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Primary Health Care Interventions and Social Ties in Kenya

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To my Mum, Dad and Sisters

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Josephine G. Gatua
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Contents

Introduction

Despite the remarkable health advances made globally in the 20th century, every day about 15,000 children die before the age of 5 (UNICEF, 2017). Yet, 87% of these deaths are due to preventable and treatable diseases such as malaria. Also, the burden of preventable diseases varies greatly across countries and regions, with populations in economically richer countries enjoying better health and higher life expectancy (Weil, 2007). The health improvements in high-income countries are possible because higher living standards lead to enhanced prevention and treatment of disease. However, in less developed countries, there is a lack of improvement in health due factors such as limited resources and shortages of health care workers.

To improve the health of people in low-income countries, substantial investments are required to control preventable and treatable diseases such as malaria. As an example, according to the World Health Organization (WHO), from 2014 to 2016 a total of 582 million insecticide-treated nets (ITNs) (for malaria prevention) were reported to have been delivered globally. Of these, 505 million were delivered in sub-Saharan Africa, with 75% being distributed through free mass distribution campaigns. And for the treatment of malaria, 269 million rapid diagnostic tests (RDTs) were delivered in sub-Saharan Africa. Moreover, in 2016, an estimated USD 2.7 billion globally was invested by malaria endemic countries with international partners for malaria control and elimination efforts, and 74% of this amount was spent in the sub-Saharan African region. Yet, despite the large investments in 2016, 90% of all malaria cases occurred in sub-Saharan Africa.

Investing in health without considering poverty may be a possible explanation as to why investments in health do not fully translate into better health. This is because of the negative association between disease and economic growth (Bleakley, 2010; Cutler et al., 2010). Health and poverty were first addressed together in 2000 through the Millennium Development Goals (MDGs). The MDGs were a set of eight measurable global goals designed to reduce poverty for 15 years from 2000 to 2015 . All of the goals impacted health, with at least four being directly related to child health or nutritional status (Todaro and Smith, 2003). This is because child health is a key indicator of economic development and can also have significant long-term effects on outcomes such as educational attainment, intergenerational poverty, and productivity (Alderman et al., 2006; Bhargava et al., 2001; Savedoff and Schultz, 2000). Various health interventions aimed at achieving the MDGs were introduced in developing countries. Although substantial progress was made toward the achievement of the MDGs, by 2015 hardly any African country had succeeded in meeting any of the health-specific goals (AfDB, 2014). Hence, a set of new goals, the UN Sustainable Development Goals (SDGs), were integrated with the MDGs to form a new agenda 2020, which set new goals aimed at controlling or fully eliminatingd diseases such as malaria, HIV/AIDS and tuberculosis.

To further understand how the objectives of the SDGs can be achieved, it is important to look at the financing of health care in developing countries, where a substantial size of the population live below the poverty line. Standard public finance analysis implies that health goods generating positive externalities should be publicly funded, or even receive full subsidy if the private non-monetary costs (such as side effects) are high (Cohen and Dupas, 2010). In light of such positive externalities and high poverty levels, developing countries have highly subsidized products for prevention and treatment of malaria. However, even with subsidies present, a puzzle still remains: on the one hand, the consumption of antimalarial drugs creates a trade-off between targeting (ensuring that only true malaria cases are treated with antimalarial drugs) and effectiveness (the ability of antimalarial drugs to cure malaria). On the other hand, the use of bed nets has remained low relative to the increase in supply. Why do people fail to correctly utilize goods that are beneficial to their health and are freely provided?

To begin with, a central prediction of psychology and economics is that higher prices will cause greater product use through a *sunk-cost effect* (Eyster, 2002; Thaler, 1980). This prediction implies that if goods are provided freely or at a highly subsidized price, the use of such goods decreases since people do not experience the sunk-cost effect. However, as stated previously, charging a positive price for health products in developing countries will most likely dampen demand. This type of situation obviously creates a dilemma for governments of developing countries. Next, households in developing countries, often under-invest in preventive health care in part due to lack of information on illness prevention or on the effectiveness of preventative behaviors (Dupas, 2011; Madajewicz et al., 2007). Lastly, access to health care may be an impediment to better health services (Peters et al., 2008). How to improve access to health care and health information so as to achieve better health outcomes has remained a key challenge in developing countries.

As noted above, it is evident that further solutions to health problems facing developing countries are needed. Decentralization has been advocated as a desirable process through which the provision of public goods and services can be improved, especially in developing countries (Crook, 2003; Galasso and Ravallion, 2005). Likewise, decentralized governance in health service delivery is becoming increasingly common (Anderson and Hussey, 2001). Decentralization has two main benefits: first, local leaders are almost surely more informed about the differing needs of people in their village than a centralized bureaucracy can ever be, and second, local leaders are typically more accountable to villagers (Besley and Coate, 2003). On the downside, decentralization may open the door for corruption and nepotism (Bardhan and Mookherjee, 2006). In developing countries, it is becoming popular to shift basic primary health care from conventional health care facilities to service provision in under-served communities through so-called community health workers (CHWs) (Singh and Sachs, 2013). CHWs are community members who are selected and trained to support health service delivery and act as a link between the community and the health system. CHWs have a potential to provide the much needed solution to the health crisis facing developing countries by conducting home visits within the community, educating households on essential health behaviors, providing basic medical advice, and referring the more severe cases to the closest health facility. This dissertation explores the local dynamics of this community-based health system, and whether the system meets the desired objectives of improved health and health care behavior, in Kenya. It does this by looking at whether the program provides a solution to the mismatch between health and investment as stated previously, whether households within the community are sufficiently informed to make health choices that benefit the community, and whether corruption exists in such a community-based health program.

Summary of chapters

In order to investigate the various aspects of health and health care behavior noted above, this dissertation explores two interventions in Kenya. The first is a CHW intervention through which locally elected volunteers offer health care to their communities. The second is an original information intervention whereby households are provided information on community effects of their preventive health behavior. Chapter I analyzes the role of social connections between households and CHWs. Chapter II focuses on the effect of CHWs on child health outcomes and health related behavior, and Chapter III explores the effect of health information on households' preventive health behavior. To identify these effects, I use a novel household and CHW survey dataset, as well a nationally representative household survey dataset.

In the first chapter, *Decentralization, Social Connections and Primary Health Care: Evidence from Kenya*, I use survey data to investigate the role of social connections in the provision of health care and examine whether these connections matter for health-seeking behavior. In particular, I look at whether relationships between CHWs and households affect the number of health care visits households receive, and the probability that households receive free essential drugs from CHWs. I find that CHWs tend to visit households with which they have some social relationship (relatives and close friends) with significantly greater frequency than they visit households with which they have no social relationship. Similarly, socially connected households are more likely to access antimalarial drugs for free. I also show that the health-seeking behavior of households that are socially connected to a CHW is better than that of households that are not socially connected.

In Chapter II, *Community Health Workers, Child Health and Health Care Utilization in Kenya* (co-authored with Jessica Coria), I explore the causal effects of a CHW program on child health and health-related behavior. This chapter uses the spatial rollout of CHWs in Kenya as a quasi-experiment. The identification strategy relies on spatial variation of CHW presence in a propensity score matching analysis. Using a large sample of households with children under age 5, the analysis shows that the introduction of CHWs had little impact on child health and health care outcomes in both rural and urban areas. These findings imply that the SDGs related to child health will not be achieved using the current setting of the CHW program.

In chapter III, *Information and Cooperation in Preventive Health Behavior: A Case Study of Bed Net Use*, I explore the effect of preventive health information on cooperation in the use of bed nets in Kenya. Bed nets are effective for preventing malaria, and the Kenyan government actively informs people on the private benefits of using them. Even if bed nets are provided for free or at a highly subsidized price, the daily use of them has remained low. I use a survey experiment to test whether informing people about the community benefits of using bed nets, and whether others are using bed nets, affects people's bed net use decisions. I do this because the use of bed nets confers two types of benefits: the first is the private benefit and the second, which is currently not in the public domain is the public benefit. I find that individuals who received information on the public benefits of bed net use, as well as those who received such information together with information on how own use affects the health of their neighbors, are more willing to use bed nets than individuals who were only given the existing information on the private benefits of bed net use. The findings further show that people who have information on the public benefits of bed nets use are willing to increase their own use of bed nets when they know that more people in the community are also sleeping under bed nets. The observed behavior is consistent with people being conditionally cooperative in decisions involving bed net use.

To sum up, these three independent chapters show that decentralizing primary health care has some potential to improve public health. Chapter 1 considers an aspect of the delivery of the CHW program, nepotism, that could contribute to the program's lack of impact revealed in Chapter II. The CHW program has some positive impact as well, namely improved health seeking behavior among beneficiaries of the nepotism. But, the results also show that households that are not socially connected to CHWs are more likely to store anti-malarial drugs at home, which is a likely indicator of presumptive treatment. The presence of presumptive treatment prevents proper targeting of antimalarial drugs and as a result leads to wastage and potential drug resistance. Chapter III shows that people are responsive to extra information on public benefits of their preventive health behavior. In fact, people are willing to cooperate in preventive health when they know that others cooperate, too. Therefore, providing information on the public benefits of bed net use in addition to the already existing information on the private benefits is a potential path to reduce malaria. Indeed, CHWs could easily provide the information but the presence of nepotism in service delivery introduces discrimination, which could potentially deprive people of information that would otherwise be valuable for their decision making. This dissertation demonstrates why there is a disconnect between investments and improved health, and also that the current CHW program is unlikely to align investments with health unless a closer look at its implementation is taken. A caveat of the dissertation is that the focus is somewhat narrow in only examining one country, Kenya, but the insights generated are likely transferrable to a variety of contexts, especially in sub-Saharan Africa.

The findings also highlight some useful avenues for future research. First, while I find that localizing primary health care promotes nepotism, I do not investigate whether the health advice and information provided by CHWs differs from the information CHWs obtain from training. Second, while I do not find strong evidence on the effects of CHWs, the dissertation does not explore the potential mechanisms behind the observed effects. Finally, it would be useful to consider the observed short- and long-term behavior of households that receive information on the benefits of preventive actions.

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Chapter I

Decentralization, Social Connections and Primary Health Care: Evidence from Kenya*

Josephine G. Gatua†

Abstract

This paper estimates the role of social connections in primary health care provision and its effect on health-seeking behavior. The study employs novel survey data from Kenya, which combines information on households and Community Health Workers (CHWs). The results show that social connections strongly influence the provision of health care. Being a relative or close friend to a CHW increases the probability that a household will be visited by about 100 percent (with respect to the mean). I also find that socially connected households demonstrate better health-seeking behavior. The evidence indicates the existence of nepotism in primary healthcare provision, with beneficiaries of nepotism having better health-seeking behavior.

Keywords: Community Health Workers, Malaria, Visits, Health-seeking behavior.

JEL Codes: I10, I12

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1 Introduction

Decentralization of public services, particularly in developing countries, is a subject of long-standing interest to economists and policy makers (e.g., Bardhan et al., 1998; Besley et al., 2011; Fisman and Gatti, 2002). The logic underlying decentralization is that it brings the government closer to the people; which fosters greater trust, capacity for collective action, and legitimacy of decision-making, especially among more homogeneous groups (Meagher, 1999). In developing countries, it is becoming popular to shift basic primary healthcare from facilities to underserved rural communities through community health workers (CHWs)(Singh and Sachs, 2013). Whether this type of community involvement in healthcare allows for the provision of better and more equitable health services to all citizens is far from obvious, and remains a major question for both policymakers and researchers.

This paper therefore seeks to answer the question: what is the effect of bringing health care services closer to the community, in terms of healthcare benefits to the population? In particular, I assess whether CHWs favor any group of individuals, and which ones, in their distribution of effort in the delivery of primary health care in the community. I do this by looking at the role of social connections between CHWs and households, and whether social connections are relevant for household health-seeking behavior. The extent to which social connections can influence service provision in a community setting – and more so in a developing country context – has not been studied before, and is an important question. To the best of my knowledge, this is the first study to address social connections in a decentralized health care setting.

I use cross-section data from a field survey on randomly selected households, and data from a field survey of CHWs in rural Kenya. Social connections in a community setting can be defined as whether a household is a relative, close friend or acquaintance of a CHW, or has no relation to the CHW at all. I estimate the effect of social connections on delivery of healthcare by examining the mandatory healthcare visits that a CHW makes to households, as well as households' access to antimalarial drugs. I also assess whether social connections influence household health-seeking behavior. To assess health-seeking behavior, I look specifically at health behavior related to malaria treatment. I do this because malaria accounts for a large proportion of the burden of disease globally, and especially in sub-Saharan Africa.[1] Treatment of malaria is therefore central to limiting the spread of malaria. This paper therefore further contributes to the ongoing debate on treatment of malaria where consumption of antimalarial drugs creates a trade-off between targeting (ensuring only true malaria cases get treated with antimalarial drugs) and effectiveness (ability of antimalarial drugs to cure malaria)(see Cohen and Dupas, 2010).

Different types of connections have been studied. One distinct strand of the literature documents that connections to politicians are relevant to the fortunes of individuals, groups and organizations (Faccio, 2006; Fisman, 2001; Johnson and Mitton, 2003; Khwaja and Mian, 2005). The findings from these studies indicate that connections can be viewed as generating favoritism that leads to unequal outcomes for individuals, groups and organizations. Another fast-growing strand of literature looks at how family connections to officials in public office affect private market outcomes for the connected individuals (Fafchamps and Labonne, 2017; Gagliarducci and Manacorda, 2016; Markussen and Tarp, 2014). These studies find that individuals with family members who hold public office have better jobs, higher incomes, and more investments, compared to those with no connections.

