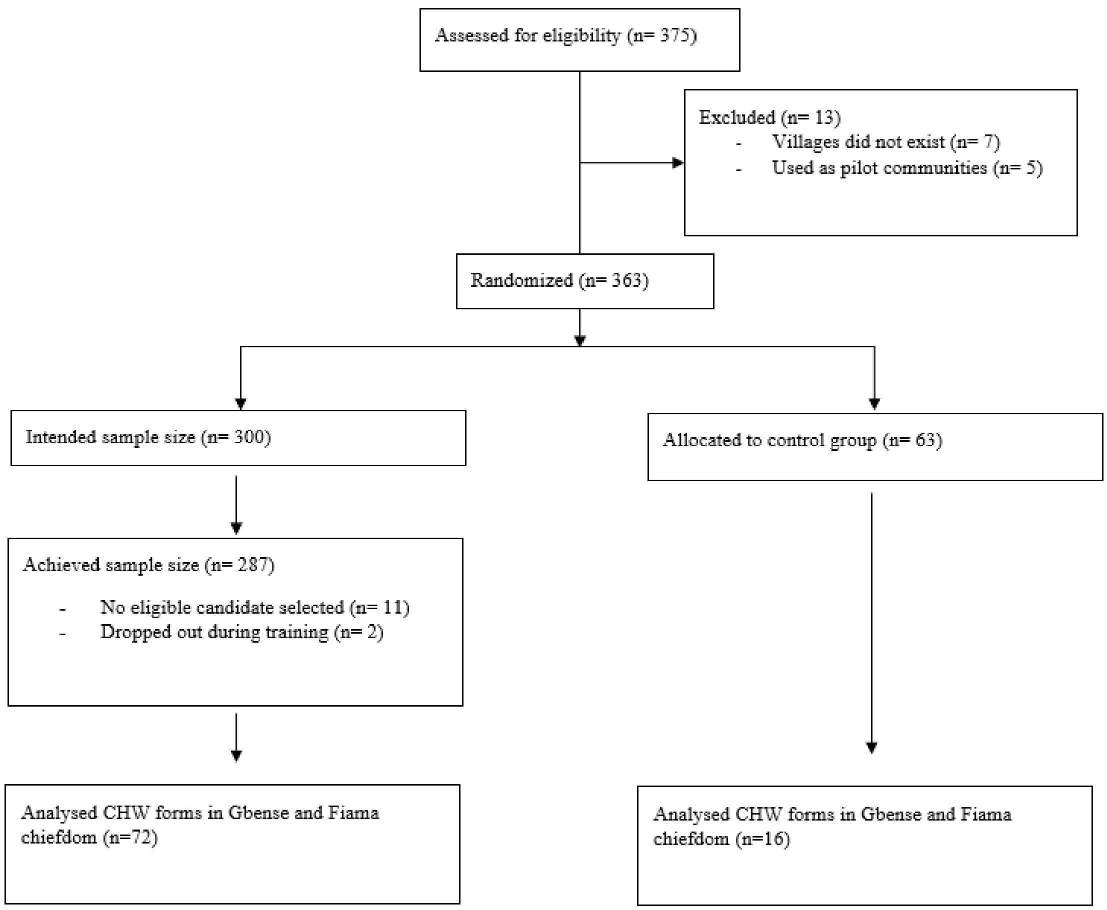

Figure 2: CONSORT diagram

Notes. This flow diagram illustrates the progress of selecting the treatment and control group of the One Health intervention. Initially, 375 communities were assessed for eligibility, 287 communities received the intervention and 63 communities serve as a control group. This thesis looks at two out of the seven chiefdoms, resulting in a sample size of 88 communities.

4. METHODOLOGY AND RESULTS

4.1 Data and Sample

In May and June 2018, CHW registers from Gbense and Fiama chiefdom were collected from their PHUs and digitized at a central location using a survey programmed in surveyCTO. All submitted forms between May 2017 and April 2018 were digitized. This time period encompasses the period from CAHW selection to installment and the first four months of operation. Figure 3 below depicts the timeline of the One Health intervention.

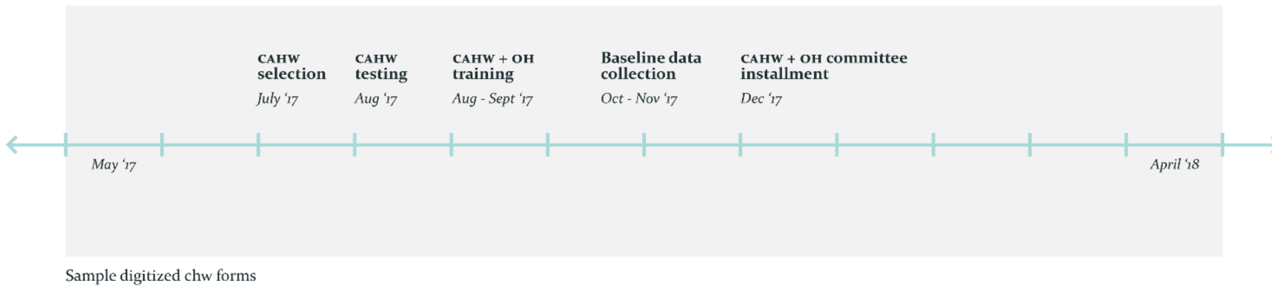

Figure 3: Timeline intervention

Notes. This figure depicts the implementation of the One Health intervention over time. CHW have been submitting monthly forms since 2012. Forms for the period May 2017 to April 2018 were collected and digitized in May and June 2018. The 12 months for which we have the forms digitized are represented by the light grey area. The timeline contains all the components of the One Health intervention, starting with CAHW selection in July 2017. The intervention was fully implemented in December 2017 and is currently ongoing.

One submission consists of at least one register per CHW per month. The most recent registers consist of an Integrated Community Case Management (iCCM) register, a medicine register and a Community-Based Surveillance (CBS) register (see Figure A.1-A.3 in Appendix). All three forms are required to be submitted monthly and are stored by the peer supervisor at the PHU. The iCCM register (Figure A.1) focusses on children between 2 and 59 months and aims to record symptoms related to priority diseases, such as pneumonia, malaria and diarrhea. One line is filled out per sick child, including age, sex, and follow-up status. Figure 4 provides an overview of the reported symptoms in the digitized iCCM register. The medicine register (Figure A.3) contains data on community treatments, medicine stock and family planning distribution stock. The CBS register (Figure A.2) serves to report any occurrence of alarming illnesses, such as polio, cholera, measles, Ebola or clustered deaths in the community. In the sample of digitized CHW reports, there were 40 live births (22 girls and 18 boys) reported, four deaths of a newborn, one suspected case of cholera, one suspected case of measles, one suspected case of polio and one fever with yellow eyes.

CHW registers are frequently updated and improved. Until December 2017, several CHWs made use of older forms. These forms consisted of a Patients Register and a Maternal and Newborn Register. As these new forms are provided by the national government and then dispersed to the CHWs through the PHU, the transition between outdated and newer forms occurred at different dates for different CHWs.

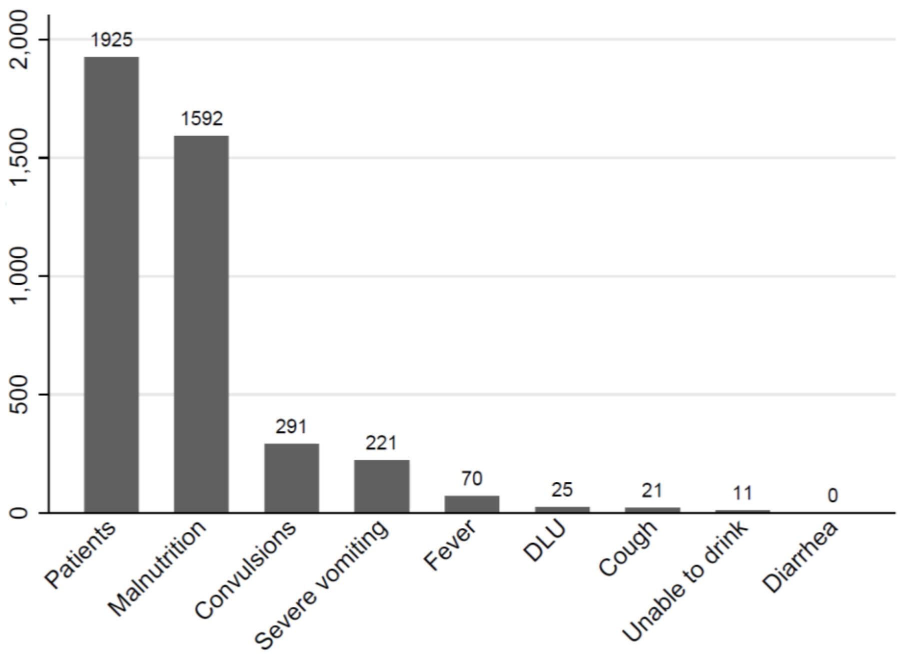

Figure 4: Reported symptoms in digitized iCCM registers

Notes. This figure lays out the reported symptoms in the digitized iCCM registers. In total, 439 iCCM registers were submitted over the course of 12 months. This resulted in a total assessment of 1925 patients in the submitted iCCM registers. The number of patients per submitted register ranges from 0 to 28, with an average of 4.38 patients per submitted register. Per patient, CHWs report on a variety of symptoms including fever, cough, diarrhea, inability to drink/breastfeed, malnutrition, convulsions, severe vomiting and drowsiness, lethargy and unconsciousness (*DLU)*. Most of these patients (82.70%) had a fever. There was mention of 102 dangerous symptoms. These danger signs are unable to drink/breastfeed, convulsions, drowsiness, lethargy and unconsciousness (*DLU)* and vomiting everything. Cough and diarrhea were reported in 291 and 221 cases respectively. Malnutrition was reported for 25 patients.