A related but distinct literature examines the role of social heterogeneity for the availability of public goods (e.g., Alesina and La Ferrara, 2000), and concludes that there is a paucity of work that provides explanations for how social connections affect public service delivery. The paper with the most similar focus to the current paper is Besley et al. (2011), which

[1]The global incidence of malaria is estimated at 350 to 500 million clinical cases annually, resulting in 1.5 to 2.7 million deaths each year in sub-Saharan Africa and parts of Asia WHO (2000). Moreover, in Kenya, malaria is the leading cause of morbidity and accounts for 19% of hospital admissions and 30-50 % of outpatient cases in public health institutions (Kioko et al., 2013).

investigates how political influence is used in the allocation of public resources in southern India, where villages are allowed to govern themselves (as opposed to falling under central governance). In this setting, policymaking and allocation of public resources are delegated to elected village councilors. The state introduced a subsidized program that entitles households to buy food at below market prices, giving politicians the power to allocate a Below Poverty Line (BPL) card to households, according to need. The study finds that politicians' households are more likely to be BPL-program beneficiaries, that BPL-card-holding politicians are less likely to allocate BPL cards to socially and economically disadvantaged households, and that villagers are more dissatisfied with the performance of these politicians than with others.

So far, the literature indicates that family ties are important; but are ties to relatives and friends in 'public office' important for the delivery of healthcare services? A priori, it is not clear whether public officials will discriminate in favor of their relatives or friends. There are several reasons to expect that family ties to public officials should not matter to how they deliver public services. First, these public officials are serving the members of the community they live in, and are unlikely to be driven by a desire to discriminate against any household; a possible reason is that the officials are determined to work together for the benefit of the community. Second, the officials' performance is likely to be monitored by existing institutional structures. However, there are competing reasons for why we might expect that family ties would matter. If a public official volunteers to deliver services to the community, he may do so for the sole motive of discriminating in favor of his relatives and friends. This could be because the official attaches greater weight to the health and well-being of his relatives and friends, and would want to see those improved; and hence, would offer more services. Similarly, the official might be motivated to offer more services to those with whom he has ties, with the expectation that they will reciprocate in some way.

Whether or not differential treatment by public officials to relatives and friends exists is therefore an empirical question that has not previously been addressed in the literature, and which this study seeks to explore.

The importance of studying this issue is that it enables us to investigate the efficiency of service provision by public officials, by exploring whether the level and quality of services offered differs according to family ties or a lack thereof.

After controlling for household characteristics and village-fixed effects, results show that the provision of health care services by CHWs is biased. On average, households that are relatives or close friends of a CHW receive two more visits within three months than households with no social relationships. Similarly, relatives and close friends of a CHW are more likely to receive essential antimalarial drugs for no payment, compared to similar households in the village that have no social relations with the CHW. In addition, the evidence suggests that households of relatives and close friends of CHWs tend to have better health-seeking behavior, compared to households that do not have social relations with a CHW. Although the paper does not explicitly explore the quality of services provided by CHWs, the results on health-seeking behavior of households reflect on the quality of the services provided by CHWs. That is to say, CHWs provide the expected health education during the CHW visits to households.

The remainder of the paper is organized as follows. Section 2 explains the Community Health Worker intervention. Section 3 discusses the data and variables. Section 4 addresses the empirical strategy and identification issues. Section 5 discusses the results. Section 6 discusses robustness tests, and Section 7 concludes.

2 Community Health Worker Policy

In Kenya in 2005, the National Health Sector Strategic Plan (NHSSP II-2005-2010) introduced a health reform known as the Kenya Essential Package for Health (KEPH). This reform introduced the community (villages and households) as a new level in the delivery of healthcare; this level would be the lowest level in the healthcare delivery system. The primary aim of the reform was to enhance community access to healthcare, providing affordable, equitable and effective healthcare by empowering households and communities to take charge of improving their own health.

For the community level to be functional, the policy required the introduction of Community Health Workers (CHWs). CHWs are lay members of the community who offer health care services to the local population. Thus, they act as an interface between the community and the dispensary, which was previously the lowest level. The policy requires one CHW to serve 20 households, which implies that one or more CHWs may serve a single community. The process of selecting CHWs is as follows: first, the local dispensary tells local administrative leaders that they can make an announcement calling for volunteers to work as CHWs. Community members are informed of the need for volunteers to serve the community as CHWs. To be eligible for election as a CHW, one must be a member of the particular community one wishes to represent, and also be able to read and write in English or Kiswahili.[2] Second, the local administrative leaders (chiefs), in conjunction with the local dispensary, inform the community who the potential candidates are who want to volunteer as CHWs. And third, through a voting process the community decides whether or not they want to be served by these candidates.[3] Announcements cease to be made once the community has attained its target number of CHWs.

Once a CHW is elected by the community, the local administrative leaders and the local dispensary allocate households in that community to the CHW. The assignment of households to CHWs typically occurs in two steps: the community is divided into sections, and all the households in a particular section become the responsibility of one CHW. It may be that a CHW could influence to which section he or she is allocated, but it would be difficult to select particular households, since they would have to serve all the households in that section. For example, in this

[2] This is because training of CHWs is conducted in either of these two languages which are the official languages in Kenya.

[3] From discussions held with the local administrative leaders, it appears the voting process follows the principle of majority rule. However, there is no clear-cut definition of ‘majority’, since the voting is conducted through the ‘yea and nay’ process.

study, none of the CHWs interviewed reported having been allocated households belonging to relatives or close friends exclusively. When a CHW ceases working as a CHW, whether voluntarily or involuntarily, their place is filled by another community member through the same process outlined above.

The CHW policy was designed in such a way that CHWs work on a part-time basis without compensation for their services. In a community setting in a developing country context, people may be willing to volunteer for no payment. This is because there may be other, competing reasons that an individual might want to volunteer, for example: people may be altruistic, and want to help their communities; in rural areas, holding an elected position brings respect and recognition from other community members; and being elected as a CHW improves your chances of being involved in future community projects – such as government and donor-funded projects, which attract compensation.[4]

CHWs provide preventive/promotive healthcare, but some provide curative services as well. The duties performed by CHWs are: (a) the treatment of malaria and the provision of Long-Lasting Insecticide-Treated Nets (LLITNs); (b) the provision of information on water and sanitation hygiene; (c) advice on maternal and child health; (d) the provision of family- planning commodities; (e) growth monitoring for children under the age of five; (f) deworming of children; (g) management of diarrhea, injuries, wounds, jiggers and other minor illnesses; (h) the provision of Information, Education & Communication (IEC) materials; (i) defaulter tracing[5]; (j) referrals to health facilities; and (k) first-aid services.[6]

In order for CHWs to perform their tasks, they receive basic health care training from health care professionals, and are re-trained from time to time. Once they have completed basic training, they are allocated specific households in the community. They are then required to make

[4] This statement was informed by conversations I had with CHWs from the study area.

[5] Individuals with HIV/AIDS or tuberculosis (TB) are required to undergo antiretroviral therapy and take TB medicine, respectively.

[6] As described at `www.hsrs.health.go.ke`.

at least one mandatory visit per month to each of the households, to offer health care services. Therefore, CHWs in the same village focus on their assigned households, and work independently of each other. However, a CHW has discretion as to which households to visit on a given day, and the number of times these households are visited in a month. Households may also call upon CHWs to provide health care outside of the mandatory visits. A separate group of individuals called Community Health Extension Workers (CHEWs) – who are medical personnel, and attached to the local dispensary – are responsible for monitoring the CHWs' activities, but they do not themselves perform the CHWs' duties.

The introduction of CHWs is expected to lower the cost of primary healthcare, increase access to health care and the health knowledge of households, for the following reasons. First, the distance travelled to receive primary health care is no longer an issue, because people do not have to travel; instead, CHWs visit the households and provide the necessary health care services. This saves both the travel costs and the waiting time that would have been incurred if CHWs did not exist. Second, some essential drugs are currently supplied free of charge, such as antimalarial drugs for those suffering from malaria. This means that households do not have to incur user fees for treatment. Finally, the provision of primary healthcare by CHWs through direct motivation for behavior change is expected to improve the overall health knowledge of households, in addition to influencing their health-seeking behavior. Given this change in relative costs and introduction of supply-driven interventions, one would expect the provision of primary health care to improve for all households. The success of a CHW intervention may therefore depend on the quantity and quality of the health care services a CHW offers to households.

3 Data

3.1 Setting

The data for this study comes from a cross-section survey designed by the author and conducted in Kisumu and Kericho counties in Kenya, between February and March 2016. Kisumu and Kericho are in the Nyanza and Rift Valley regions of Kenya respectively. Each of these regions has a distinct malaria pattern. In Kisumu, malaria transmission occurs all year round (endemic); while in Kericho, malaria occurs only intermittently (epidemic). Kisumu county has a 47.6% rural population, while Kericho county has 61.3% – compared to a national average of about 67.7% (KNBS, 2014). The poverty incidence in Kisumu is 39.9%; in Kericho, 39.3%, compared to a national average of 45%. The dependency ratio for both Kisumu and Kericho is 0.9, compared to the national average of 0.87 (Ngugi et al., 2013).[7] As my study population, I chose a division from each of these counties: Nyando division in Kisumu, and Soin division in Kericho, which adjoin one another, separated by a boundary. A total of 41 villages were randomly selected from the two divisions. Details of the sampling strategy (Table A.1) and a map of the study area (Figure A.1) are provided in Appendix A.

For this study, two types of surveys were collected: a household survey, containing information on malaria and CHW activities; and a CHW survey, administered to CHWs and containing information on CHW activities. A list of households for each of the sampled villages was obtained from the chief (local leader) in each case, and 20 households were randomly selected from each village list. Out of the 41 villages, 3 villages did not have CHWs and were excluded from this analysis. A total of 767 households from 38 villages were interviewed. For the purposes of this study I sought to interview respondents who were most involved in the health issues of their households, and therefore best placed to respond to a health-related survey. If for some reason a randomly se-

[7] The number of people under 15 or over 64, divided by the number of people between 15 and 64.

lected household was not eligible for participation in the survey (e.g. a household that had only children, who were supported by relatives), that household was replaced with the household closest to it.

All CHWs in the sampled villages in both regions were eligible for interviews. In the epidemic region, of the 128 eligible CHWs, 122 were interviewed (95% response rate); while in the endemic region, of the 158 eligible CHWs, 144 were interviewed (91% response rate). I then matched the household survey to the CHW survey by matching each household with the CHW responsible for its health care needs. In the end, 722 (94%) of the households were matched with 249 (93%) CHWs. The unmatched households (45) were served by some of the CHWs who were not interviewed. In addition, 17 CHWs were not matched because none of the households they serve was sampled. A team of thirteen enumerators underwent a three-day training, including multiple group sessions to ensure consistency in asking questions and in the interpretation of responses. The enumerators administered the survey to households in the local languages.[8]

3.2 Variables

I use two variables as my principal measures of access to primary healthcare. The first is *VISITS*, a measure of physical access that measures the number of visits a CHW makes to a household to provide primary healthcare. *VISITS* have previously been used in economics literature on demand for health care(e.g. Deri, 2005; Hollard and Sene, 2016). While existing studies on health care visits look at visits made by an individual to a health care provider (demand visits), this study looks at both demand and supply visits as the main outcome variables.

In the data, three types of visits are measured: supply visits (*SUPPLY VISITS*), demand visits (*DEMAND VISITS*), and social visits. 'Supply visits' refers to formal health care visits a CHW makes to a particu-

[8] Kipsigis is the language spoken in Kericho while Dholuo is the language spoken in Kisumu.

lar household, without the household having requested the visit. The question households were asked was: ‘How many health care visits did (name) make to your household in the last three months without you requesting the visit?’ ‘Demand visits’ refers to visits made by a CHW to a household upon request by the household. Such a visit may occur if, for example, a household member suffers ill health, and requires the services of a CHW; or if a household is in need of some health care advice. Households were asked: ‘In the last three months, how many times did your household request health care services from the CHW?’ ‘Social visits’ refers to informal visits between CHWs and households. Households were asked: ‘In the last three months, how many times has your household had social (non-health related) visits from the CHW?’ Furthermore, when CHWs make formal household visits they bring teaching materials with them, and this helps the households to differentiate the formal from the informal visits. The *SUPPLY VISITS*, which are visits that a CHW makes to each of the allocated households, are central to this analysis. The response period for visits was limited to a short period of three months, to minimize the recall bias. Previous studies have shown that individual characteristics of respondents such as education can affect a respondent’s recall period, thereby increasing the recall error. Thus, shorter recall periods are preferred, as they induce a smaller bias for less aggregated data (Kjellsson et al., 2014).

As part of the government’s policy to subsidize healthcare, all healthcare services provided by CHWs are provided at full subsidy. Therefore, in the treatment of malaria, antimalarial drugs given to households should be freely provided by CHWs. My second measure of access to healthcare is intended to capture the likelihood that a household will receive free antimalarial drugs. The outcome variable for measuring access to drugs is (*FREE ACCESS*). Households were asked if they had ever purchased antimalarial drugs from a CHW. This question was asked halfway through the interview, when the enumerator(s) would presumably have established credibility and trust with the households. In addition, enumerators were trained on how to ask the question without raising the suspicion of the household. The households were well aware that anti-malarial drugs are meant to be freely provided.