The final sample consists of 12 PHUs in total. Seven are situated in Gbense Chiefdom and five in Fiama Chiefdom. The choice of these two chiefdoms was driven by logistical considerations, as they are closest to the district capital. In total, CHW registers from 88 communities, of which 72 in the treatment group and 16 in the control group, were collected and digitized. The ratio of treatment and control communities in these two chiefdoms is similar to the ratio in the overall sample of seven chiefdoms: in both cases, about 82% of the communities are allocated to treatment. Three bigger communities in the sample have two CHWs, who are each in charge of part of their community. As these observations are not independent units, we chose to randomly drop one CHW. The expected number of submissions is 1056 (t=12, i=88). The achieved number of submissions is 533, due to missing forms.

Next to the digitization of CHW forms, data from various other sources will be used to assess the factors influencing timeliness of CHW data. In October and November 2017, a baseline survey was conducted among eight randomly selected households in each community. This dataset contains information on the residency of the CHW in the community and the closeness of villagers to the CHW. Simultaneously, a household census was conducted, providing us with data on community sizes. Last, DHMT and the implementing partner IRC shared a dataset containing information on the CHWs in Kono district, such as age, gender, training center and number of CHWs per PHU.

To give a first insight into the uniqueness of our study sample, we compared CHW and community characteristics from our sample with characteristics in the One Health project sample and the entire Kono district using t-tests. The results are reported in Tables A.4 and A.5 in Appendix. When comparing the difference in means of four variables between the different samples, we find the CHWs in our sample are, on average, slightly older compared to other CHWs in Kono district. The gender of the average CHW, on the other hand, does not differ. The average number of CHWs per PHU and the average distance from the community to the PHU significantly differs between our sample and the One Health sample and between our sample and the entire Kono district. This is important to bear in mind when extrapolating our results to different settings.

4.2 Empirical strategy and results

This research primarily aims to assess the causal impact of the One Health program on CHW reporting performance. The central outcomes are the timeliness of reports and four different dimensions of the quality of community disease reporting. The first one, timeliness of data, focusses on the number of reports submitted. Timeliness is defined as information being on up-to-date and submitted on time (Mitsunaga, 2014; The Global Fund, 2008). CHWs are obliged to submit reports to their peer supervisors on a monthly basis, even if there are no cases to report. We use the term timeliness to refer to the number of monthly reports submitted by the CHW to their peer supervisor. In addition to estimating the causal impact of One Health on the timeliness of CHW reports, we also explore the factors affecting the number of monthly reports submitted. These factors are split up in CHW, community and program characteristics. The other four measures we use, non-emptiness of reports, coverage, completeness and coherence, focus on the content of the submitted reports. These are standard dimensions used to evaluate quality of data in health information systems (see for example The Global Fund (2008)). All four measures are conditional on the CHW submitting a report. Non-emptiness of reports captures whether there were patients assessed in the submitted reports or not. Coverage quantifies the number of patients per submitted report, as a proportion of the community size. Completeness captures whether submitted forms have missing data, or that there is a value documented when needed (Mitsunaga, 2014). Last, coherence measures the congruency between different registers submitted by the same CHW. These outcome variables are discussed in more detail below.

TIMELINESS OF REPORTS

CHWs are required to submit their registers on a monthly basis to the Peer Supervisor. Figure 5 depicts the percentage of monthly submissions over expected submissions per treatment arm. The implementation of the intervention started in July 2017 with CAHW selection.

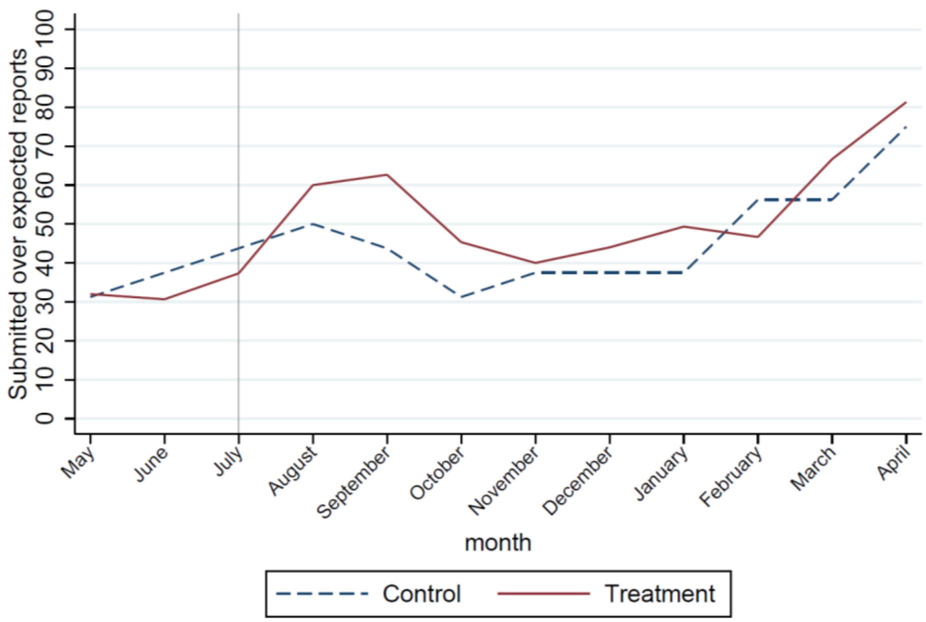

Figure 5: Percentage submissions per treatment arm

Notes. This figure depicts the percentage of submitted reports over expected reports per treatment arm. The red line represents the reports submitted by CHWs in the treatment group, while the dashed blue line are the reports submitted by CHWs in the control group. The x-axis ranges from May 2017 to April 2018, the 12 months for which CHW forms were digitized. The y-axis contains the number of monthly submissions per treatment arm, divided by the expected number of submissions for that arm, multiplied by 100. A value of 100 would correspond to zero missing reports, meaning that all CHWs in that treatment arm submitted a report in that month. The vertical line in July 2017 corresponds to the start of the implementation of the intervention. A detailed timeline of the intervention can be found in Figure 3.

Figure 5 shows an increase in the percentage of monthly submissions over expected submissions in both treatment arms. In May 2017, 32% and 31.25% of the expected reports were submitted in treatment and control communities respectively. In April 2018, this increased to 81.33% in the treatment group and 75% in the control group. This increase is not surprising, given that reports were collected from the PHUs in May and June 2018. Reports easily get lost over time, despite the requirement for peer supervisors to store them in a secured room at the PHU. Figure 5 also illustrates the scope for improvement in CHW reporting. CHWs are tasked to submit a report every month, even if no patients were assessed. Nevertheless, despite the increase of submissions over time, the overall share of submissions in both treatment arms is still below 100%. A final observation based on this figure is that, after CAHW selection in July 2017, CHWs in the treatment group submitted a higher share of reports compared to the control group in all months but one. Hereafter, we formally assess the impact of One Health on CHW form submission.

Due to randomization of treatment, a simple linear regression measures the causal impact of the One Health program on our outcome variables. What we measure here are intention-to-treat (ITT) impacts. This is important to highlight as there might be non-compliance from communities that were assigned to the treatment group but, for some reason, did not receive the full intervention. For example, trained CAHWs were not installed in their communities, installed CAHWs relocated after being trained or CHWs did not participate in the One Health workshop. From a policy perspective, it is interesting to measure the ITT effect as it allows us to estimate the impact of a program on the entire target population.

The identification of a causal effect of the One Health intervention on CHW reporting performance is subject to the absence of spillovers between treatment and control communities. For example, movement of CAHWs to control areas, or communication between CHWs could induce spillovers. The risk of spillovers is minimized because it was required upon selection that both the CHW and the CAHW reside in the communities they serve.

Three different dependent variables capture the timeliness of reports submitted.

The first variable has been created in a balanced panel dataset (t= 10, i = 88). The variable $submit_{it}$ is a dummy variable with value 1 if CHW i submitted a report in month t and value 0 if not. The following regression is estimated using OLS.

$$submit_{it} = \alpha_0 + \beta T_i + \alpha_c + \varepsilon_{it} \tag{1}$$

α_c are fixed effects for the chiefdoms (c ∈ {Fiama, Gbense}), on which treatment assignment was stratified. T_i is the One Health treatment indicator, with value 1 if the community was allocated to the One Health program and value 0 if the community only has a CHW. β is the coefficient of interest which captures the ITT effect. ε_{it} is the idiosyncratic error term. We estimate the above regression for the sample since selection of the CAHW (t = {July 2017, ..., April 2018}).

Second, the impact of the treatment on the timeliness of reports submitted is estimated in a cross-sectional dataset. This way, we only have one observation per CHW and hence focus on differences between subjects. The outcome variable, $quantity_i$, captures the total number of reports submitted per CHW.

Third, also in the cross-sectional dataset, a dummy variable capturing whether the CHW submitted above or below the mean is used as dependent variable. This variable, $quantity\_dummy_i$, has value 1 if the total number of reports submitted is above the mean and 0 otherwise.

Descriptive statistics of these variables are shown in Table 1. 475 out of the expected 880 reports were submitted between July 2017 and April 2018. On average, a CHW submitted 5.40 reports over the course of 10 months, with some CHW submitting every month and some CHWs never.

Table 1: Descriptive Statistics: timeliness

	n	mean	sd	min	max
$submit_{it}$	880	0.54	0.50	0	1
$quantity_i$	88	5.40	3.24	0	10
$quantity\_dummy_i$	88	0.50	0.50	0	1

Notes. Table 1 contains descriptive statistics for the three variables capturing the timeliness of CHW reports. Descriptives are shown for the period between July 2017 and April 2018 (10 months). $submit_{it}$ is a dummy with value 1 if the CHW i submitted at least one report in month t and 0 otherwise. $quantity_i$ captures the total number of reports submitted by CHW i. The best scoring CHWs submit a report every month. $quantity\_dummy_i$ is a dummy variable with value 1 if the number of CHW reports submitted is above the mean and value 0 if below.

Results from the OLS regressions are reported in Table 2. All columns contain CHW reports submitted since CAHW selection in July 2017 (t=10).

Table 2: One Health treatment effects on timeliness of CHW reports

	(1) submit$_{it}$: monthly submission dummy	(2) quantity$_i$: Number of reports submitted	(3) quantity dummy$_i$: 1=above mean
treatment (=1)	0.090**	0.902	0.082
	(0.043)	(0.890)	(0.139)
chiefdom (Fiama = 1)	0.099***	0.992	0.162
	(0.034)	(0.689)	(0.107)
constant	0.413***	4.130***	0.347**
	(0.043)	(0.893)	(0.139)
Mean of dep var in control	0.47	4.69	0.44
R^2	0.014	0.034	0.029
Observations	880	88	88

Notes. OLS Estimates. Three outcome variables capture the quantity of reporting: column (1) has a monthly submission dummy as dependent variable, using a balanced panel dataset with one observation per CHW per month. Column (2) has the total number of submitted reports per CHW as outcome variable, using a cross sectional dataset with one observation per CHW. Theoretically, the maximum for *quantity$_i$* per CHW is 10. Column (3) has a dummy variable as outcome variable, with value 0 if the number of submissions is below the mean and 1 if above. Treatment (=1) is a dummy with value 1 for One Health communities. Chiefdom fixed effects are captured by the variable Chiefdom (Fiama = 1, Gbense = 0). All columns contain CHW reports submitted since CAHW selection in July 2017 (t=10). Standard errors are reported in parentheses and significance levels are based on naïve p-values and are indicated by * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2 shows that CHWs in the treatment group submit more reports compared to CHWs in the control group, using all three different measures for timeliness. Column (1) reports a large and precisely estimated effect of One Health the timeliness of CHW reports: CHWs in treatment communities are 9 percentage points more likely to submit a register compared to control communities. This effect represents a 19.15% increase from the control group mean. The result is significant at the 5% significance level. Above that, we also find CHWs in Fiama chiefdom to be significantly more likely to submit a report. Based on our experience in Kono district and conversations with people in Sierra Leone, we provide two plausible explanations. First, Gbense is close to the district capital and other bigger cities. This could lead to more travelling by CHWs or peer supervisors, which could, in turn, lead to the lower submission of reports. Second, the Paramount Chief of Fiama is very active, which may lead to higher top-down pressure on health actors in these communities. Similar to Column (1), Column (2) shows that CHWs in treatment communities on average submit 0.90 more registers over the course of 10 months. Column (3) shows that CHWs in treatment communities are 8.2 percentage points more likely to submit above the mean. Due to the limited sample size, we lack the power to precisely estimate the treatment effect in Column (2) and (3).

Despite the CHWs being obliged to hand in reports to their peer supervisor on a monthly basis, there are a substantial number of instances where reports were not submitted, as illustrated by Figure 5. This can be due to the fact that the CHW did not fill out a report or did fill out a report but did not submit the report to the peer supervisor. Alternatively, it is also plausible that the CHW did submit a report, but the peer supervisor did not store the report well. Even though we cannot distinguish between these reasons for missing reports, we have no reason to believe that treatment affected the performance of peer supervisors in storing the reports. Above that, most peer supervisors were responsible for CHWs in both treatment arms. However, to make this statement more powerful, we will add peer supervisor fixed effects to regression (1). In this regression, β is the treatment effect in cases with the same peer supervisor. Results of regression (1) including peer supervisor fixed effect can be found in Table A.1 in Appendix. The estimate of the treatment effect is robust to these within peer supervisor-estimates: CHWs in treatment communities are 6.5 percentage points more likely to submit a register compared to control communities with the same peer supervisor and this estimate is significant at the 10% level. This confirms our expectation that the difference in the number of reports submitted in both treatment groups is not due to the peer supervisor behaving differently when working with CHWs in the treatment or control group.

Next to estimating the impact of the One Health program on the timeliness of CHW reports, we are interested in seeing which factors influence CHW reporting performance. CHW characteristics consist of *age, gender, residency* and embeddedness. *age* and *gender* are obtained from a dataset of the implementing partner, IRC. *residency* is a binary variable, composed of the replies from respondents in the household survey. Embeddedness of the CHW is proxied by two variables. First of all, the variable *closeness* captures the replies from community members on how close they are to the CHW. The scores range from 1 (not close at all) to 5 (very close) and are averaged over different respondents. The variable *borrow* consists of the replies of community members on how likely the CHW would borrow them rice or money. The scores range from 1 (definitely not) to 5 (definitely). The variable *borrow* is the mean of the average score per CHW on both variables (*borrow_rice* and *borrow_money*). Cronbach's alpha, a measure of the interrelatedness of variables, of *borrow_money* and *borrow_rice* is 0,97. Community characteristics consists of the continuous variables *distance to PHU,* containing the distance between the community and PHU in km, and *community size,* capturing the number of structures in the community. This variable serves as a proxy for patient volume. Chiefdom fixed effects are added using a dummy with value 0 for Gbense and value 1 for Fiama chiefdom. Program characteristics consist of the One Health program (variable *T_C)* and the number of CHWs per peer supervisor (*chw per PHU*). *training center* is a categorical variable capturing at which location CHWs follow their trainings. A detailed description of these variables can be found in Table A.2 in Appendix.

Table 3 provides basic descriptive statistics for the CHW, community and program characteristics. On average, CHWs are 45.01 years old. Of all CHWs in this sample, 87.50% is male and 12.50% female, despite the explicit preference for women during CHW selection. According to the surveyed households, only four CHWs did not have permanent residency in their communities. On average, CHWs received a rating of 4.34 on closeness by their community members on a scale from 1 (not being close to the CHW) to 5 (being close to the CHW). The overall likeliness of CHWs to borrow their community members rice or money is lower, 2.69 on a scale from 1 to 5. On average, CHWs live 6.33 km from the PHU. The number of structures in a community ranges from 1 to 75, with mean 22.30. One structure can be inhabited by more than one household. One peer supervisor in our sample is responsible for about 10 CHWs on average, with the number of CHWs ranging from 1 to 17.

Table 3: Descriptive Statistics: CHW, community and program characteristics

	n	mean	sd	min	max
CHW characteristics					
age (years)	88	45.01	10.26	24	72
female (=1)	88	0.13	0.33	0	1
residency in community (=1)	88	0.95	0.21	0	1
closeness to CHW	88	4.34	0.57	2	5
borrow from CHW	87	2.69	0.96	1	5
Community characteristics					
distance to PHU (km)	88	6.33	2.21	2.50	12.00
number of structures in community	85	22.30	12.96	1	75
chiefdom (Fiama = 1)	88	0.53	0.50	0	1
Program characteristics					
number of CHWs per PHU	88	10.14	3.92	1	17
treatment (=1)	88	0.82	0.39	0	1

Notes. Table 3 contains descriptive statistics (n, mean, standard deviation, minimum and maximum) for CHW characteristics, community characteristic and program characteristics. A detailed description of these variables and their sources can be found in Table A.2 in Appendix. The number of structures per community was divided by two for communities with two CHWs as these communities have each CHW operating separately in a delineated part of their communities.

We regress these characteristics on the measures for the timeliness of CHW reports using regression (2).

$$Y_i = \beta_0 + \beta_1 age + \beta_2 gender + \beta_3 residency + \beta_4 closeness + \beta_5 borrow + \beta_6 distance\ to\ PHU + \beta_7 community\ size + \beta_8\ chw\ per\ \text{PHU} + \beta_9 training\ center + \beta_{10} T\_C + \alpha_c + \varepsilon_i \quad (2)$$

The left-hand side variables are the three variables capturing timeliness of CHW reports ($submit_{it}$, $quantity_i, quantity\ dummy_i$). The right-hand side variables are defined in Table A.2 in Appendix. Multicollinearity was checked using the Variance Inflation Factor (VIF), which quantifies how much the variance is inflated by correlation among right-hand side variables. A VIF of 1 means that there is no correlation between the right-hand side variables. As a rule of thumb, the VIF should be smaller than 10. The mean VIF of our model is 3.99, meaning that we have no reason to fear multicollinearity among the right-hand side variables.

Results from the regression (2) are shown in Table 4 below.