Social relationships are hard to measure, since the likelihood of reporting connections may correlate with the benefits that are derived from them (Comola and Fafchamps, 2014). In order to identify the role of social connections in influencing household access to healthcare, I exploit a specific question from the household survey that asks the respondent to indicate the social relationship they had with the CHW before the CHW began serving the village. This social relationship could be as a relative, a close friend, an acquaintance, or someone unrelated other than living in the same village. This method of proxying for social closeness is not new, and is seen in the economics literature (e.g. Breza, 2015; Devillanova, 2008).

To further mitigate the bias that may result from reporting social connections, households' social closeness was classified using the following criteria: first, a household is classified as being a relative if they have a kin relationship with the CHW. Second, a household is classified as having a close friendship with the CHW if (a) they report that they used to share risk with the CHW – the question was phrased as "*If you required a loan of Ksh200 (2), would you have borrowed it from (name) before he/she became a CHW?*"; and (b) they report that they used to visit or make social phone calls to the CHW – this question was phrased as "*Did you make social phone calls or visits to each other before (name) became a CHW?*".[9] Third, a household is classified as being acquaintances with the CHW if they report being friends with the CHW, but not close, and they do not fit the eligibility criteria of close friends. And fourth, a household is classified as having no relation if they do not have any of the three relationships above. The social connection variable is referred to as *SOCIAL TIE* in this analysis.

To isolate the effect of social connection on visits, the physical distance between a CHW's household and the households he serves may be an

[9] These two criteria were obtained from a pilot study conducted a few months prior to the actual field work.

important factor, because travel time is reduced when individuals live close to one another. In this study, the distance between a CHW's household and a household he serves was measured by classifying all the four categories of social ties as being either neighbors or non-neighbors of the CHW. Households were regarded as neighbors if they reported living within a kilometer (about 15 minutes walk) of the CHW's home, and as non-neighbors if they lived more than a kilometer away.[10]

To measure household health-seeking behavior, I use three main dependent variables: *TEST*, *COMPLETE DOSAGE*, and *STORAGE*. As stated previously, the choice of the first two variables was motivated by the fact that consumption of antimalarial drugs creates a trade-off between targeting (ensuring only true malaria cases are treated with antimalarial drugs) and effectiveness (ability of antimalarial drugs to cure malaria). This is because over-consumption (presumptive treatment) and under-consumption (taking a lower dosage) of antimalarial drugs produces negative spillovers, thus contributing to antimalarial drug resistance. Furthermore, the recommended antimalarial drugs (Artemisinin-based therapies) now constitute the only effective class of antimalarial drugs in Africa, where the malaria parasite has developed resistance to earlier generations of antimalarials.[11] Therefore, how to increase access while maintaining the effectiveness of this class of antimalarial drugs is an ongoing debate in the international community.[12]

The first measure, *TEST*, is a binary variable measuring whether a household reports that in the past six months any of its members took antimalarial drugs without testing for malaria parasites. The question asked was: '*When a member of your household had malaria symptoms, were they always able to test for malaria parasites before taking antimalarial drugs?*' This variable captures the presumptive intake of antimalarial drugs by households. The second measure, *COMPLETE DOSAGE*, is a binary variable measuring whether a household reports that, conditional on having malaria, any of its members failed to complete the

[10] A village is about 25 km^2, on average.
[11] See Shretta et al. (2000).
[12] See Cohen et al. (2015).

recommended malaria dosage. The question asked was: '*When a member of your household got malaria and was given treatment for malaria, were they always able to complete the dosage?*' This variable captures under-consumption of antimalarial drugs by households. Both questions covered the last six months, to ensure that at least one member of the household had suffered from malaria, since a six-month period covers both malarious and non-malarious months.

The third measure, $STORAGE$, is a binary variable measuring whether a household has antimalarial drugs stored in the household. If a household reported having antimalarial drugs in their home, they were asked to produce the drug package with the drugs, and the enumerator would record the name of the drug. The enumerator would then ask if a household member was currently ill from malaria and taking the antimalarial drugs. If that was the case, then the household would be recorded as not storing drugs. But if the household had extra drugs in addition to those being consumed by the sick household member, then they were recorded as storing antimalarial drugs. Even if storage of drugs at home is not necessarily a bad thing, it may be indicative of an undesirable health behavior. For example, antimalarial drugs should be stored at certain temperatures, and the dosage for children is given in terms of a child's weight. Hence, if one is to store the drugs at home, they may be exposed to unwanted temperatures, or households may consume them presumptively; thus, the advice given generally is not to store antimalarial drugs at home.

4 Empirical Strategy

The main empirical specification for access to primary health care is represented in Equation 1.

$$Y_{ij} = \beta_0 + \beta_1 SOCIALTIE_{ij} + \beta_2 \mathbf{X}_{ij} + \gamma_j + \epsilon_{ij} \tag{1}$$

Where, Y is the outcome measure (that is, *VISITS* and *FREE ACCESS*). *VISITS* is the total number of visits (both demand and supply) made by a CHW to a household. *SOCIAL TIE* is a measure of social connection between a CHW and a household, and **X** is a vector of household socioeconomic, demographic and health controls, where ij denotes household i in village j; γ_j is a village and/or CHW fixed effect and ϵ is the error term.[13]

The empirical specification for household health-seeking behavior is represented in Equation 2.

$$BEHAVIOR_{ij} = \alpha_0 + \alpha_2 SOCIALTIE_{ij} + \alpha_3 \mathbf{X}_{ij} + \gamma_j + \epsilon_{ij} \tag{2}$$

Where, *BEHAVIOR* is the outcome measure (that is, *TEST*, *COMPLETE DOSAGE*, and *STORAGE*). *SOCIAL TIE* is a measure of social connection between CHW and the household, and **X** is a vector of household socioeconomic, demographic, and health controls, where ij denotes household i in village j, γ_j is the village fixed effect and ϵ is the error term.

4.1 Identification concerns

CHWs may self-select themselves as volunteers, introducing a self-selection bias. In this study, it is not fully possible to ascertain if there was self-selection, as the data is collected ex post; however, I try to rule out self-selection in a number of ways. First, I exploit the fact that not all CHWs went through the election process, as some were directly appointed. For example, if those appointed exhibit differences in service delivery compared to those who were elected by the villagers, this would be an indication of selection. Second, there may exist observable differences between the elected and appointed CHWs (as shown in Table A.4 in the appendix), and this is addressed by controlling for the observable characteristics in the analysis as well as by including CHW fixed effects.

[13] Since there are villages with only one CHW, village and CHW fixed effects cannot be included together.

Third, the connection between households and CHWs can be explained in three different ways: 1) one or more household members may themselves be CHWs; 2) a household may have relatives living outside the household who are CHWs; and 3) friends or other non-family relations of the household may be CHWs. The data contains examples of all three relationships, but I focus on the second and third; that is, households that have one or more members who are CHWs are not included in the analysis.[14] This is because connections with relatives outside the household are arguably more exogenous. For example, a household's health care decisions do little to affect the probability of relatives in other households volunteering to become CHWs.

However, even after excluding one of these relationships, the existing relationships in the village described above pose an empirical issue: potential endogeneity, due to reverse causality between social ties and access to health care. A person may form a strategic friendship with a CHW before the CHW has been elected; or the household visits themselves may cause friendships to form between CHWs and households. This problem is particularly salient for close friends and acquaintances, relationships that could be defined as being endogenously formed; as opposed to relatives, who belong to groups that are exogenously formed. Such endogenous group formation could bias the coefficients; this study mitigates this potential bias by asking about the form of relationship that existed between a CHW and a household prior to the CHW working in the village. In addition, since CHWs are not certain to be elected, it may not be possible for households to form strategic friendships prior to a CHW being elected. Being a relative outside the household is therefore arguably the most exogenous social tie.

Some unobserved CHW characteristics may introduce the omitted variable bias problem. For example, if a CHW is an extrovert, this might determine both the probability of having some form of social tie with the CHW, and the probability of accessing healthcare. It is difficult to control for such variables, given the data available. However, most of the

[14] Six of the sampled households had a household member who was a CHW.

CHW characteristics that would affect access to health care are time-invariant. Therefore, I include CHW fixed effects which further mitigate the potential omitted variable bias, although the problem may not be fully eliminated.

4.2 Summary statistics

The characteristics of CHWs in the sample, are summarized in Table 1. The CHWs have on average 10 years of schooling, which is equivalent to high-school-level education, and 38% of them are male. There are no CHWs with no education, due to the eligibility criterion that requires a CHW to have the ability to read and write. The CHW policy requires that CHWs are elected by the members of the village. However, the data shows that only 64% of the CHWs were elected by the villagers; the remaining 36% were appointed by link dispensary, in conjunction with the local administrative leaders (chiefs), without going through the election process. The differences between the observable characteristics of elected and appointed CHWs, seen in Table A.4 in the appendix, show that there are systematic differences in terms of sex and education between CHWs who are elected and those who are appointed. While 46% of CHWs reported that they volunteered their services because they wanted to help the community, the others reported that they were motivated by the prospect of earning income or gaining respect in the community, which would attract some benefits.[15] Of the elected CHWs, none reported a failed application to become a CHW. This implies that they were all elected at the first attempt.

A CHW is allocated 12 households on average, which is below the 20 households recommended by the policy. A typical CHW had worked for about four years on average. A CHW works slightly more hours per week (ten hours) than is recommended by the policy (eight hours); and 18% of CHWs have full-time employment outside their CHW duties.

[15]For example: if a project or study is about to be launched in the community and requires the services of a community member, being a CHW increases the probability of being selected to participate, since CHWs are known and respected in the community; which also means the possibility of earning an income.

Although the work effort by CHWs is meant to be monitored, not all CHWs are, with the average being six visits in a year. Similarly, 67% of CHWs have one member of their household in a leadership position. An example of a leadership position would be if the person belongs to a village development committee, political party or self-help group.

When CHWs offer to work for villages, they do so as volunteers, and therefore do not receive compensation for services rendered. However, on average, CHWs in the endemic region received four months of compensation in the past year, with the average yearly compensation being $75. Similarly, 53% have received some form of material benefit in the past year, for example bicycles, certificates, a training allowance, bags, t-shirts and benchmarking trips. The compensation is offered by the link dispensaries when surplus funds are available; and therefore, compensation is not dependent on CHW performance.

Table 2 presents summary statistics of the household variables used in the econometric model(s). In the data, 27% of the respondents were male. This is because I sought to interview household members who are more involved in the health issues of their households, and are in a better position to respond to a health-related survey; in most cases, these people were female. A typical sample household is Protestant and has five family members. The average household head is 42 years old, and has completed seven years of education. Average household wealth calculated as the sum of the value of assets is $8582.[16] The average number of visits in total (supply + demand) made by a CHW to a household is 3.2 visits.

When a household experiences malaria symptoms, in 71% of cases households report testing for malaria. Not all households report accessing free antimalarial drugs, though. In the endemic region, only 54% of households have accessed free antimalarial drugs from CHWs.[17] Conditional on receiving antimalarial drugs, 65% of the households report that they adhere to the prescribed antimalarial treatment by complet-

[16] Including: land, mobile phone, bicycle, cart, radio, television, motorbike, house, motor vehicle, solar panel, poultry, donkey and livestock.

[17] Only CHWs in the endemic region can distribute antimalarial drugs.

ing the dosage, and 44% of households were observed to have stored antimalarial drugs in their homes. Of the sampled households, 50% are neighbors of CHWs. The risk-aversion variable shows that on average, most of the respondents are risk-loving.[18] Additionally, 25% of respondents were relatives of the CHW, 10% were close friends, 14% were acquaintances and 51% other relations.

About 88% of household members reported having contracted malaria at least once in their lifetime, and an average of three members of the household had contracted malaria in the six months prior to the interview. On average, 63% of the interviewed households have a child who is below five years of age. When asked if they were concerned about developing resistance to the current antimalarial drugs, only 27% responded that it was of great concern to them. On average, households live within 3 km of the nearest health facility.

5 Results

5.1 CHW household visits

Figure 1 provides preliminary evidence as to whether visits made by CHWs vary with relationship status. Specifically, Figure 1 plots total visits (supply + demand), supply visits, and demand visits in panels (a), (b), and (c), respectively. Panel (a) shows that on average, relatives and close friends receive more visits than acquaintances and others with no social connections. The error bars that represent the 95% confidence interval (CI) show a substantial overlap between the mean number of visits to relatives and friends, but no overlap with acquaintances and

[18] The risk-aversion level of the respondent was calculated from an incentivized experiment in which individuals completed a series of 20 ordered choices between playing a lottery and having 50% chance of winning (risk), or receiving a sure amount. If an individual chose the lottery, they could win a constant amount of money (Ksh200) by betting on the color of a ball drawn blindly from a bag containing 10 balls. An individual could opt for the sure amount of money at any point in the series of choices. The amount gambled was kept constant, while the sure amount increased monotonically from Ksh10 to Ksh200.

others. This points to a possible statistical insignificance between number of visits made to relatives and close friends, but a possible statistical significance between number of visits that are made to relatives and close friends, and number of visits that are made to acquaintances and others. Panel (b), which depicts the supply visits, follows a similar pattern to that shown in panel (a). However, panel (c) has a somewhat different pattern, showing a substantial overlap of error bars for all relationship statuses, which may imply a lack of statistical significance between mean demand visits for the different relationship categories. Furthermore, I test whether there is a difference in mean visits across different relationship groups. Table A.2 in the appendix shows that mean total visits for different group combinations are statistically significant, except for relatives and close friends. Similarly, for the supply visits, there are statistically significant differences between the different combinations of relationship statuses, except for the combination between relatives and close friends. As for demand visits, there is no statistically significant difference between any of the different combinations of relationship status.