Table 4: Correlation CHW characteristics and reporting quantity

	(1) $submit_{it}$: monthly submission dummy	(2) $quantity_i$: Number of reports submitted	(3) quantity $dummy_i$: 1=above mean
age (years)	0.001	0.008	0.002
	(0.002)	(0.031)	(0.005)
female (=1)	-0.055	-0.548	-0.058
	(0.050)	(0.880)	(0.146)
residency in community (=1)	0.153*	1.533	0.089
	(0.084)	(1.492)	(0.248)
closeness to CHW	0.011	0.115	-0.007
	(0.030)	(0.524)	(0.087)
borrow from CHW	0.007	0.068	0.036
	(0.018)	(0.315)	(0.052)
distance to PHU (km)	-0.017**	-0.170	-0.018
	(0.008)	(0.149)	(0.025)
number of structures in community	0.003**	0.030	0.002
	(0.001)	(0.025)	(0.004)
number of CHWs per PHU	-0.018***	-0.182	-0.045**
	(0.007)	(0.119)	(0.020)
training center			
Gbangadu	0.449***	4.485***	0.585**
	(0.079)	(1.393)	(0.231)
Koakor	0.145*	1.447	0.150
	(0.083)	(1.475)	(0.245)
Kombayendeh I	0.188	1.877	0.461
	(0.130)	(2.302)	(0.383)
Motema II	-0.003	-0.034	0.096
	(0.137)	(2.430)	(0.404)
Njagbwema Fiama	-0.235*	-2.350	-0.060
	(0.122)	(2.160)	(0.359)
Small Sefadu	0.234**	2.342	0.478
	(0.113)	(2.001)	(0.333)
treatment (=1)	0.016	0.164	-0.008
	(0.044)	(0.772)	(0.128)
chiefdom (Fiama = 1)	0.319***	3.190	0.222
	(0.117)	(2.066)	(0.343)
constant	0.322**	3.220	0.554
	(0.161)	(2.846)	(0.473)
R^2	0.215	0.516	0.445
Observations	880	88	88

Notes. See Table A.2 in Appendix for a detailed description of the right-hand side variables. Missing values for borrow and number of structures were imputed with the treatment group mean. Boroma is the reserve category for training center. Three left-hand side variables capture the quantity of reporting: (1) is a monthly submission dummy, using a balanced panel dataset with 1 observation per CHW per month. (2) is the total number of submitted reports per CHW, using a cross sectional dataset with one observation per CHW. (3) is a dummy variable with value 0 if the number of submissions is below the mean and 1 if above. Chiefdom fixed effects are captured by the dummy Chiefdom (Fiama = 1, Gbense = 0). All columns contain CHW reports submitted since CAHW selection in July 2017 (t=10). Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Results show that the number of structures in a community are positively and significantly correlated with the submission of a report. In Column (1), an increase of one structure per community is correlated with an increase of 0.3 percentage points probability to submit a report. This coefficient is significant at the 5% significance level. Above that, the number of CHWs per PHU is significantly correlated with report submission. A one unit increase in the number of CHWs per PHU leads to a decrease of 1.8 percentage points probability to submit a report. Not surprisingly, CHWs residing in their communities are significantly more likely to submit a report. Being further away from the PHU is correlated with a lower timeliness of reports; the coefficient for Distance to PHU (in km) is negative and significant at the 5% confidence level for $submit_{it}$. We again find CHWs in Fiama chiefdom to be significantly more likely to submit a report; being a CHW in Fiama chiefdom is associated with a 31.9 percentage point increase in probability for submitting a report. We also see that the training center is correlated with report submission. For Gbangadu, Koakor, Njagbwema Fiama and Small Sefadu, the coefficients are significant at the 10% confidence level in the first specification. Being a male CHW, a well-embedded CHW (captured by closeness to CHW and borrow from CHW) and a CHW in the treatment group is positively correlated with the probability to submit a report and the number of reports submitted (Columns (1) and (2)). However, none of these coefficients are significant.

We also added interaction terms of the right-hand side variables with the treatment effect (results not shown). However, none of these interaction terms were significant, meaning that in this sample, we cannot identify an interaction effect between certain CHW characteristics and the treatment status.

CHW REPORTING QUALITY

Next, we want to estimate the causal impact of the One Health project on a variety of outcome variables capturing the quality of the submitted CHW reports. Four outcome variables, *non-empty reports*$_{it}$, $coverage_{it}$, $completeness_{it}$ and $coherence_{it}$, were constructed using a balanced panel dataset of digitized CHW forms (see Table A.3 in Appendix for an overview). All four outcome variables are conditional on the CHW submitting a report. More specifically, this implies that if being a One Health community impacts the timeliness of reports, it will also affect the variables that measure the different dimension of quality of reports through $submit_{it}$. We will discuss this in more detail below.

The first variable, *non-empty reports*$_{it}$, captures the number of non-empty reports per CHW per month, conditional on the CHW submitting a report. The variable *non-empty reports*$_{it}$ is important to include as the government provides financial incentives to CHWs based on the number of forms they submit, regardless of the content or emptiness of the forms. Consequently, CHWs can be triggered to submit empty forms.

The second variable, $coverage_{it}$, is calculated as the average number of patients per submitted iCCM or Patient Register as a share of the community population. Patient Registers were the predecessor of the iCCM register. CHWs switched from the patient register to the iCCM register at different times as new forms were dispersed by the national government through PHUs at irregular intervals. The iCCM register has slightly different requirements than the outdated Patient Register, therefore we will add a control variable capturing whether the submitted forms were outdated or not. Since we do not have an exact measure for community population, we use the number of structures in a community as a proxy. The higher the score for $coverage_{it}$, the higher the proportion of patients visited. We consider more reporting as better reporting, based on the assumption that there is underreporting now.

The third variable, *completeness*$_{it}$, captures whether there is a value recorded when there should be one for reports that have patients in the iCCM registers. This variable is constructed as a score between 0 and 8. There are eight possible mistakes to be made in the non-empty iCCM register, per mistake, one point is deducted from the completeness score. Possible mistakes are split up in two categories, mistakes related to patient information and mistakes related to symptom information. The former includes entering an age outside of the required range or not entering the gender of the patient, while the latter includes the reporting of zero or missing days of fever, cough or diarrhea, when stated that the patient had these symptoms and missing information on the malnutrition status, referral and outcome of the patients. A formal breakdown is shows in Table A.3 in Appendix. The higher the score, the more complete the submitted registers.

The fourth variable, *coherence*$_{it}$, measures whether there is coherence between multiple reports within one month. In theory, CHWs are required to submit three registers per month. Each register has a header containing basic information on the CHW, the village and the month. In order to be able to link the correct form to the correct CHW and month, CHWs need to be able to fill the header out correctly, which is not self-evident given the low levels of literacy among CHWs. *Coherence*$_{it}$ is a dummy variable constructed for CHWs who submitted more than one form in a month. The dummy has value 1 if all the general information between all registers is corresponding. Whereas the third outcome variable, *completeness*$_{it}$, is a score for the completeness of each submitted iCCM register, the fourth variable, *coherence*$_{it}$, scores the congruity between multiple registers submitted simultaneously. From a policy maker's perspective, it is crucial that the information on the top of each form is filled out correctly. This is a necessary requirement that will ultimately allow DHMT and the government to link the forms to the correct villages. Therefore, we opted to construct a dummy variable, rather than a score. It is important to note that larger errors cannot be captured by this outcome variable. Only minor errors, such as discrepancies in CHW name, village, month and year between the different registers are captured here.

Chronbach's alpha measures the internal consistency of a test or scale (Cronbach, 1951). The coefficient, a number between 0 and 1, captures the interrelatedness of items or variables (Tavakol & Dennick, 2011). Cronbach's alpha for our four variables capturing CHW performance is 0.32, which implies that our four outcome variables have a low interrelatedness.

Table 5 contains descriptive statistics for these four outcome variables for the period between July 2017 and April 2018 (t=10). Of the 475 submitted reports, 142 did not log a household visit or community event in the submitted registers. Even though it is possible that no cases of illness occur in a month, this number seems rather large given a high disease burden in these rural areas. This indicates that either the CHW did not visit every sick community member or did not log every visit. Mean coverage was 0.17 and range from 0 to 1.13. This number represents the number of patient reports divided by the number of structures in a community. Scores for coherence of the reports ranges between 4 and 8 out of 8 possible points. The average scores for CHWs that submitted a non-empty iCCM register is 6.84 out of 8. However, only 65 forms received a score for 8/8. Even though the average score of 6.84 may seem promising, only a small minority of the forms were filled out in a perfectly coherent way. Last, for CHW submitting more than one form, 76 out of 467 (16.27%) did not have corresponding information between the different forms submitted that month. Filling out basic information on each submitted form is of crucial importance in order link the correct forms to the correct communities. It is worrisome that many CHWs in our sample were not able to do so. Overall, these statistics demonstrate the poor quality of submitted CHW registers.

Table 5: Descriptive Statistics: quality of reports

	n	mean	sd	min	max
Non-empty reports$_{it}$	475	0.70	0.46	0	1
Coverage$_{it}$	471	0.17	0.20	0.00	1.13
Completeness$_{it}$	308	6.84	1.03	4	8
Coherence$_{it}$	467	0.84	0.37	0.00	1.00

Notes. Table 5 contains descriptive statistics (n, mean, standard deviation, minimum and maximum) for the four outcome variables capturing CHW reporting performance. Descriptives are shown for the period between July 2017 and April 2018 (t=10). A detailed description of these variables and their source can be found in Table A.3 in Appendix. All four variables are conditional on the CHW submitting a report.

Figure 6 depicts the average of four different dimensions of reporting quality over time separated by treatment status.