To empirically investigate whether social connections matter for healthcare visits, I run a regression that examines the effect of social connections on CHW healthcare visits. The outcome variables (*VISITS*) are count data. Count data are made up of non-negative integers that represent the number of occurrences during a fixed time period, with the variance increasing with the expected number of visits. Ideally, Poisson models are used when dealing with count data. However, results in count data are often characterized by over-dispersion. For example, in the dataset, the unconditional variance of the outcome variable for total visits is 14, which is quite large relative to the mean (3). This over-dispersion can be corrected for by modifying the poisson models using negative binomial models.[19] The reported estimates are therefore marginal effects from negative binomial regressions. The estimated coef-

[19]The data includes a significant number of zero visits, which necessitates the use of a zero-inflated model. However, after testing based on AIC and BIC, the standard negative binomial model was shown to be a significant improvement over the zero-inflated negative binomial model.

ficients of interest are shown in Table 3, and indicate the effect of social ties on the number of visits for total visits, supply visits and demand visits.[20]

Column (1) shows total visits, which are a combination of the mandatory healthcare visits that a CHW makes to a household, and the healthcare visits that a household requests from a CHW. Relatives, close friends and acquaintances receive on average 2.8, 3.0 and 0.9 more visits respectively, compared to those with no social connection with a CHW, within a three-month period. However, the results do not tell us whether these visits made by CHWs to households are 'unbiased'. For example, if certain households request healthcare visits, we might observe those households receiving fewer supply visits, compared to households that did not request any visits. This can be seen as somewhat unbiased , since the CHWs are compensating by visiting those that did not receive any visits. In order to further assess the unbiasedness of visits, I decompose total visits into demand and supply visits. Column (2), which depicts demand visits, shows that there is no statistically significant difference between demand visits made by the different social-ties categories. A further look at the coefficient estimates of column (3) – supply visits – shows that compared to those with no relations, being a relative, close friend or acquaintance of a CHW increases the number of visits by 2.6, 2.7 and 0.8 visits respectively, and these associations are statistically significant.

The results in column (3) imply biasedness by CHWs in their effort distribution, since households with no social ties to CHWs have less access to primary healthcare compared to those who have some social relationship. The observed differential effect in visits is large and economically significant. For instance, being a relative increases the probability of visits by 99% with respect to the mean, while being a close friend by 103%, and being an acquaintance by 30%. We see that close friends of CHWs tend to receive similar numbers of visits to relatives of CHWs.

[20] The observations reduce to 714 due to the inclusion of the variable 'number of CHW households', which is a variable from the CHW survey; not all households in the survey could be matched with the CHW survey.

However, as mentioned earlier, even if respondents are asked explicitly about their relationship status before the CHW started serving them, there may be an overestimation of the 'close friends and acquaintances' coefficients, due to reverse causality. The most reliable estimate is that of relatives, since it rules out possible reverse causality. Nevertheless, the observed behavior of CHWs can be categorized as being that of unequal healthcare distribution. In the literature, this has been described as being indicative of nepotism. Nepotism is defined as 'discriminating in favor' of a group member relative to the population (see Becker, 1971; Fershtman et al., 2005) for a detailed discussion.

Additionally, households that have children younger than five years old and those with members who have a chronic illness are more likely to receive visits from a CHW. This result indicates that CHWs are aware of the existence of vulnerable members of the population that they serve, and therefore give them more attention compared to the non-vulnerable members of the population. Similarly, compared to non-neighbors, neighbors tend to be visited more. This result is robust to different estimation techniques, and to the inclusion of CHW fixed effects and controls.

5.2 **Access to antimalarial drugs**

The second measure of access to healthcare is whether households are able to access free antimalarial drugs from CHWs. In the data, only CHWs serving the endemic region are allowed to treat malaria, which makes it possible for them to be in possession of antimalarial drugs for distribution to households in need. In this region, not all households report that they access free antimalarial drugs; 54% did, while the remaining 46% had to make a payment to get the same drugs. Figure 2 shows the access to free antimalarial drugs for each social connection category. One striking feature is that access to antimalarial drugs varies across the social connection groups. Close friends have the highest chance of accessing free drugs (81%), followed by relatives (71%), and those with no relationship (47%); acquaintances are the least likely (33%) to receive free drugs from CHWs. A pairwise comparison of means between access to free drugs by relationship status as shown in Table A.3 in the appendix confirms that there are no statistically significant differences in access to antimalarial drugs between close friends and relatives, but that there are significant differences for other combinations of social connections.

I empirically investigate the relationship between social ties and access to antimalarial drugs using a probit regression that corresponds to Equation 1. Table 4, column (1) reports marginal effects for a probit model with village-fixed effects included and standard errors adjusted to account for clustering at the CHW level. Relatives are 15 percentage points more likely to access free drugs compared to those who do not have a relationship with a CHW. Similarly, close friends are 33 percentage points more likely to access free drugs compared to those with no relations. These results provide suggestive evidence of nepotism in access to drugs for rural households. Svensson (2005) defines corruption as "the misuse of public office for private gain", while Shleifer and Vishny (1993) define corruption as "the sale by government officials of government property for personal gain". Therefore, any form of payment by households to CHWs for health services received is a form of corruption. In the study area, a complete treatment regime of an antimalarial drug sells for between USD 0.40 and USD 1 (USD 1 = Kenya shilling 99). From a macro perspective, the sums of money involved are not large, so this form of corruption can be defined as petty corruption. Jancsics (2013) defines petty corruption as involving relatively small sums of money or exchanges between street-level bureaucrats and ordinary citizens.

5.3 Relationship between social ties and health-related behavior

The previous section suggests that CHWs make more visits to relatives, close friends and acquaintances compared to those with no social relations. The next question is whether we observe households that have social connections with CHWs also making better health care decisions, which would be an indication of the quality of healthcare provided by CHWs.

Table 5 presents the results of estimating Equation 2 for the entire sample in both regions, and with all specifications, including village-fixed effects and standard errors, adjusted for clustering at the CHW level. Column (1) presents marginal-effects estimates after probit of the effect of social connections on a dummy for whether all household members test for malaria following malaria symptoms. The results in column (1) show that relatives and close friends are 10 percentage points more likely to test for malaria, compared to those with no social relationship with the CHW. The estimated coefficient for distance to a health facility shows that a one-kilometer increase in distance from household to a health facility decreases the likelihood of testing for malaria by 5 percentage points. In the literature, geographic access has been cited as an important part of accessing health care in low- and middle-income countries. An inverse relationship between distance/travel time to health facilities and the use of health services is an important barrier to access (Hjortsberg, 2003).

Column (2) examines whether – after contracting malaria and receiving antimalarial drugs – all household members are able to complete the recommended dosage. The outcome variable is a dummy for completing dosage. Compared to those with no close relationship with a CHW, close friends are 19 percentage points more likely to complete dosage. The marginal effect of the variable *relatives* is insignificant.

In column (3), where I examine whether households store antimalarial drugs, I find that relatives and close friends are 11 and 16 percentage points respectively less likely to have drugs stored at home, compared to those with no social connection to a CHW. This result indicates presumptive treatment, because – as is shown in column (1) – compared to relatives and close friends, those with no relationship are less likely to test for malaria; and the same group is more likely to have drugs stored at home. Similarly, households with more members having had malaria are more likely to have stored drugs.

6 Robustness Tests

A CHW is expected to make at least one mandatory visit per month to each of their allocated households. Thus far, the estimated coefficients on supply visits may have been driven partly by the zero visits in the data; about 28% of observations in the data reported receiving zero supply visits in the three months prior to the survey. I assess the sensitivity of the visits findings using an alternative specification, where I estimate Equation 1 using visits as a dummy rather than as count data. Column (1) of Table 6 presents the marginal effects after probit, with the full set of controls, village-fixed effects and standard errors adjusted for clustering at the CHW level. The supply visits results are robust for this specification. Next, I restrict the sample to only positive visits and estimate Equation 1. The overall significance of the social connection effect remains unchanged, as shown in column (2) and column (3).

Additionally, there may be unobserved time-invariant characteristics of CHWs that make them more likely to make household visits. I include CHW fixed effects, as shown in Table 7 column (1); the supply visit results are robust.[21] Column (2) includes observable CHW controls; the results are robust to the inclusion of these controls.

7 Conclusion

Individuals in poor countries tend to have less access to health services than those in better-off countries; and within poor countries, the poor have less access to health services. The provision of health services at the community level is crucial, both for increasing access to healthcare and for reducing the future burden of disease through changing health-seeking behavior. Despite these significant benefits of health provision at a decentralized level, there has been little empirical research conducted to help policy makers understand the effect of decentralizing health ser-

[21]Observations with only one household being served by a CHW are dropped.

vices. In this study, I estimate the role of social connections in primary health care provision, and the effect of social connections on health-seeking behavior. I find that CHWs tend to visit households that have some social relationship with them more than those households with no social relationship. Similarly, households with a social relationship with the CHW are more likely to access free antimalarial drugs. I also show that the health-seeking behavior of households that are socially connected to a CHW is generally better than that of households that are not socially connected.

So far, I have provided suggestive evidence of nepotism in the provision of healthcare. One possible explanation of such findings is that there is a lack of motivation among CHWs, as well as a lack of proper monitoring of CHWs in the field. For example, in the data, 46% of CHWs reported having volunteered because they wanted to help the community, while the rest volunteered in anticipation of earning some income. Similarly, CHWs receive only six supportive visits in a year on average from the monitoring officers, and 57% report having discretion in how they perform their duties. It is possible to reconcile these findings with previous studies; for example, Das et al. (2008) show that lack of local control and inadequate accountability relationships are among the determinants of poor public-service provision in developing countries. A second possible explanation for the observed nepotism by CHWs is the weak incentive structure that they have, due to the largely voluntary nature of their work. From the data, I find that CHWs in one region do not receive any monetary benefits; and in the second region, where some CHWs receive some compensation, it is often low and irregular. If the incentives are insufficient, CHWs may be tempted to discriminate by providing healthcare services selectively. Indeed, Gilmore and McAuliffe (2013) point out that lack of incentive is one of the factors accounting for the failure of CHWs to deliver timely and appropriate services.

The results presented here have the potential to provide policy guidance. As Caria et al. (2014) acknowledge, policymakers who want to promote human cooperation should pay attention to the behavior of central individuals in networks. In this case, closer attention could be paid to the allocation of households, and also to the monitoring of CHWs, to ensure unbiased access to healthcare and better health-seeking behavior outcomes. Lastly, while this study was carried out in only two regions in Kenya, the nature of the work done by CHWs and the treatment-seeking environment in our study are very similar to the situation in many countries in sub-Saharan Africa, and this study can provide useful insights.

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Figures and Tables

Figure 1: Relationship between visits and social connection

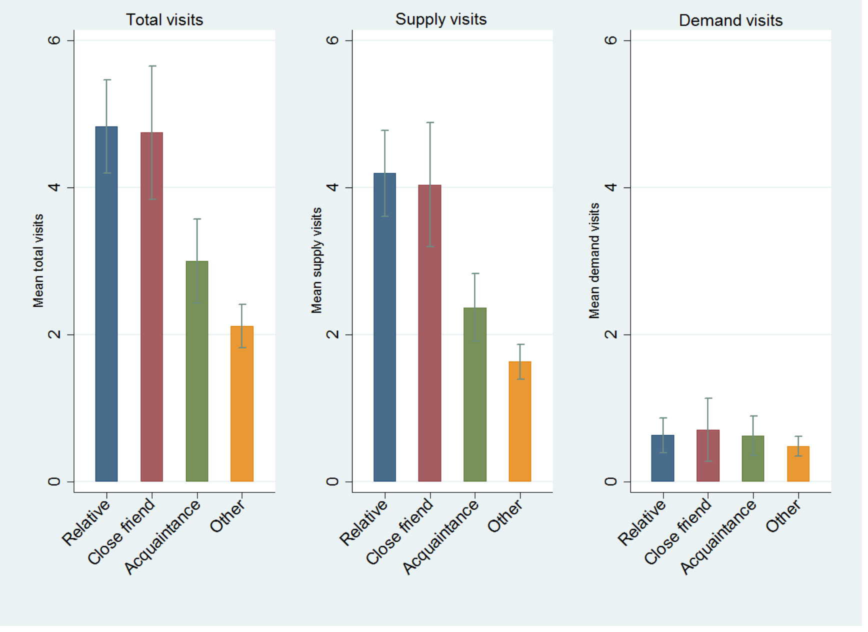

Figure 2: Access to free drugs

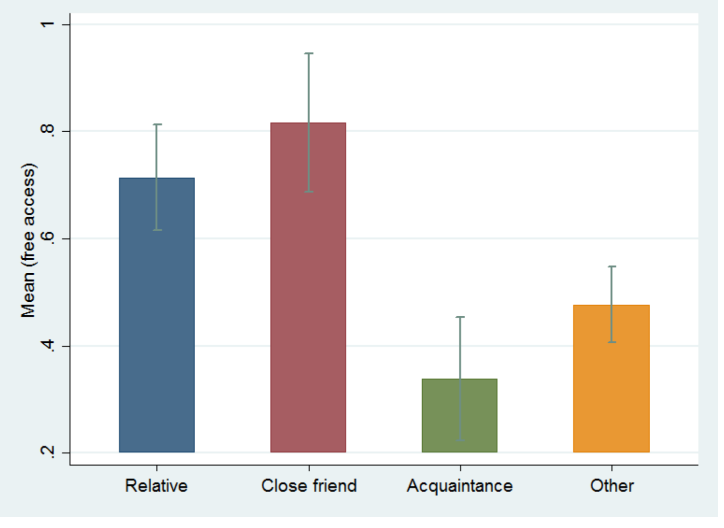

Table 1: *CHW summary statistics*

Variables	**Variable definition**	**Mean**	**SD**	**Min**	**Max**	**N**
Socioeconomic variables						
Male	1 if CHW is male	0.38		0	1	266
Age	Age of CHW	41.32	10.01	21	73	266
Education	Respondent years of schooling	9.58	2.54	1	16	266
Catholic	1 if religion is Catholic	0.18		0	1	266
Seventh Day Adventist	1 if religion is Seventh Day Adventist	0.13		0	1	266
Traditional/ No religion	1 if religion is Traditional/No religion	0.05		0	1	266
Protestant	1 if religion is Protestant	0.64		0	1	266
Years in village	# of years lived in the village	27.99	13.08	1	66	266
Material benefit	1 if CHW received any material benefit in the past 1 year	0.53		0	1	266
Compensation (USD)	Annual compensation for CHW activities	75.49	112	0	727	144
# of months compensation	# of months CHW received compensation in the past 1 year	3.69	4.92	0	12	144
Wealth (USD)	Total value of CHW household assets	9175	14794	205	141227	266
CHW work - related characteristics						
Motivation	1 if CHW volunteered so as to help the community	0.46		0	1	266
Elected	1 if CHW was elected	0.64		0	1	266

Continues

Table 1 – *Continued*

Variables	Variable definition	Mean	SD	Min	Max	N
# Allocated	Number of households allocated to CHW	12.15	5.22	7	52	266
Leadership	1 if one or more members in a CHW household are in a leadership position	0.67		0	1	266
Independence	1 if CHW is independent in his or her work	0.57		0	1	266
Trust	1 if households trust CHWs	0.59		0	1	266
Years worked	# of years worked as a CHW	3.73	2.13	1	10	266
Full - time job	Whether a CHW has a fulltime job	0.18		0	1	266
# of hours worked	Number of hours worked in a week	10.22	8.95	1	56	266
# of supportive visits	Number of supportive visits in the past 1 year	6.10	7.94	0	36	266
# of Village meetings	Number of village meetings in the past 1 year	5.74	9.95	0	52	266
Satisfaction	1 if CHW has high work satisfaction	0.21		0	1	266
Sociable	1 if CHW is highly sociable	0.50		0	1	266
Resistance concern	1 if concerned about antimalarial drug resistance	0.30		0	1	266
Sell drugs	1 if CHW sells antimalarial drugs	0.73		0	1	131

Exchange rate: \$1 = Ksh99. Only 144 CHWs received compensation in the past year. Since not all households could be matched to CHWs, the sale of drugs has only 131 observations.

TABLE 2: *Household summary statistics of variables used in the econometric model*

Variables	Variable definition	Mean	SD	N
Outcome				
Supply Visits	Number of health visits by CHW to a household in the last 3 months	2.63	3.25	761
Demand visits	Number of health visits requested by a household in the last 3 months	0.56	1.48	761
Total visits	Supply + demand visits to a household	3.19	3.69	761
Access drugs for free	1 if household receives free drugs	0.54		385
Test for malaria	1 if household members test for malaria	0.71		761
Complete dosage	1 if household members complete antimalarial dosage	0.65		761
Storage	1 if antimalarial drugs stored at home	0.44		761
Socioeconomic				
Age	Age of the respondent in years	42.35	15.63	761
Male	1 if respondent is male	0.27		761
Education	Respondent years of schooling	6.72	3.45	761
Household size	Number of household members	5.39	2.16	761
Catholic	1 if religion is Catholic	0.15		761
Protestant	1 if religion is Protestant	0.60		761
Seventh Day Adventist	1 if religion is Seventh Day Adventist	0.09		761
Traditional/ No religion	1 if religion is Traditional/No religion	0.16		761
Wealth (USD)	Total value of household assets	8582	11061	761
Community				
# of village meetings	Number of village meetings in the past 6 months	0.60	1.40	761
Neighbor	1 if neighbor to CHW	0.50		761
Relatives	1 if related to CHW	0.25		761
Close friends	1 if close friends with CHW	0.10		761
Acquaintances	1 if acquaintances with CHW	0.14		761

Continues

Table 2 – *Continued*

Variables	**Variable definition**	**Mean**	**SD**	**N**
Other relation	1 if no relation to CHW	0.51		761
Voted for CHW	1 if household voted for CHW	0.16		761
Distance (km)	Distance to health facility in kilometers	2.82	1.62	759
Region	1 if endemic region	0.51		761
Health				
Household malaria	Dummy for whether any household member contracted malaria in past 6 months, 0 otherwise	0.88		761
Chronic illness	Dummy for whether any household member has chronic illness, 0 otherwise	0.22		761
Under 5yrs	Dummy for whether household has a child 5 years or under, 0 otherwise	0.63		761
Behavioral				
Resistance concern	1 if household is concerned about antimalarial drug resistance, 0 otherwise	0.27		761
Risk Aversion	$\theta < 0.5$: risk loving, $\theta > 0.5$: risk-averse and $\theta = 0.5$: risk-neutral	0.47	0.23	761

Exchange rate: \$1 = Ksh99. The access to free drugs variable has 385 observations because only one region receives antimalarial drugs from CHWs.

TABLE 3: *Marginal effects of the effect of social connection on visits*

Dependent variable: # of visits in the past 3 months

Variables	Total	Demand	Supply
Base: Others			
Relatives	2.788***	0.149	2.584***
	(0.360)	(0.147)	(0.317)
Close friends	2.990***	-0.029	2.738***
	(0.514)	(0.141)	(0.455)
Aquaintances	0.921***	0.168	0.816***
	(0.303)	(0.165)	(0.238)
Age	0.003	-0.012**	0.011
	(0.012)	(0.005)	(0.010)
Male	-0.275	0.310**	-0.542**
	(0.315)	(0.148)	(0.267)
Education (years)	0.028	-0.046**	0.053
	(0.041)	(0.019)	(0.036)
Catholic	0.252	-0.182	0.604
	(0.579)	(0.217)	(0.528)
Traditional	0.766	0.070	0.764
	(0.598)	(0.213)	(0.530)
Protestant	0.392	0.023	0.498
	(0.492)	(0.204)	(0.419)
Married	-0.279	-0.153	-0.169
	(0.355)	(0.135)	(0.319)
# of CHW households	-0.032	0.002	-0.025
	(0.024)	(0.011)	(0.018)
Household size	-0.030	-0.029	-0.006
	(0.065)	(0.027)	(0.055)
Under 5 years	0.524	0.022	0.545*
	(0.331)	(0.124)	(0.282)
Household malaria	0.206	-0.058	0.185
	(0.423)	(0.186)	(0.366)
Chronic illness	0.860***	-0.028	0.920***
	(0.240)	(0.075)	(0.215)
Neighbor	1.130***	0.141	0.943***
	(0.242)	(0.103)	(0.192)
Voted	0.484	0.020	0.489*
	(0.301)	(0.153)	(0.253)
# of village meetings	0.171**	0.128***	0.052
	(0.083)	(0.039)	(0.072)
Log of wealth	-0.141	0.056	-0.129
	(0.134)	(0.053)	(0.112)
Distance to health facility (km)	0.172	0.131	0.093
	(0.188)	(0.088)	(0.153)
Village fixed effects	YES	YES	YES
Mean of dep. var	3.19	0.56	2.63
Observations	714	714	714

Note: Marginal effects computed from the negative binomial regression using the margins command in Stata. Standard errors in parentheses are adjusted to take into account clustering at CHW level, and *p*-values are *** p<0.01, ** p<0.05,* p<0.1.

TABLE 4: *Effect of social connection on access to drugs*

Dependent variable: Access to free drugs (1=Yes)

Variables	**Marginal effect**
Base: Others	
Relatives	0.147**
	(0.061)
Close friends	0.330***
	(0.062)
Acquaintances	-0.113*
	(0.064)
Male	0.057
	(0.060)
Age	0.001
	(0.002)
Education (years)	-0.002
	(0.008)
Catholic	-0.055
	(0.114)
Traditional	-0.136
	(0.114)
Protestant	-0.110
	(0.107)
Log of wealth (USD)	0.010
	(0.025)
Household size	0.016
	(0.011)
Neighbor	0.158***
	(0.044)
Voted	0.064
	(0.088)
Under 5 years	0.036
	(0.052)
Household malaria	-0.182*
	(0.096)
Chronic illness	-0.001
	(0.048)
Distance to health facility (km)	0.012
	(0.037)
Village fixed effects	Yes
Observations	348

Note: Marginal effects computed from the probit regression. Standard errors in parentheses are adjusted to take into account clustering at CHW level, and p-values are *** p<0.01, ** p<0.05,* p<0.1.

TABLE 5: *Effect of social connection on access to drugs*

Variables	**Test for malaria**	**Complete dosage**	**Storage**
Base: Others			
Relative	0.101***	-0.021	-0.113***
	(0.035)	(0.044)	(0.036)
Close friends	0.183***	0.185***	-0.162***
	(0.043)	(0.045)	(0.052)
Aquaintances	-0.047	0.056	0.052
	(0.050)	(0.049)	(0.043)
Age	0.001	-0.001	0.000
	(0.001)	(0.002)	(0.001)
Male	0.051	-0.044	-0.003
	(0.037)	(0.046)	(0.037)
Education (in years)	0.004	0.010*	0.000
	(0.005)	(0.005)	(0.005)
Catholic	-0.064	-0.018	-0.116***
	(0.054)	(0.059)	(0.044)
Traditional	0.028	0.062	-0.092**
	(0.041)	(0.051)	(0.042)
Protestant	-0.073	0.067	-0.077
	(0.060)	(0.051)	(0.067)
Married	-0.069	-0.062	0.021
	(0.047)	(0.048)	(0.042)
Log of wealth	-0.018	0.015	0.007
	(0.017)	(0.018)	(0.017)
Household size	0.005	0.003	0.001
	(0.008)	(0.010)	(0.008)
Neighbor	0.116***	0.110***	-0.084***
	(0.030)	(0.034)	(0.030)
Under 5 years	0.070*	-0.027	-0.014
	(0.036)	(0.040)	(0.035)
Household malaria	0.064	0.105**	0.104**
	(0.049)	(0.051)	(0.051)
Chronic illness	0.075**	0.060	0.051
	(0.036)	(0.041)	(0.035)
Resistance concern	0.049	0.151***	-0.004
	(0.039)	(0.037)	(0.032)
Risk aversion	0.017	0.068	-0.049
	(0.072)	(0.077)	(0.069)
Distance to health facility (km)	-0.049*	0.030	0.010
	(0.025)	(0.027)	(0.023)
Village fixed effects	Yes	Yes	Yes
Observations	714	714	714

Note: Marginal effects computed from the probit regression. Standard errors in parentheses are adjusted to take into account clustering at CHW level, and *p*-values are *** p<0.01, ** p<0.05,* p<0.1.

TABLE 6: *Effect of social connections on visits*

	1 if visits>=1	visits>1	
Variables	**Marginal effect**	**coef. (OLS)**	**Marginal effect**
Base: Others			
Relative	0.182***	2.492***	2.579***
	(0.037)	(0.379)	(0.335)
Close friends	0.277***	1.862***	1.926***
	(0.041)	(0.454)	(0.388)
Aquaintances	0.115**	0.475	0.510*
	(0.049)	(0.333)	(0.262)
Age	-0.001	0.024*	0.024**
	(0.001)	(0.012)	(0.011)
Male	0.005	-0.902***	-0.842***
	(0.038)	(0.322)	(0.294)
Education (years)	-0.000	0.091**	0.085**
	(0.005)	(0.046)	(0.041)
Married	-0.009	0.056	-0.021
	(0.042)	(0.376)	(0.318)
# of CHW households	-0.006**	-0.006	-0.001
	(0.003)	(0.021)	(0.018)
Household size	0.013	-0.093	-0.106*
	(0.008)	(0.073)	(0.060)
Under 5 years	0.002	0.814**	0.813***
	(0.044)	(0.326)	(0.290)
Hhold malaria	0.053	-0.008	0.109
	(0.049)	(0.548)	(0.442)
Chronic illness	-0.015	1.473***	1.286***
	(0.028)	(0.368)	(0.238)
Neighbour	0.130***	0.508*	0.427*
	(0.029)	(0.273)	(0.226)
Voted	0.114**	0.375	0.363
	(0.050)	(0.295)	(0.263)
# of village meetings	0.012	-0.066	-0.037
	(0.015)	(0.117)	(0.083)
Log of wealth	0.016	-0.316**	-0.290**
	(0.016)	(0.140)	(0.121)
Distance to health facility (kms)	-0.004	0.243	0.181
	(0.024)	(0.209)	(0.177)
Constant		2.738	
		(1.916)	
Village fixed effects	YES	YES	YES
Observations	714	518	518
R-squared		0.295	

Note: Standard errors in parentheses are adjusted to take into account clustering at CHW level, and p-values are *** p<0.01, ** p<0.05,* p<0.1.