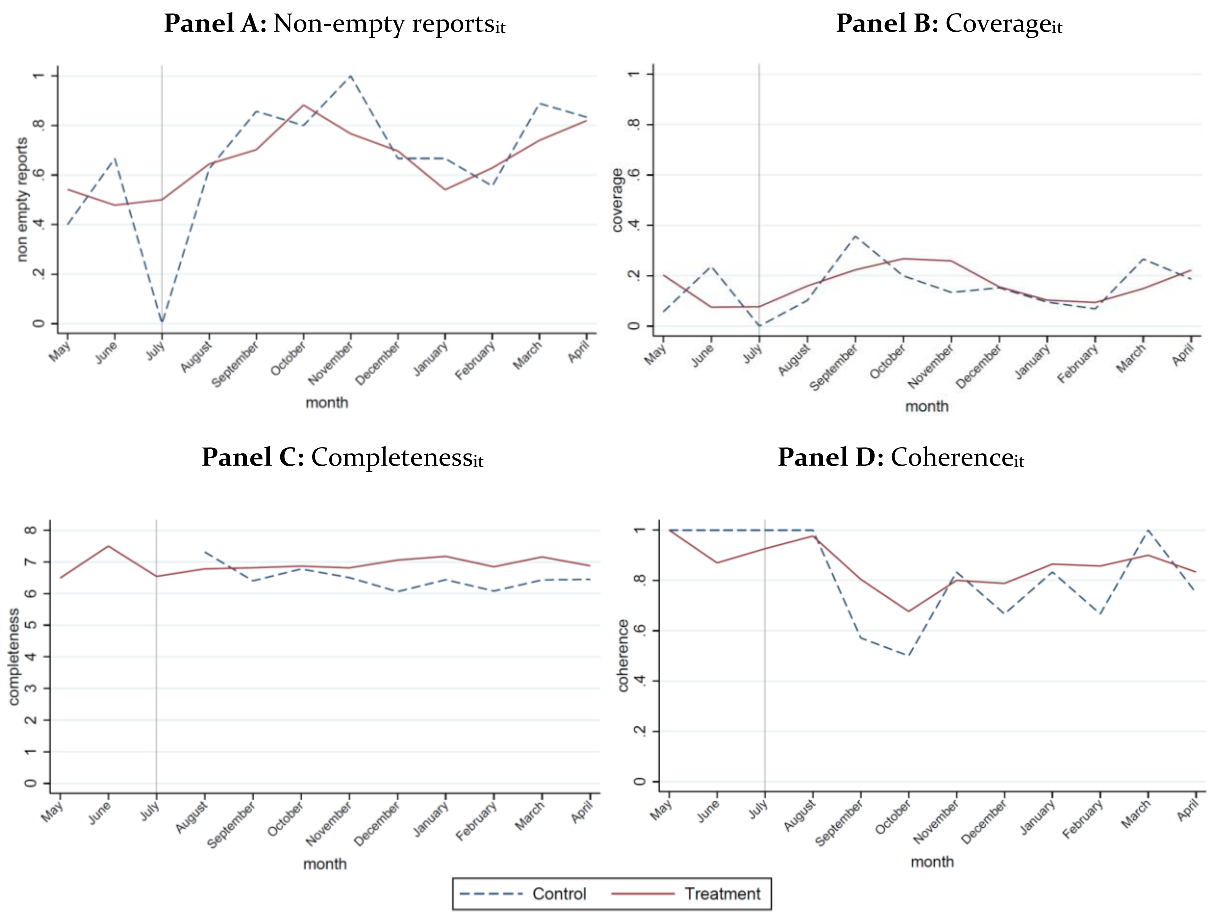

Figure 6: Dimensions of CHW reporting quality per treatment arm over time

Notes. This figure depicts the four different dimensions of CHW reporting quality per treatment arm. The red line represents reports submitted by CHWs in the treatment group, while the dashed blue line are the reports submitted by CHWs in the control group. The lines represent the average scores of CHWs in that treatment arm, per month per dimension. The x-axis ranges from May 2017 to April 2018, the 12 months for which CHW forms were digitized. The vertical line in July 2017 is the start of the implementation of the intervention. A detailed timeline of the intervention can be found in Figure 3. The four variables are non-emptiness of reports, coverage, completeness and coherence. All four are conditional on the CHW submitting a report. A detailed explanation of the variables can be found in Table A.3 in Appendix.

Figure 6 sheds a first light on the impact of One Health on the quality of CHW surveillance reports. At first sight, CHWs in the treatment and control group seem to perform similarly for all four outcome variables measuring the quality of submitted reports. The variable capturing non-empty reports (Panel A) is rather volatile over time, especially in the control group. In July 2017, none of the seven submitted reports in the control group logged a patient. Similar to Panel A, we observe some volatility in the control group in Panel B, for the variable $coverage_{it}$. Completeness of the reports remains rather stable over time (Panel C). Since September 2017, CHWs in the treatment group have a slightly higher average score for $completeness_{it}$ compared to CHWs in the control group. Last, in Panel D, scores on coherence of reports decreased slightly over time, this could be due to the replacement of older reports by newer forms. The headings of newer reports slightly differed from previous reports and could have led to confusion among CHWs. Overall, based on these graphs, we do not expect CHWs in the treatment group to score significantly higher on the quality of their submitted reports compared to CHWs in the control group. However, important to note is that the number of submissions with a score in the control group is rather low. For example, for the variable completeness, there are no scores for the control group between May and July 2017. Above that, the volatility of scores in the control group (especially in panels A, B and D) could also be driven by the small sample size and hence low number of submissions. Similar to the assessment of a treatment effects on the timeliness of reports, we expect our small sample size to limit the power to estimate an effect on these four outcome variables.

The impact of the One Health project on these outcome variables is estimated using the following regression.

$$y_{it} = \alpha_0 + \beta T_i + \alpha_c + \varepsilon_{it} \tag{3}$$

Where y_{it} are the four outcome variables described above (*non-empty reports*$_{it}$, *coverage*$_{it}$, *completeness*$_{it}$ *and coherence*$_{it}$). T_i is the One Health treatment indicator, with value 1 if the community was allocated to the One Health program and value 0 if the community only has a CHW. α_c are chiefdom fixed effects for the chiefdoms Gbense (=0) and Fiama (=1) and ε_{it} is the idiosyncratic error term.

We estimate the regression (3) for the sample since selection of the CAHW (t = {July 2017, …, April 2018}). All four outcome variables are standardized by subtracting the mean and dividing by its treatment group standard deviation, such that we can interpret changes as a one standard deviation change. The results are shown in Table 6. Since testing multiple hypotheses using the same dataset, we adjust p-values to account for the risk of over-rejecting the null hypothesis (Anderson, 2008). We apply False Discovery Rate (FDR) corrections to adjust the p-values for multiple inference using Benjamini Krieger Yekutieli (2006) two stage procedure for sharpened q-values (Anderson, 2008; Benjamini, Krieger, & Yekutieli, 2006). The q-values, reported in square brackets in Table 6, correct for testing four outcome variables and should be interpreted as the smallest level of significance at which each hypothesis would be rejected, in parallel to the p-values (Anderson, 2008).

Table 6: One Health treatment effects on reporting quality

	(1) non-empty $reports_{it}$	(2) $coverage_{it}$	(3) $completeness_{it}$	(4) $coherence_{it}$
treatment (=1)	0.022	0.011	0.012	-0.002
	(0.125)	(0.125)	(0.156)	(0.128)
	[1]	[1]	[1]	[1]
chiefdom (Fiama = 1)	0.251***	0.356***	-0.006	-0.033
	(0.093)	(0.093)	(0.116)	(0.094)
	[0.044]	[0.002]	[1]	[1]
constant	-0.164	-0.180	0.004	0.021
	(0.130)	(0.132)	(0.163)	(0.132)
	[0.704]	[0.704]	[1]	[1]
control outdated forms	No	Yes	No	No
R^2	0.015	0.050	0.000	0.001
Observations	475	471	308	467

Notes. This table shows the impact of the One Health program on the quality of CHW reports for those CHWs that submitted forms ($submit_{it}$ = 1). A detailed description of the outcome variables can be found in Table A.3 in Appendix. Outcome variables are group mean standardized. The sample consists of digitized CHW reports submitted since CAHW selection in July 2017 (t=10). Chiefdom fixed effects are included by variable Chiefdom (0 = Gbense, 1 = Fiama). Column 2 controls for outdated forms by adding a dummy variable with value 1 if the CHW uses outdated forms for that month and value 0 if not. The sample size varies within outcome variables due to attrition for some variables. OLS standard errors are shown in parentheses. Significance levels based on naïve p-values are indicated by * p < 0.10, ** p < 0.05, *** p < 0.01. Benjamini Krieger Yekutieli sharpened q-values (Anderson, 2008), used to correct for testing four outcomes, are shown in squared brackets .

Looking at the coefficients, we find that CHWs in treatment communities are more likely to score higher on three out of the four outcome measures. Table 6 shows that in the treatment group, CHWs on average score a 0.022 standard deviation higher on non-empty reports, a 0.012 standard deviation better on completeness of reports, a 0.011 standard deviation better on coverage and a 0.002 standard deviation worse on coherence. However, these treatment effects do not significantly differ from 0, for all four dimensions of CHW reporting quality.

One concern with using CHW reports as an outcome is that the One Health program could have caused a decrease in disease prevalence in treatment communities and consequently the number of patients assessed by the CHW. This is captured by two of the four dimensions used to measure the quality of reports, i.e. *Non-empty* $reports_{it}$ and $Coverage_{it}$. If the treatment caused a decrease in disease prevalence, then our estimates combine changes in disease prevalence and disease surveillance such that the estimates understate the impact of the project on CHW disease reporting. On the other hand, it could also be that, due to the presence of an additional health worker, villagers become more aware about their health status and visit the CHW more frequently. In that case, even if CHWs do not change their reporting quality, an increase in the uptake of services will be captured by the variables *Non-empty* $reports_{it}$ and $Coverage_{it}$. However, both arguments are not applicable to the timeliness of CHW reports, as CHWs are required to submit reports on a monthly basis, regardless of having assessed patients or not.

As stated before, we are dealing with missing data as our outcome variables that capture the quality of CHW reports are conditional on CHW submitting a report. If being a One Health community influences the number of months a report was submitted, it will also influence other variables that capture the quality of reports through $submit_{it}$. Even though assignment to treatment was randomized, there can still be non-random missing data. When this missing data is correlated to treatment, the validity of our estimators is compromised (DiNardo, McCrary, & Sanbonmatsu, 2006). The first-best solution to deal with non-random sample attrition is to collect information on all items for all sample units. However, as this is often not feasible, a variety of approaches to correct attrition and selection bias have been proposed in the literature. Heckman (1976, 1979) is using a 2-step selection correction estimator in which the process underlying the missing data is modeled. However, this approach relies on strict assumptions such as joint normality and is prone to misspecification (Tauchmann, 2014). Estimators that need fewer assumptions have been developed in response. Horowitz & Manski (2000) developed an estimator in which they impute missing outcome variables based on minimum and maximum values. However, using minimum and maximum values restricts the estimator to a certain interval and yields wide bounds (Tauchmann, 2014). To deal with non-random sample attrition, Lee (2009) proposed an estimator that bounds the treatment effect by comparing unconditional means of (trimmed) subsamples. The advantage of Lee bounds is that they rely on only two assumptions, namely random assignment of treatment and monotonicity, meaning that treatment only affects attrition in one direction for every individual (Tauchmann, 2014).