TABLE 7: *Effect of social connections on visits*

Dependent variable: # of supply visits

Variables	(1) Marginal effect	(2) Marginal effect
Base: Others		
Relatives	2.904***	2.571***
	(0.346)	(0.311)
Close friends	2.671***	2.833***
	(0.453)	(0.473)
Acquaintances	1.038***	0.833***
	(0.297)	(0.237)
Age	-0.002	0.012
	(0.011)	(0.010)
Male	-0.608**	-0.559**
	(0.262)	(0.265)
Education (in years)	0.051	0.058
	(0.038)	(0.036)
Married	-0.172	-0.183
	(0.346)	(0.320)
# of CHW households	-1.08**	-0.030*
	(0.445)	(0.018)
Household size	0.013	-0.015
	(0.059)	(0.056)
Under 5 years	0.524*	0.616**
	(0.311)	(0.283)
Household malaria	-0.0851	0.176
	(0.362)	(0.368)
Chronic illness	0.606***	0.897***
	(0.217)	(0.217)
Neighbor	1.047***	0.932***
	(0.208)	(0.192)
Voted	0.847***	0.471*
	(0.269)	(0.253)
# of village meetings	-0.003	0.055
	(0.080)	(0.074)
Log of wealth	-0.150	-0.117
	(0.122)	(0.112)
Distance to health facility (km)	0.229	0.093
	(0.191)	(0.154)
CHW Controls	No	Yes
CHW fixed effects	Yes	No
Village fixed effects	No	Yes
Observations	693	714

Note: Marginal effect computed following negative binomial regression using the margins command in Stata.Standard errors in parentheses are adjusted to take into account clustering at CHW level, and *p*-values are *** p<0.01, ** p<0.05,* p<0.1. CHW controls include: Age, Sex, Education in years, Married, Religion and Log of wealth (USD)

A Appendix

A.1 Sampling

The selected divisions (Nyando and Soin) had a total of 127 villages. I excluded villages in urban areas, leaving a total of 109 villages in the rural areas (Nyando 47 and Soin 62). The mean number of households in Nyando was 100, with a standard deviation of 27.8, a minimum of 53, and a maximum of 186 households. In Soin division, 1 village had 435 households, making it distant from other villages in terms of number of households. I regarded this village as an outlier which could affect the mean; and I therefore excluded it from the sample, leaving a total of 61 villages. The mean number of households in Soin was 71.5, with a standard deviation of 19.8, and a minimum of 42 and a maximum of 151 households. I then included the villages with a number of households within one standard deviation from the mean, so as to avoid over- or under-representation of villages. Therefore, in Nyando, villages with fewer than 72 households and those with more than 128 were excluded from the sample of my study population; while in Soin, villages with fewer than 27 households and with more than 127 households were excluded from the sample of our study population In the end we had a total of 84 villages from the two divisions. I then randomly sampled 19 villages from Nyando and 22 villages from Soin. Table A.1 provides a summary.

TABLE A.1: *Sampling*

	Nyando	*Soin*
Total number of villages	47	61
Mean number of households	100	71.5
Std. Deviation	27.8	19.8
Villages included	100 $\pm$27.8	71.5 $\pm$19.8
Total villages before sampling	38	46
Villages sampled	19	22

A.2 Map of Study Area

Figure A.1: Map of Study Area

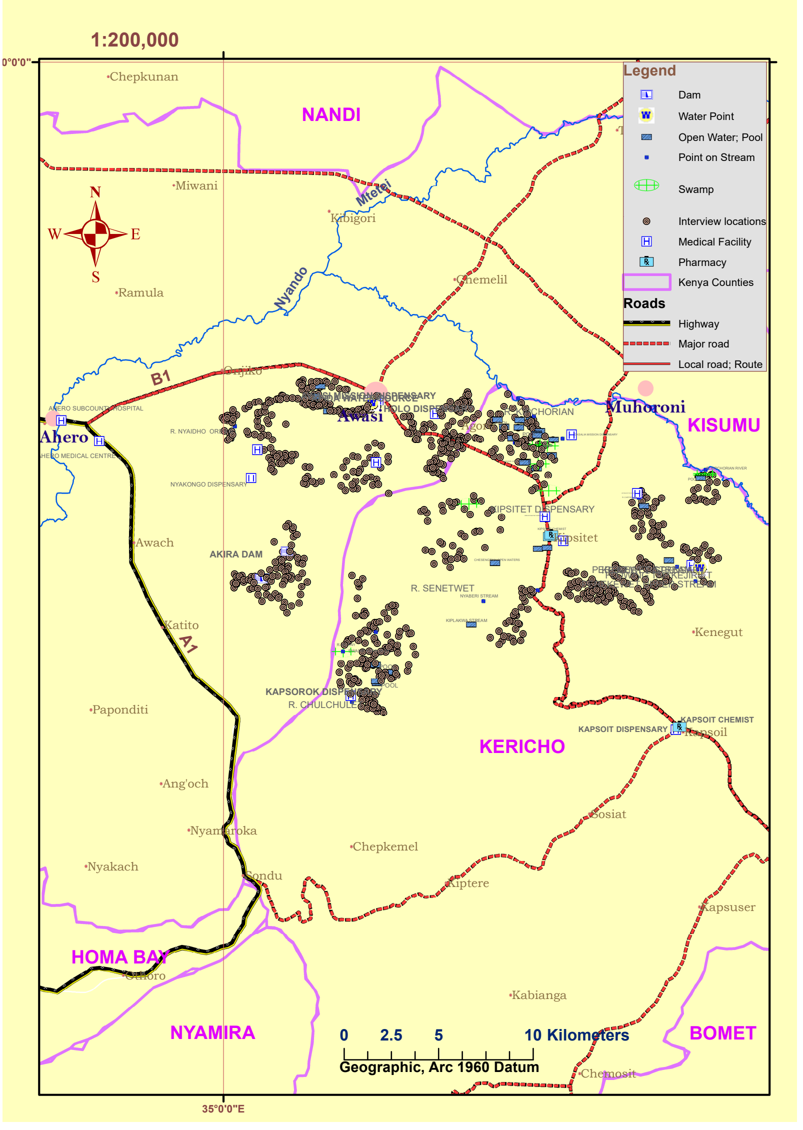

Table A.2: *Pairwise comparison of means between visits by relationship status*

Total visits

	Close friend	Acquaintance	Other
Relative	0.863	0.000	0.000
Close friend		0.001	0.000
Acquaintance			0.023

Supply visits

	Close friend	Acquaintance	Other
Relative	0.702	0.000	0.000
Close friend		0.000	0.000
Acquaintance			0.030

Demand visits

	Close friend	Acquaintance	Other
Relative	0.704	0.989	0.256
Close friend		0.726	0.221
Acquaintance			0.373

Table A.3: *Pairwise comparison of means between drug access by relationship status*

	Relative	Close friend	Aquaintance	Other
Relative		0.501	0.000	0.000
Close friend			0.000	0.001
Aquaintance				0.000

Table A.4: *Characteristics of elected versus appointed CHWs*

	Appointed					Elected					
Variables	**Mean**	**SD**	**Min**	**Max**	**N**	**Mean**	**SD**	**Min**	**Max**	**N**	**Diff**
Age	42.53	10.04	23	66	95	40.65	10.05	21	73	171	−1.87
Male	0.28		0	1	95	0.43		0	1	171	0.15**
Education in years	8.87	2.48	1	15	95	9.97	2.49	3	16	171	1.09***
Years lived in village	27.04	12.63	6	60	95	28.51	13.34	1	66	171	1.47
Years worked as a CHW	3.87	1.91	1	9	95	3.65	2.24	1	10	171	−0.22
Leadership	0.67		0	1	95	0.67		0	1	171	0.00
Allocated households	12.23	6.07	7	52	95	12.11	4.70	7	37	171	−0.13
Full time job	0.16		0	1	95	0.19		0	1	171	0.035
Hours worked	10.34	9.55	1	56	95	10.15	8.62	1	42	171	−0.19
Household visits	6.94	4.71	1	35	95	7.41	4.66	1	25	171	0.47
Salary	0.24		0	1	95	0.26		0	1	171	0.02
Benefits	0.52		0	1	95	0.54		0	1	171	0.02
Wealth (USD)	10 418	19 256	206	141 227	95	8485	11 610	263	106 823	171	−1932

Exchange rate: USD 1 = Ksh 99

Chapter II

Community Health Workers, Child Health and Health Care Utilization in Kenya*

Josephine G. Gatua† Jessica Coria‡

Abstract

This paper investigates the impact of a community-based health program on malaria and nutrition outcomes among children under the age of five, and health care behavior related to these outcomes. In 2005, Kenya initiated a community-based health program where community members, called community health workers (CHWs), are selected and trained to support health service delivery and act as a link between the community and the health system. We combine the Kenya demographic health survey collected in 2014 with data on the introduction of community health workers (2005–2014) to estimate the impact of the CHW program. Using the propensity score matching method, we find no strong evidence that the CHW program has had an impact on child health and health care outcomes, neither in rural nor in urban areas. These findings imply that the envisioned improvement in access to health care and health outcomes through CHWs has not been realized.

Keywords: Malaria, Kenya, Child health, Community Health Workers.

JEL Codes: I12, I14, I15, I18

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1 Introduction

Child health is a key indicator of economic development; among the eight UN Millennium Development Goals (MDGs), at least four were directly related to child health or nutritional status (Todaro and Smith, 2003). Furthermore, one aim of the UN Sustainable Development Goals (SDGs) is to end the epidemic of preventable diseases such as malaria by 2030.[1] Sub-Saharan Africa remains the region with the highest under age-5 mortality rate in the world, with one child in 13 dying before age 5, which is nearly 15 times the average rate in high-income countries (UNICEF, 2015).

In countries like Kenya, malaria is estimated to cause 20% of all deaths of children in this age group (Kisia et al., 2012). Childhood malaria has been found to have undesirable long-term effects on educational attainment, adult income, disease rates, and productivity (see Alderman et al., 2006; Bleakley, 2010; Cutler et al., 2010; Maluccio et al., 2009; Thomas and Strauss, 1997). Also, malnourished children, particularly those with severe acute malnutrition, have a higher risk of death from illnesses such as diarrhea, pneumonia, and malaria. It is estimated that nutrition-related factors contribute to about 45% of all deaths in children under 5 years of age (WHO, 2017b). This is to say, a large share of all under age-5 child deaths are due to diseases that are preventable and treatable through simple interventions designed to improve access to primary health care and nutrition. The inteverventions are particularly helpful in rural areas, where the shortage of health workers is quite pronounced. WHO (2006) estimates that in Africa, the number of health care workers per thousand population in 2006 was 2.9, compared with 40.3 in Europe. Moreover, people in rural areas experience poorer health status than their urban counterparts (Scheil-Adlung, 2015).

To overcome the lack of access to primary health care, many countries in sub-Saharan Africa have initiated community-based health pro-

[1] The United Nations Rio+20 summit in 2012 committed governments to create a set of sustainable development goals (SDGs) that would be integrated with the Millennium Development Goals (MDGs) after their 2015 deadline.

grams with the long-term objective of controlling preventable diseases through community participatory efforts in a primary health care setting (Pagnoni et al., 1997). Members of the community – referred to as community health workers (CHWs) – are selected and trained to perform a wide range of health-related activities, delivered through home visits. Thus, CHWs act as a link between households in the community and the health care system. Addressing primary health-care shortage in low-income countries through CHWs has therefore become a national priority (WHO, 2017a). With significant policy emphasis being placed on the role of CHWs in reversing undesirable health trends, it becomes increasingly important to investigate whether CHWs have an impact on child health and health care outcomes.

An increasing body of evidence indicates that CHWs can undertake actions that lead to improved health outcomes, especially but not exclusively in the field of child health (see for example, Bejenariu and Mitrut (2017) for evidence on the Roma Health Mediation program aimed to improve the health status of pregnant and postpartum Roma women, infants, and children). The existing literature on Africa shows mixed evidence regarding the impact of CHWs. On the one hand, systematic reviews of existing studies and some randomized control trials (RCTs) show that CHWs have an effect on preventive and curative health care (see, e.g., Christopher et al., 2011; Gilmore and McAuliffe, 2013; Kidane and Morrow, 2000; Kisia et al., 2012; Kumar et al., 2008; Nyqvist et al., 2017; Perry and Zulliger, 2012). On the other hand, some RCTs show that CHWs do not have an impact on health and health care outcomes (Bhandari et al., 2012; Kirkwood et al., 2013; Nyqvist et al., 2017; Sloan et al., 2008). Though we do have evidence regarding the effectiveness of CHWs, it stems from projects that are more controlled and that differ in other aspects compared with the national CHW programs. Therefore, the potential effectiveness of large-scale nationwide CHW programs remains an empirical question that needs to be studied further (WHO, 2017a).

A major difference between the RCTs evaluating the impact of CHWs and large-scale nationwide CHW interventions is that in RCTs, the setting under which CHWs operate is controlled and well monitored, which may not mimic how nationwide CHW programs are implemented. A nationwide CHW program roll-out is likely to be subject to institutional failures such as weak health systems, as well as lack of adequate training, supervision, and remuneration of health workers, all of which are common problems in low-income countries (Haines et al., 2007). For example, Gatua (2017) finds that the monitoring and accountability of the nationally implemented CHW program in Kenya is weak or nonexistent. CHWs are meant to be supervised and supported by health extension workers. However, this is usually not the case in practice as the extension workers often lack resources to oversee CHW activities. This makes it difficult to effectively account for the activities of CHWs in the field. Similarly, community health work is largely voluntary, and hence, CHWs do not have explicit monetary incentives, which may affect their output. Providing CHWs with monetary incentives could increase their work effort and reduce the high attrition rates (see Nyqvist et al., 2017). Thus, looking at the effects of CHWs in an existing nation-wide program will contribute to the growing literature on CHWs besides providing information that could be used in upscaling the program.

The present paper helps to bridge the discussed research gap by providing empirical evidence on the effects of a nationwide CHW program implemented in Kenya in 2005 for rural and urban households. We use the Kenyan program as a quasi-experiment and exploit the geographical variation in CHW program rollout by October 2014, as we compare households that were exposed to the program with households that were not exposed. We combine information from the 2014 Demographic Health Survey (DHS) – a nationally representative dataset – with information on CHW program roll-out to determine whether a geographic area was exposed to CHWs. We use propensity score matching to estimate the impact of CHWs on child health and health care outcomes. The main results show that CHWs did not have an impact on child health outcomes such as malaria fever, wasting, and stunting. Limited evidence of an impact on preventive health care behavior, such as households in rural areas getting tested for malaria, is observed, however. This paper therefore provides evidence that the studied CHW program generally does not have significant effects on child health and health care outcomes.

The remainder of the paper is structured as follows. Section 2 provides an overview of the implementation of health care by CHWs in Kenya. Section 3 presents the empirical approach. Section 4 discusses the data. Section 5 presents the empirical results. Section 6 discusses some policy implications and concludes the paper.

2 Community Health Workers Policy

In low-income countries, CHWs have been identified as a strategy to address the growing shortage of health workers and increased disease burden. In 2005, the Kenyan government introduced CHWs in the health system with the aim of building the capacity of households not only to demand services from providers, but also to know and progressively realize their rights to equitable and good quality health care. In what follows, we describe the background and implementation of the CHW program in Kenya.

2.1 Background

Before 2005, Kenyan health care services were delivered through five service delivery levels: tertiary hospitals, secondary hospitals, primary hospitals, maternity clinics and nursing homes, and health centers/dispensaries. The tertiary hospitals represented the highest level (level 5) of health care service provision. Health centers and dispensaries represented the lowest level (level 1), the level of the health system dealing with curative, preventive, and health promotion activities.

However, declining health indicators prior to 2005 seemed to indicate that this structure was insufficient. For example, the country's infant mortality rate rose from 64 per 1,000 live births in 1993 to 72 in 1998, 74 in 2000, and 77 in 2003, and the under-5 mortality rates rose from 90.9 per 1,000 live births in 1989 to 115 per 1,000 live births in 2003. Moreover, 30.7% of children under age 5 were stunted, only 4.3% of children under age 5 and 4.5% of pregnant mothers slept under insecticide-treated bed nets, and only 59.2% of children in their second year of life were fully immunized (KNBS, 2004). The government acknowledged that most of the unfavorable health trends facing the population were preventable and that the burden of ill health could be reduced by enabling the community to actively participate in decision making processes related to health matters concerning the community. Hence, through its health strategic plan (2005–2010), the Kenyan Government introduced a major health reform known as the Kenya Essential Package for Health (KEPH) in 2005. The KEPH introduced a new level of service delivery in the health system – the community level – bringing the total number of levels to six, with CHWs serving at this new level. CHWs were to be members of the communities where they work, be selected and managed by the communities, accountable to the communities for their activities, be supported by the health system (though not necessarily part of its organization), have shorter training than professional workers on various health care-related issues, and be regularly retrained.[2]

To provide the health care services to the community, CHWs initially receive basic health care training from health care professionals. The health services performed by CHWs included: a) treatment of malaria and provision of durable insecticide treated nets, b) growth monitoring of children under age 5, c) advising on maternal and child health, d) provision of family planning commodities, e) provision of information on water and sanitation hygiene, f) deworming of children, g) prevention and management of diarrhea, injuries, wounds, jiggers, and other minor illnesses, h) provision of information, education, and communica-

[2]This is similar to the WHO definition of recruitment and management of CHWs (WHO, 1989).

tion material, i) defaulter tracing,[3] j) referrals to health facilities, and k) first aid services.[4]

The expectation was that in performing these duties, CHWs would help households to overcome physical barriers to accessing effective healthcare. In addition, since CHWs were members of the community, they were expected to contribute to an increase in people's confidence in the formal health sector, improvements in patient adherence to treatment regimens, and enhanced provision of information on preventive health behavior. CHWs were expected to remain in their home villages or neighborhoods and, as mentioned, would usually work part time as volunteers. The lack of national funds was the major reason for the lack of remuneration; no major budgets were expected from the ministry for salaries other than funds for CHW training. Furthermore, health services provided by CHWs were meant to be free of charge to households and proactively provided through home visits.

Regarding the organizational structure of the CHW program, CHWs were organized in groups known as community units (CUs). A CU consisted of up to 50 CHWs serving about 5,000 people, implying that each CHW would serve approximately 20 households or 100 people. CUs were administratively linked to a local health facility in an administrative location covering a well-defined geographical area.[5]

2.2 Program implementation

The CHW policy is formulated at the national level but implemented and enforced at the regional level. The implementation was decentralized due to the superior ability of local authorities to identify the local needs of the population. Due to the decentralized nature of the implementation of the CHW policy, CHWs were not introduced simultaneously

[3] Individuals with HIV/AIDS or tuberculosis (TB) are required to undergo antiretroviral therapy and take TB medicine, respectively, and children under age 5 must get immunized

[4] `www.hsrs.health.go.ke`

[5] An administrative location is the third smallest administrative unit in Kenya, with an average size of 208.13 km^2.

across all regions of the country. In addition, some locations were more likely than others to have CHWs introduced, and this will be addressed in the empirical strategy section of this paper. In 2006, fewer than 20 CUs existed, but the number increased substantially from 2008 to 2014, leading to the existence of about 2,570 CUs at the end of that period, as shown in Table A.1 in the appendix.

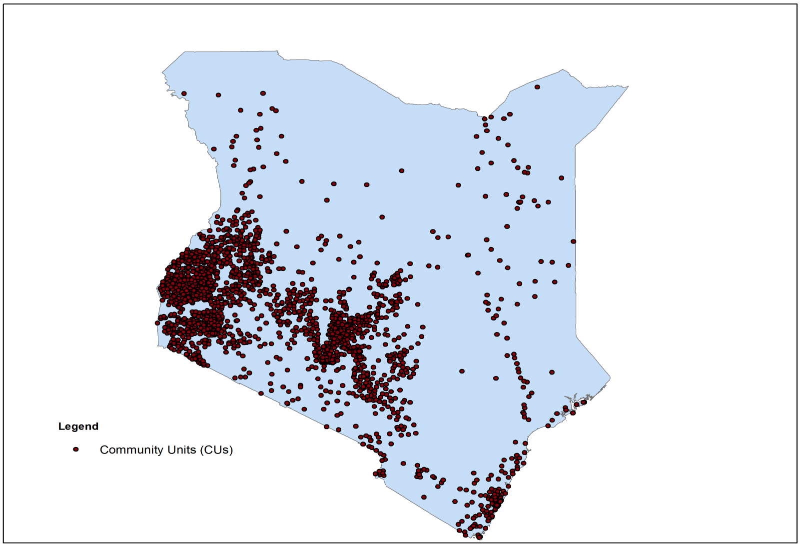
Two factors seem to affect the likelihood of CHWs being introduced in a region. The first factor is the ability of local administrative leaders in conjunction with the local health facility to implement the program, which requires making an announcement calling for volunteers to work as CHWs, informing the community about the potential candidates who would like to volunteer, and organizing the election process through which CHWs would be selected by the community. All of this requires planning, sustained political leadership, and good governance to ensure community participation, as well as ownership and support of the CHW program. Second, CHWs were more likely to be introduced in areas that were potentially worse off in terms of health outcomes as they were expected to benefit the most from the intervention. Examples of such areas include poor areas, areas with a high prevalence of malaria and/or HIV, and rural areas with limited access to formal health care.[6] Figure 1 shows the geographical distribution of CHWs across the country.

As can be seen, the introduction of CHWs was concentrated to the western, central, and southern parts of Kenya. The western part had a high prevalence of malaria and HIV. The southern part also had a high prevalence of malaria, while the central region had a low prevalence of malaria but a high prevalence of HIV. The northern and eastern parts of Kenya had a low rollout of CHWs and were characterized by a high fraction of the population living below the poverty line, as shown in Figure A.1 in the appendix.[7]

[6] This information is based on conversations with Ministry of Health officials working in the community health and development unit.

[7] Figure taken from Ngugi et al. (2013).

Figure 1: Distribution of CUs in Kenya in 2014



3 Data and Empirical Strategy

3.1 Data

The data used in this paper is derived from two sources. The first source is the 2014 DHS survey of Kenya, which is a nationally representative cross-sectional dataset containing rich information on socioeconomic, demographic, and health-related variables such as fertility, child mortality, nutritional status of mothers and children, and general health. DHS data is drawn from the sampling frame used to conduct household-based surveys throughout Kenya (the National Sample Survey Evaluation Program). This frame divides the population into clusters that correspond to one or several geographically close villages (or a neighborhood in the case of urban areas). The DHS uses a two-stage sampling design where, in the first stage, clusters are randomly sampled from a national census dataset and, in the second stage, households are randomly sampled from a cluster. Kenya is divided into eight administrative regions (provinces) and the number of clusters in each region is usually chosen such that it is proportional to the region's population.[8] The primary survey respondents are women of reproductive age (15–49 years), since individuals in this group are deemed to have the best information on the health status and welfare of their children and households.[9]

The second type of information utilized in this paper is the distribution of CUs in Kenya (as well as the year in which each CU was established). This information was obtained from the Kenya Master Health Facility List (KMHFL), which lists all CUs in Kenya. As discussed earlier, CUs are linked to health facilities that are located within certain geographic administrative boundaries, an area known as an *administrative location*. The latitude and longitude of each health facility were obtained from various sources. It is important to note that CUs can only serve the population in the administrative location that the health facility hosting the CU belongs to.

We hand-matched administrative locations across the two data sources. That is, we identified administrative locations that both hosted one or more CU(s) and contained one or more DHS clusters. Next, we defined the identified administrative locations as areas where the CHW program *has* been rolled out, and administrative locations containing one or more DHS clusters but no CUs as areas where the CHW program *has not* been rolled out. The first year in which a CU appears in the records is used as the year in which CHWs were introduced in that administrative location. As shown in panel (A) of Table 1, the 2014 DHS covered 1,593 clusters and 1,223 administrative locations, comprising a total of 36,430 households (thus, on average, each cluster had about 23 households).[10] Panel (B) shows that CHWs had been introduced in 1,308 of Kenya's 2,750 administrative locations in 2014 (47.5%). Thus, CHWs had been introduced in almost half of the country's administra-

[8]The Kenyan administrative structure consists of seven levels: the national level, the provincial level, districts (which have since been merged to form counties), divisions (now referred to as sub-counties), locations, sub-locations, and villages.

[9]Men living in the selected households are interviewed using the Man's Questionnaire.

[10]Initially, 1,612 were selected, but GPS coordinates were recorded and interviews successfully carried out in only 1,593 of these.

Table 1: *Administrative locations*

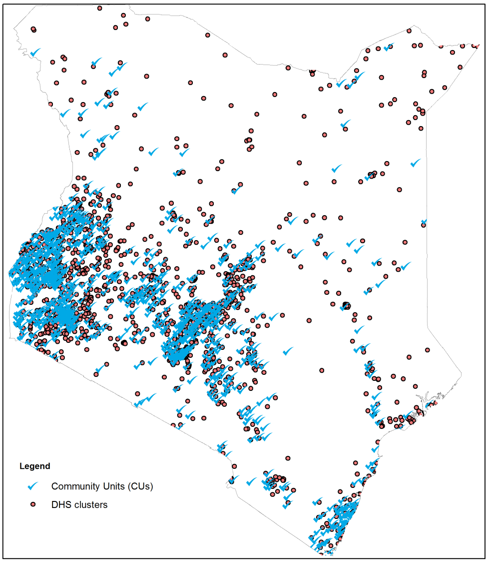
***A**. DHS (2014) - 1593 clusters*	*Number*
Administrative locations with DHS clusters	1,223
Administrative locations with both CUs & DHS clusters (CHWs introduced)	620
Locations with CHWs introduced as a share of total locations with DHS clusters	50.7 %
***B**. Administrative Locations in Kenya*	*Number*
Administrative locations in Kenya	2,750
Administrative locations with CHWs introduced	1,308
Locations with CHWs introduced as a share of total administrative locations in the country	47.5 %

tive locations, which indicates that the DHS dataset provides us with a representative sample of the introduction of CHWs in Kenya.

After identifying administrative locations that both contain DHS clusters and host CU(s), we end up with 620 administrative locations where CHWs hade been introduced and 603 where they had not.[11] Figure 2 shows the geographical distribution of DHS clusters and CUs.

[11]We could potentially have used the 2008 DHS in addition to the 2014 DHS since CHWs were largely introduced beginning in 2008. However, the 2008 DHS does not provide the names of administrative locations, making it impossible to match the health facility data with the DHS data.

Figure 2: Distribution of DHS clusters and CUs



As mentioned earlier, CHWs can only serve within the boundaries of the administrative location where the CU is located. The assignment of households typically occurs in two steps: the community within these boundaries is divided into sections and all households in a particular section are under the responsibility of one CHW. However, evidence has shown that CHWs have the discretion to choose (within that particular section) which households to visit and how many times to visit them, and that households located near a CHW's own household tend to receive more visits (Gatua, 2017). Unfortunately, we lack information about the number of visits made to individual households and instead measure "presumptive visits" assuming that households in areas where CHWs have been introduced will be visited. Nevertheless, we cannot control for the fact that some households might not have been visited at all while others might have been visited often.