To see whether our estimates change when taking non-random sample attrition into account, we impute missing CHW reports with minimum and maximum values and we estimate Lee bounds for the treatment effect. In Table 7, missing reports are imputed with the group minimum and maximum for the period of 10 months to deal with non-random attrition.

Table 7: Upper and lower bound One Health treatment effects on reporting quality

	Panel A: lower bound treatment effect				**Panel B:** upper bound treatment effect			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
	non-empty $reports_{it}$	$coverage_{it}$	complete$ness_{it}$	$coherence_{it}$	non-empty $reports_{it}$	$coverage_{it}$	completeness_{it}	$coherence_{it}$
treatment (=1)	0.009	0.012	0.007	0.006	0.003	-0.018	-0.006	-0.003
	(0.087)	(0.086)	(0.087)	(0.087)	(0.087)	(0.085)	(0.087)	(0.087)
chiefdom (Fiama =1)	0.268***	0.342***	0.212***	0.163**	0.082	-0.154**	-0.161**	-0.086
	(0.067)	(0.067)	(0.067)	(0.067)	(0.068)	(0.066)	(0.067)	(0.068)
constant	-0.151*	-0.193**	-0.119	-0.091	-0.046	0.152*	0.091	0.048
	(0.087)	(0.087)	(0.087)	(0.087)	(0.088)	(0.086)	(0.087)	(0.088)
Control outdated forms	No	Yes	No	No	No	Yes	No	No
R^2	0.018	0.029	0.011	0.007	0.002	0.064	0.006	0.002
Observations	880	880	880	880	880	880	880	880

Notes. This table shows the impact of the One Health program on the quality of CHWs reports. The values for the CHWs that did not submit a report were imputed with the treatment group minimum (panel A) and maximum (panel B). Outcome variables are group mean standardized. Sample of digitized CHW reports submitted since CAHW selection in July 2017 (t=10). Chiefdom fixed effects are included by variable Chiefdom (0 = Gbense, 1 = Fiama). Column 2 controls for outdated forms by adding a dummy variable with value 1 if the CHW uses outdated forms for that month and value 0 if not. OLS standard errors are shown in parentheses. Significance levels based on naïve p-values and indicated by * p < 0.10, ** p < 0.05, *** p < 0.01.

Table 8 reports Lee bounds for the treatment effect for the sample since CAHW selection. Whereas in Table 7, missing values were imputed with the group minimum and maximum, the estimated Lee bounds in Table 8 correspond to extreme assumptions about the missing outcome variables. Lee (2009) proposed an estimator that bounds the treatment effect by comparing unconditional means of (trimmed) subsamples. The advantage of Lee bounds is that they rely on only two assumptions, namely random assignment of treatment and monotonicity, meaning that treatment only affects attrition in one direction for every individual (Tauchmann, 2014).

Table 8: Lee bounds for One Health treatment effects on reporting quality

	(1) non-empty $reports_{it}$	(2) $coverage_{it}$	(3) $completeness_{it}$	(4) $coherence_{it}$
Treatment (=1)				
lower bound	-0.113	-0.290*	-0.312	-0.089
	(0.150)	(0.172)	(0.245)	(0.140)
upper bound	0.650***	0.206	0.371	0.352
	(0.231)	(0.165)	(0.241)	(0.225)
Observations	880	880	880	880

Notes. This table shows the impact of the One Health program on the quality of CHWs reports. The values for the CHWs that did not submit a report were imputed using Leebounds in Stata. Outcome variables are group mean standardized. Sample of digitized CHW reports submitted since CAHW selection in July 2017 (t=10). Chiefdom fixed effects included by variable Chiefdom (0 = Gbense, 1 = Fiama) to tighten the estimated Lee bounds. OLS standard errors are shown in parentheses. Significance levels based on naïve p-values and indicated by * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

In Table 7, the coefficients for the treatment effect do not significantly differ from 0, imputing missing values with group minimum and maximum. In Table 8, where we construct Lee bounds, we find the upper Lee bound for *non-empty* $reports_{it}$ to be positive and significant at the 1% confidence level. The lower Lee bound for $coverage_{it}$ is negative and significant at the 10% confidence level.

5. CONCLUSIONS AND DISCUSSION

Having an effective disease surveillance system in place to timely predict, prevent and control diseases is a key priority for Sierra Leone, as has been demonstrated by the recent EVD outbreak. This thesis reports on a One Health intervention in Kono district in Eastern Sierra Leone. The aim of the intervention, conducted in collaboration with MoHS and MAFFS, is to improve human and animal health outcomes and to increase disease surveillance capacity by installing a platform for animal disease surveillance in addition to existing systems for monitoring human health.

Since 2012, CHWs are operating in every community to monitor and report on human health events. The One Health project can affect their performance by selecting and adding an additional health worker to the community, by training both health actors on joint disease surveillance and by installing a One Health platform in the community. This thesis assesses the impact of the One Health project on the reporting performance of CHWs in two of the seven One Health chiefdoms. We measure the impact of the intervention on the timeliness of CHW health surveillance reports and four dimensions of the quality of submitted reports: non-empty reports, coverage, completeness and coherence. Above that, we also investigate the factors affecting the number of reports submitted. To construct these outcome variables, we digitized monthly reports from 88 CHWs in two chiefdoms over a period of 12 months.

There are two main findings. First, we find that CHWs in communities that are part of the One Health program submit more reports, using three different measures for timeliness. CHWs in treatment communities are 9 percentage points more likely to submit a register compared to control communities. This effect is significant at the 5% confidence level and represents a 19% increase from the control group mean. Second, we find that, despite submitting more reports, there are no significant differences in the non-emptiness, coverage, completeness and coherence of the reports submitted by treatment or control CHWs.

The finding that the One Health project leads to an increase in the number of reports submitted by CHWs is promising for two reasons. First, more reporting could indicate that the quality of health care increased. Engaging health actors in a One Health approach could incentivize CHWs to exert better quality care. Hence, we can also expect human health outcomes to improve. Second, a well-functioning health system requires transferring community level data to higher levels of decision-making. More reporting at the community level can lead to more data at the district and country level, which enables the government to be more prepared for and more responsive to future outbreaks.

It is encouraging that the One Health project incentivizes CHWs to submit more reports without compromising the quality of the submitted reports. Nevertheless, our study shows that the overall quality of CHW reports is very low. About 30% of the submitted reports were empty. Despite repeated trainings, CHWs seem to struggle with filling out these forms correctly: scores for coherence and completeness are far below the maximum. The quality of CHW registers is crucial in order to allow governments to work with these reports. Exploring strategies to improve the quality of reporting, such as simplified forms or increased training and supervision should be a priority for future research.

In the literature, CHW characteristics, financial and non-financial incentives, training, peer relationships and community engagement are all identified channels influencing health workers' performance. Future research should further probe the mechanism behind increased CHW performance in a One Health intervention and to what extent increased performance improves health outcomes.

A certain degree of caution is needed when interpreting our findings. Most importantly, this study has been implemented using a limited sample of CHW reports. The small sample size has consequences for power, the ability to avoid making Type-II errors. Above that, carefulness is required when extrapolating the results of an RCT beyond the study sample. The two study chiefdoms were chosen non-randomly from a set of seven chiefdoms due to their proximity to the district capital. Hence, our findings on the timeliness and quality of CHW reports are only valid in this setting and do not necessarily apply to other chiefdoms, districts or countries. The scale-up of this analysis to the five other One Health chiefdoms will allows us to draw more meaningful conclusions on the external validity of our findings. Above that, we used CHWs reports from the start of the intervention until 10 months after the first contact with the intervention. This period should be large enough to rule out novelty effects but too short to say something on the long run effects of the intervention. Future research should extend the time horizon of the evaluation to see whether the effects persist in the long run.

Overall, bearing the abovementioned cautions in mind, this thesis presents some of the first evidence that the introduction of the One Health project can trigger CHWs to report more without affecting the quality of those reports submitted. The One Health project could be step in the way towards an efficient, strong and resilient system for public health that is prepared to respond to future outbreaks of emerging infectious diseases.

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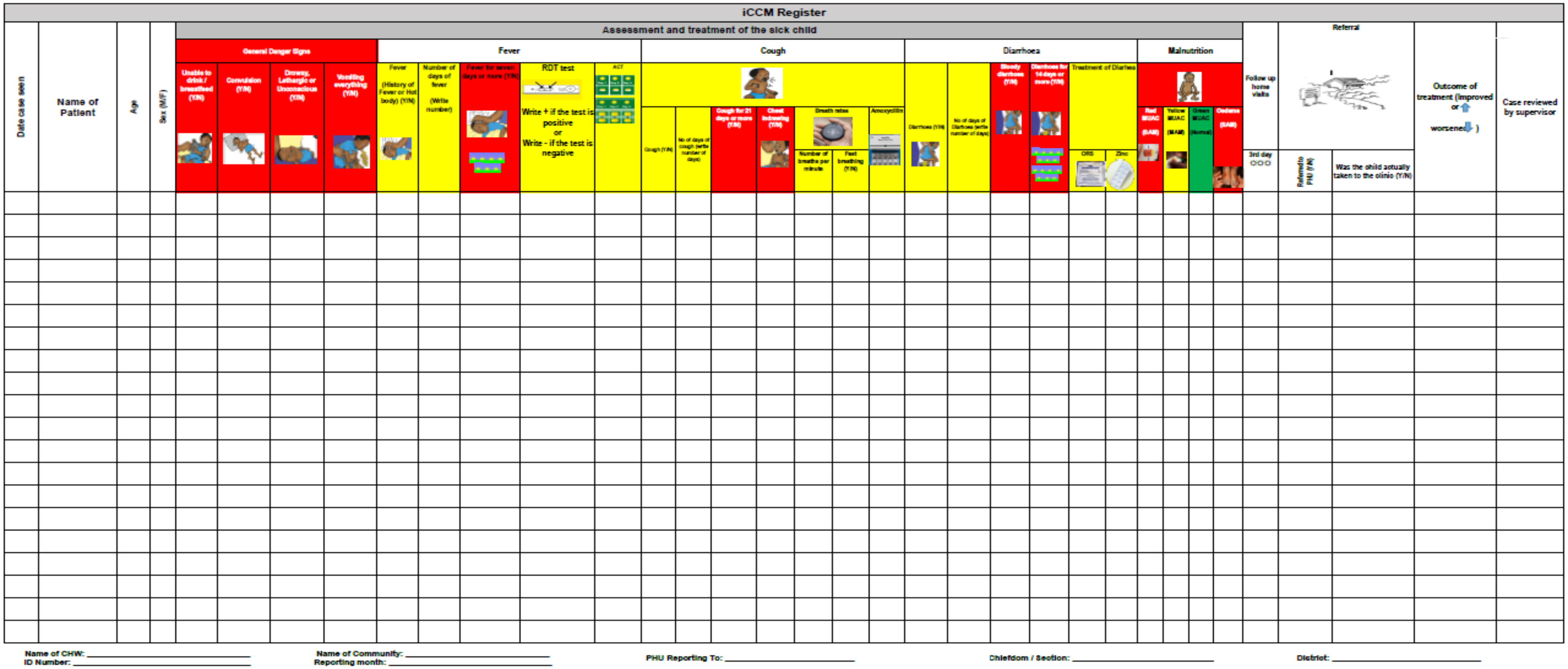
Appendix



iCCM Register

Assessment and treatment of the sick child

Date case seen | Name of Patient | Age | Sex (M/F)

General Danger Signs: Unable to drink / breastfeed (Y/N) | Convulsion (Y/N) | Drowsy, Lethargic or Unconscious (Y/N) | Vomiting everything (Y/N)

Fever: Fever (History of Fever or Hot body) (Y/N) | Number of days of fever (Write number) | Fever for seven days or more (Y/N) | RDT test: Write + if the test is positive or Write - if the test is negative | ACT

Cough: Cough (Y/N) | No of days of cough (write number of days) | Cough for 21 days or more (Y/N) | Chest indrawing (Y/N) | Breath rates: Number of breaths per minute, Fast breathing (Y/N) | Amoxycillin

Diarrhoea: Diarrhoea (Y/N) | No of days of Diarrhoea (write number of days) | Bloody diarrhoea (Y/N) | Diarrhoea for 14 days or more (Y/N) | Treatment of Diarhea: ORS, Zinc

Malnutrition: Red MUAC (SAM) | Yellow MUAC (MAM) | Green MUAC (Normal) | Oedema (SAM)

Follow up home visits: 3rd day

Referral: Referred to PHU (Y/N) | Was the child actually taken to the clinic (Y/N)

Outcome of treatment (Improved or ⇧ worsened ⇩)

Case reviewed by supervisor

Name of CHW: ____________
ID Number: ____________
Name of Community: ____________
Reporting month: ____________
PHU Reporting To: ____________
Chiefdom / Section: ____________
District: ____________

Figure A.1: iCCM register

Notes. This register was obtained from the DHMT. The iCCM register focusses on children between 2 and 59 months and aims to record symptoms related to priority diseases, such as pneumonia, malaria and diarrhea. One line is filled out per sick child.

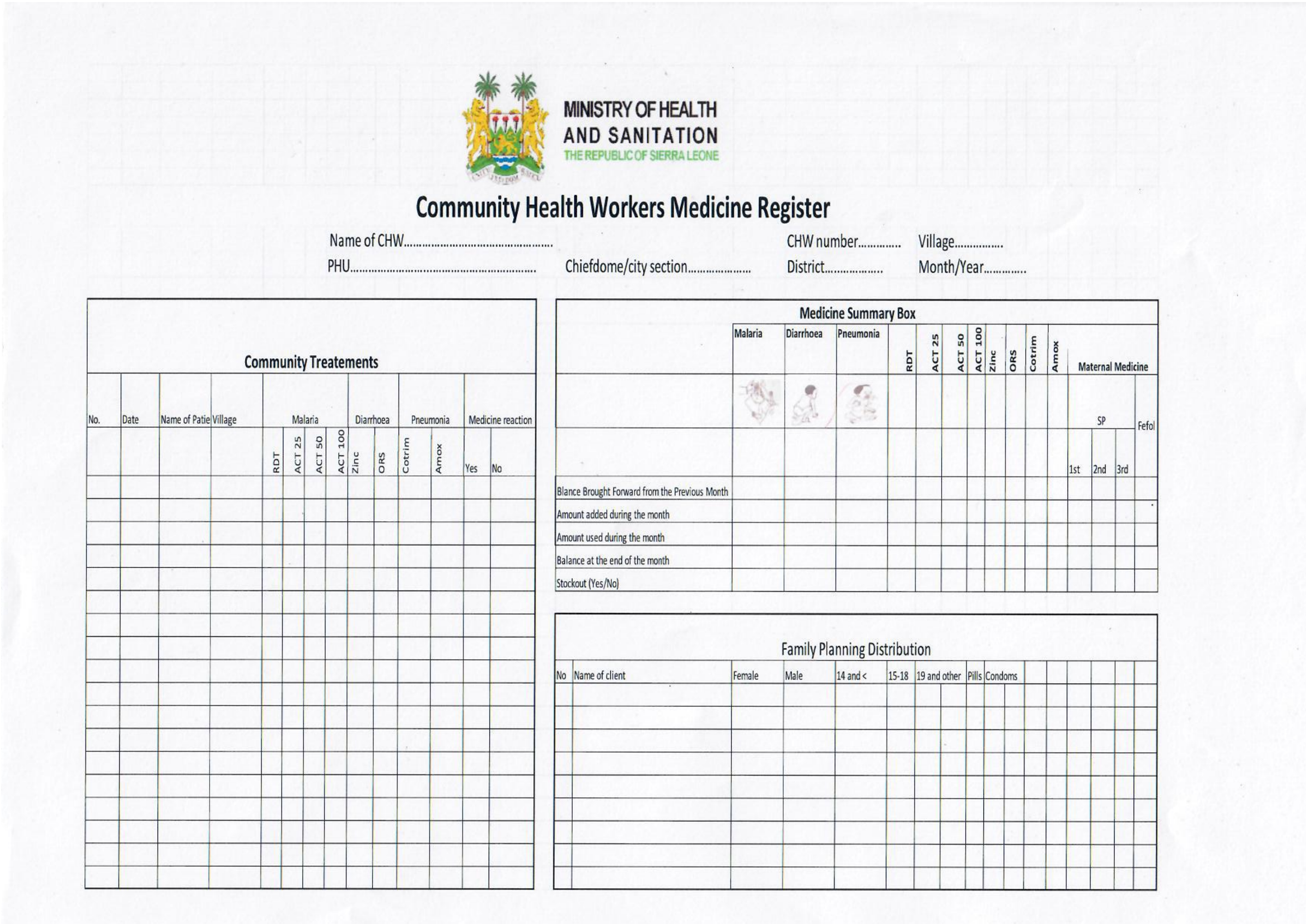
Community Based Surveillance Register																			
Basic information					Births			Conditions											
Date of Occurrence	House Number	Name (Mother's name, in case of births)	Age	Sex (M/F0	Live birth - girl	Live birth - boy	Stillbirth	Death of Newborn	Neonatal Tetanus	Death of Mother	Clustered Deaths	Polio	Run belleh / Suspected Cholera	Fever with rash / Suspected Measles	Fever with yellow eyes	Guinea worm	Suspected Ebola	Informed peer supervisor	Supervisor check and date

Name of CHW: ____________________ Name of Community: ____________________________

ID Number: _________________________ Reporting month: ______________________ PHU Reporting To: ___________________ Chiefdom / Section: _________________________ District: ___________________________

Figure A.2: Community Based Surveillance Register

Notes. This register was obtained from the DHMT. The CBS register serves to report any occurrence of alarming illnesses, such as polio, cholera, measles, Ebola or clustered deaths in the community. One line is filled out per patient.



MINISTRY OF HEALTH AND SANITATION
THE REPUBLIC OF SIERRA LEONE

Community Health Workers Medicine Register

Name of CHW.. CHW number............. Village................
PHU... Chiefdome/city section...................... District.................... Month/Year..............

Community Treatements

No.	Date	Name of Patie	Village	Malaria				Diarrhoea		Pneumonia		Medicine reaction	
				RDT	ACT 25	ACT 50	ACT 100	Zinc	ORS	Cotrim	Amox	Yes	No

Medicine Summary Box

	Malaria	Diarrhoea	Pneumonia	RDT	ACT 25	ACT 50	ACT 100	Zinc	ORS	Cotrim	Amox	Maternal Medicine			
												SP			Fefol
												1st	2nd	3rd	
Blance Brought Forward from the Previous Month															
Amount added during the month															
Amount used during the month															
Balance at the end of the month															
Stockout (Yes/No)															

Family Planning Distribution

No	Name of client	Female	Male	14 and <	15-18	19 and other	Pills	Condoms

Figure A.3: Community Health Workers Medicine Register

Notes. This register was obtained from the DHMT. The medicine register contains data on community treatments, medicine stock and family planning distribution stock. For this register, we digitized the number of patients in the community treatment box and family planning distribution box and whether the medicine summary box was filled out or not.

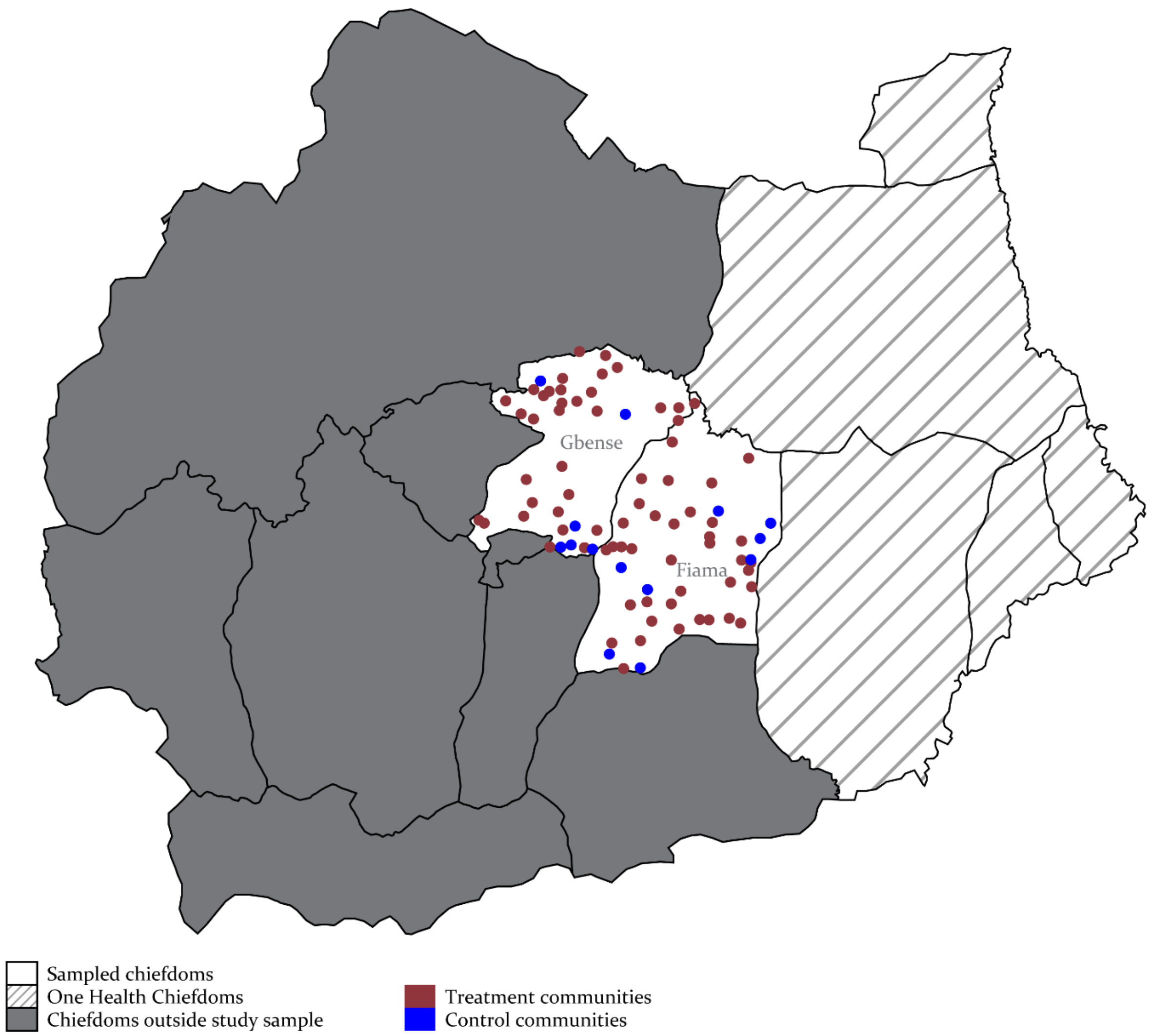


Figure A.4: Map of sampled villages

Notes. This map is an own drawing. The map depicts Kono district. Areas in dark grey are chiefdoms in Kono district outside our study sample. The white areas contains chiefdoms that are part of the One Health project. The shaded area are the five chiefdoms that are part of the One Health project but not of this study sample. We digitized CHW reports in Gbense and Fiama chiefdom. The treatment and control communities in those two chiefdoms are depicted with red and blue dots respectively. GPS coordinates were obtained during Chief and Household census in October/November 2017. GPS coordinates of two control communities (Kafaidu and Yendu) are missing.

Table A.1: One Health treatment effects with PS fixed effects

	(1)
	$submit_{it}$
treatment (=1)	0.065*
	(0.038)
chiefdom (Fiama = 1)	0.159
	(0.103)
constant	0.685***
	(0.098)
PS fixed effects	Yes
Observations	880
R^2	0.352

Notes. OLS Estimates. Dependent variable is $submit_{it}$, a monthly submission dummy in a balanced panel dataset with 1 observation per CHW per month. Chiefdom fixed effects are captured by the variable Chiefdom (Fiama = 1, Gbense = 0). Peer Supervisor fixed effects are included. All columns contain CHW reports submitted since CAHW selection in July 2017 (t=10). Standard errors are reported in parentheses and significance levels are based on naïve p-values and are indicated by * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.2: CHW characteristics

CHARACTERISTICS	Type of variable	Description	Source
CHW Characteristics			
age	Continuous	CHW age in years	IRC dataset
gender	Categorical	0 = male 1 = female	IRC dataset
residency	Categorical (binary)	Does the CHW reside in your community (0 No, 1 Yes)	OH HH survey
closeness_chw	Categorical	How close is your relationship with the CHW to you, compared your relationship with other community members (scale ranging from CHW is at the back (1) to CHW is at the front (5)).	OH HH survey
borrow_chw	Categorical	How likely would the CHW borrow you rice/money without interest, if asked for (scale ranging from definitely not (1) to definitely (5))	OH HH survey
Community Characteristics			
distance to PHU	Continuous	Distance in KM between community and PHU	IRC dataset
community size	Continuous	Number of structures in the community, proxy for community size – 'patient volume'	OH HH census
chiefdom	Categorical (binary)	0 = Gbense 1 = Fiama	
Program Characteristics			
chw per PHU	Continuous	Number of CHWs per peer supervisor	IRC dataset
training center	Categorical	Training center for general trainings	IRC dataset
T_C	Categorical (binary)	0 = Control 1= Treatment	

Table A.3: Data quality dimensions

Name	Description	Mathematical notation
Name	**Description**	**Mathematical notation** *subscript i (1,…,88) stands for the CHW, t (1,…,12) for month and q (0, …, 28) for the number of patient in a register.*
non-empty reports$_{it}$	Given that the CHW submitted a report, did he/she log a HH visit/case last month? Dummy with value 1 if iCCM or CBSR (or outdated forms: odpat) contains patients	If $submit_{it}$ = 1 $non-empty_{it} = 1$ if [iccm_no$_{it}$ >0 *or* cbsr_no$_{it}$>0] *or* [odpat_no$_{it}$>0], else 0
coverage$_{it}$	Average number of patients per submitted report –divided by community size	If $submit_{it}$ = 1 $Coverage_{it} = \frac{iccm\_no_{it}(or\ \text{odpat\_no}_{it})}{total\_struc\_count}$
completeness$_{it}$	Value recorded when there should be one – for example, if child is said to have a fever, number of days of fever is filled out <u>Restricted sample: o</u>nly for submitted iCCM registers	If $submit_{it}$ = 1 and non_empty_{it} =1 $Coherance_{it} = \frac{iccm\_score_{it}}{iccm\_no_{it} > 0}$ $iccm\_score_{it} = \frac{\sum_1^q patient\_score_{itq}}{q}$ $patient\_score_{itq} = 8 - \#mistakes$ *<u>Mistakes</u>:* *Iccm_age> 5y or > 60m* *Iccm_sex=999* *Iccm_fever_days =0|999 if iccm_fever = 1* *Iccm_cough_days=0|999 if iccm_cough = 1* *Iccm_diarr_no_r=0|999 if iccm_diarr= 1* *Iccm_malnutr= 999* *Iccm_refr_r = 1 (followed-up 3rd day)* *Iccm_outcome_r= 999*
coherence$_{it}$	Top of form (name of CHW/village/date) correct for all forms submitted	If $submit_{it}$ = 1 $Accuracy_{it} = \frac{form\_score_{it}}{nr\ of\ forms\ submitted_{it}}$ $form\_score_{it}$= 1 if top information is corresponding for all forms submitted, else 0

Table A.4: t-test thesis sample versus One Health sample

	Mean thesis sample	Mean One Health sample	Difference
Age (years)	45.01	42.55	2.46*
Female (=1)	0.13	0.18	-0.05
Number of CHWs per PHU	10.14	15.96	-5.82***
Distance to PHU (km)	6.33	9.15	-2.82***
Sample size	88	290	

Notes. Column 1 and 2 report sample means for CHWs in the thesis sample and One Health sample respectively. Column 3 reports the difference. P-values for the difference between the means and are indicated by * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.5: t-test thesis sample versus Kono district

	Mean thesis sample	Mean Kono district	Difference
Age (years)	45.01	43.06	1.95
Female (=1)	0.13	0.19	-0.06
Number of CHWs per PHU	10.14	15.81	-5.67***
Distance to PHU (km)	6.33	8.25	-1.93***
Sample size	88	831	

Notes. Column 1 and 2 report sample means for CHWs in the thesis sample and entire Kono district respectively. Column 3 reports the difference. P-values for the difference between the means and are indicated by * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$