We expect that the distance between the location of the household and the closest CU might impact the effect of the CHW program. In particular, the presence of CHWs on average eliminates the distance traveled to get primary health care, since households can then be visited at home. As travel costs are higher for households located far away from health facilities hosting the CUs, we expect the effect of CHW implementation to be larger for this group. Since we do not know which households were exposed to the CHWs, we use the global positioning system (GPS) data on distance between DHS clusters and CUs to more accurately proxy for the effect of presumptive exposure to CHWs. We first calculate the distance between the central point of the geographical area covered by the DHS cluster and the position of each CU within the administrative location. We classify a DHS cluster as being exposed to CHWs based on two distance bands. The first is if a DHS cluster is within 5 km from the CU, and the second is if a DHS is within 25 km from the CU. That is, the distance between the DHS clusters and the CUs within the locations in which CHWs have been introduced is used as thresholds to define presumptive exposure to treatment. We choose these distance bands as they correspond to the median and 90% percentile of the distribution of the distance between the boundaries of an administrative location and the DHS cluster central point. We choose the median instead of the mean, since as shown in Figure A.2 in Appendix A, the distribution of the distance between the central point of DHS clusters and the closest CU is very right-skewed. Moreover, we exclude the 10% right hand side of the distribution as it is mainly characterized by very large distances.

Since a major objective behind the implementation of the CHW program was to increase the availability of accessible primary health services to the population, we expect the effect of the CHW program to differ between rural and urban households. The reason for this is that people in rural areas are the most under-served in low-income countries and are thus expected to benefit the most from such an intervention. We therefore separate rural and urban areas in our analysis.

3.2 Empirical strategy

We start the analysis by estimating in Equation 1 using OLS regression to compute the single difference in mean outcomes between the treated and non-treated households, where T_i=1 denotes treated households (understood as the households located in areas where CHWs have been introduced) and T_i=0 denotes non-treated households (e.g., households located in areas where CHWs have not been introduced). Y_i denotes the outcome variable(s) such as malaria fever, which will be discussed in detail in the next section.

$$Y_i = \alpha_0 + \alpha_1 T_i + \alpha_2 T_i * Dist_i + \alpha_1 \mathbf{X}_i + \epsilon_i \tag{1}$$

As described earlier, the distance between the location of the household and the closest CU may influence the effectiveness of the CHW program. To control for this, we add the variable $T_i * Dist_i$, which accounts for the interaction between the treated households and distance. Furthermore, we control for a vector of observable pre-treatment characteristics denoted $\mathbf{X}_i$. The error term is denoted ϵ_i. The difference in means is represented by the coefficient α_1, which gives the average treatment effect on the treated (ATT) for households located 0km from the CU (assuming that assignment into treatment is random). The coefficient α_2 represents the effect of the distance between treated households and the closest CU on the mean outcomes. Finally, α_1+$\alpha_2 Dist_i$ evaluated at $Dist_i$ = 5 km and $Dist_i$ = 25 km corresponds to the ATT of for treated households located within 5 km and 25 km to the closest CU, respectively.

Since CHWs were not randomly introduced across the country, we also use the propensity score matching (PSM) method to estimate the causal effects of CHW introduction on child health and health care utilization behavior. PSM balances the distribution of observed covariates between a treatment group and a control group based on their propensity score, which corresponds to the conditional probability of receiving treatment given observable pre-treatment characteristics (Colin and

Trivedi, 2005). PSM therefore allows for the comparison of treated and untreated (control) groups based on observable characteristics by choosing control groups whose characteristics closely resemble those of the treated group. One advantage of our data is that the potential control locations are drawn from the same population as the treated units. A second advantage is that the variables used in the PSM are observable characteristics informed by policy documents from the Kenyan Ministry of Health.[12] By selecting an appropriate subset from the control group, a simple difference in means yields an estimate of the treatment effect of the program.

In the PSM regressions, we identify two groups as being treated: (i) households in areas where CHWs have been introduced and that are located within 5 km of the closest CU, and (ii) households in areas where CHWs have been introduced and that are located within 25 km of the closest CU. Treatment is now represented by D_i,which takes a value of 1 for households within the treatment distance bands, and 0 otherwise. Thus, compared with the OLS regressions where the effect of distance on the effectiveness of CHWs is assumed to be linear, the PSM formulation uses distance thresholds to account for presumptive exposure to treatment.

Households that are treated are matched with households that are not treated on the basis of propensity score, which is a single number ranging from 0 to 1 that summarizes all of the observed characteristics that influence the likelihood of being treated. The propensity score then allows matching of individuals in the control and treatment groups with the same likelihood of receiving treatment. Thus, a pair of households (one in the treatment, one in the control group) sharing a similar propensity score are seen as equal, even though they may differ on the specific values of the covariates (Holmes, 2013). The basic equation representing the propensity score is as follows:

$$P(X_i) = Prob(D_i = 1|X_i) \quad (0 < P(X_i) < 1), \tag{2}$$

[12] See www.health.go.ke.

where X_i is a vector of observable pre-treatment control variables. PSM therefore requires that for each value of X, there are both treated and control observations such that for each treated observation, there is a matched control observation with similar x (which is denoted as the overlap assumption). Since outcomes are assumed to be independent of participation given X_i, they are independent of participation given $\mathrm{P}(X_i)$, just as they would be if participation were randomly assigned (see Rosenbaum and Rubin, 1983).[13] In addition, we include pre-treatment characteristics that are not affected by the treatment to ensure that the treatment and control groups are independent. The matched households become the comparison group and are used to produce an estimate of the counterfactual. Therefore, the difference in outcomes between the treatment and the matched control households allows us to estimate the ATT as follows:

$$ATT_i = \frac{1}{N_T} \sum_{i \in D=1} \left(y_{1,i} - \sum_{j \in D=0} \varnothing(i,j) y_{0,j} \right) \tag{3}$$

where D=1 and D=0 are treated and non-treated households, respectively, and $\varnothing(i,j)$ is a weight calculated using the nearest neighbor matching method where for each treated observation i, a control observation j having the closest propensity score is selected with replacement. Since the propensity score is unknown, it has to be estimated. We then adjust the standard errors for the estimation error in the propensity score and the variation that it induces in the matching process by using the Abadie and Imbens estimator (Dehejia and Wahba, 2002). In addition, the nearest neighbor matching allows us to adjust the standard errors for clustering.

As described earlier, two factors define which areas are more likely to have introduced CHWs: the ability of the local community to implement and support the CHW program, and the benefits of the intervention, which are expected to be higher in densely populated areas and areas characterized by poor health status and high malaria risk. We use

[13] This is often referred to as the conditional independence assumption.

five pre-treatment characteristics to proxy for these factors, as well as poverty incidence estimates that come from the 2005 Kenya Integrated Household Budget Survey (KIHBS) to proxy for the ability of the local community to implement the program. The KIHBS is a nationally representative dataset designed to provide data needed to update measures of living standard, notably poverty, in Kenya. The poverty incidence is estimated at the administrative location level and provides the best estimates of poverty levels in the country before the introduction of CHWs.

Regarding the benefits of the intervention, we use information on population at the administrative location level obtained from the 2009 Kenya Population and Housing Census. Although Kenya had a housing and population census conducted in 1999, the one from 2009 is more representative of the population patterns that prevailed at the time of the launching of the CHW program as most CHWs were introduced in 2008. Health status is proxied by HIV prevalence rates and child nutrition status (measured by the share of stunted children). We use HIV prevalence estimates from the 2003 DHS, which is the best available source of HIV health-related information before the CHW program was introduced. These estimates are provided at the level of provinces, i.e., the second largest administrative unit in Kenya. Estimates of the nutrition status of children in each province are also obtained from the 2003 DHS.

Regarding malaria risks, Kenya has geographically distinct regions with widely varying risk levels. These malaria epidemiological zones are determined by the geographic characteristic of a region such as the altitude, rainfall, temperature, and humidity and can be viewed as relatively fixed over long periods of time. The zones are classified into four groups at the district level.[14] The pre-existing geographical variation in malaria in Kenya is obtained from the national malaria policy and is representative of the country's malaria risk situation prior to the introduction of CHWs. Moreover, the DHS interviews were conducted from May to October 2014. This implies that there may be variation in malaria risk across DHS clusters due to varying weather conditions during these months,

[14] A district is the third largest administrative unit in Kenya.

which in turn may affect our outcome variable, i.e., malaria incidence. We calculate a malaria weather index that takes rainfall and temperature into account and indicates whether the interview month was a so-called malarious month. To this end, we use data on precipitation and temperature from the Global Precipitation Climatology Centre (GPCC) and the University of Delaware, respectively.[15] Both types of data are recorded monthly on a 0.5*0.5 degree (55.5*55.5 km at the equator) earth grid from January 1901 to 2016. The two weather datasets are then spatially linked to the DHS clusters and the malaria index for each DHS cluster subsequently calculated.[16] Socio-demographic controls from DHS 2014 that are deemed to determine the outcome variables are also included. They also help improve the matching of treatment and control groups using the propensity scores.

3.3 Outcomes

Based on the duties performed by CHWs, and on the health and health care information available in the DHS survey, a number of health outcomes can be evaluated. However, in this study we focus on a few child health outcomes related to malaria and nutrition because these factors contribute to a large share of under age-5 child deaths and form a part of the CHW tasks. Although the selected outcomes are not exhaustive, they provide us with a fair representation of the effects of the CHW program on child health in Kenya.

The first outcome variable is malaria incidence. The DHS survey asked every household with a child under age 5 about the prevalence of fever in these children in the two weeks prior to the interview. The survey also asked if the fever was related to illness with a cough. As proxy for malaria incidence, we use the cases of fever not related to illness with a cough (hereinafter malaria fever). The survey question related to malaria fever was stated as: "*Has (name) been ill with a fever at any time in the*

[15] www.esrl.noaa.gov.

[16] We follow the procedure outlined in Kudamatsu et al. (2012) on how to construct the malaria index.

last two weeks?" and question related to cough was: "*Has (name) been ill with a cough at any time in the last two weeks?*" An indicator value of 1 is assigned for households with a child who had suffered from fever but had not been ill with a cough in the two weeks prior to the survey (and 0 otherwise).

The second group of outcome variables are measures of health care utilization behavior related to malaria. They are divided into preventive and curative health care utilization behavior. Malaria prevention is accounted for by the ownership of bed nets. The specific question in the survey read: "*Does your household have any mosquito nets that can be used while sleeping?*" An indicator value of 1 is assigned for households with children under age 5 and at least one bed net in the home (and 0 otherwise). For households owning at least one bed net, we also examine bed net usage by children under age 5. The question in the survey read "*Did (name of child under age 5) sleep under a mosquito net last night?*" An indicator value of 1 is assigned for households with both nets and children under age 5 who slept under a net the previous night (and 0 otherwise).

Malaria curative behavior is proxied by questions regarding household malaria treatment-seeking behavior (conditional on a household reporting to have had a child under age 5 who suffered from malaria fever in the two weeks prior to the survey). Households were asked: "*At any time during the (fever) illness, did (Name) have blood taken from his/her finger or heel for testing?*" An indicator value of 1 is assigned for children who were tested (and 0 otherwise). Furthermore, conditional on malaria fever in the two weeks prior to the survey, households were asked: "*Did you seek advice or treatment for the illness from any source?*" An indicator value of 1 is assigned for households that sought any type of advice/treatment (and 0 otherwise). Households reporting to have sought some type of help were also asked to state where they sought help from. Conditional on having sought care, an indicator value of 1 is assigned for households that sought formal health care (e.g., public and private health facilities), and 0 if they sought advice/treatment from other sources (e.g., pharmacies, stores, traditional practitioners, and relatives).

The third group of outcome variables comprises anthropometric measures of child nutrition. We look at stunting (low height for age) and wasting (low weight for height) as outcomes variables, where both are expressed in standard deviations (Z-scores) from the mean of the reference population, as recommended by the World Health Organization (WHO). A child's weight (in kilograms) and height (in centimeters) were measured, and an indicator value of 1 is assigned for households with a stunted or wasted child, respectively (and 0 otherwise). Stunting is caused by long-term insufficient nutrient intake and proxies for long-term growth deficiency, while wasting is due to acute significant food shortage and/or disease. We also explore the intake of vitamin A among children under age 5. Vitamin A deficiency diminishes the ability to fight infections and absorb nutrients. The survey question asked: "*Within the last 6 months, was (name) given a dose of Vitamin A?*" An indicator value of 1 is assigned for households reporting that their children had been given a dose of vitamin A (and 0 otherwise).

4 Summary Statistics

We begin by reporting summary statistics together with tests for balance of treated and non-treated areas, in rural and urban environments. Due to the high level of aggregation of the data used to construct our control variables (e.g., province, district, and administrative location), we do not observe statistically significant differences in the control variables between households located within 5 and 25 km of a CU. Thus, we only report statistics for households treated within the 25 km radius. Table 2 shows the descriptive statistics of pre-treatment characteristics that explain health outcomes and at the same time are correlated with exposure to CHWs for households. We observe significant differences in characteristics between the treated and non-treated households with expected signs. For example, the results show that there are statistically significant differences between treated and non-treated households in terms of poverty headcount, population size, HIV incidence, malaria epidemiological zones, and availability of health facilities. For instance, compared with non-treated households, treated households are to a higher extent located in endemic zones (i.e., 38% vs. 19% in rural areas, and 37% vs. 20% in urban areas), while compared with treated households, non-treated households are to a high extent located in seasonal malaria zones (i.e., 44% vs. 25% in rural areas, and 40% vs. 20% in urban areas). The availability of health facilities is also higher in urban than in rural areas. Moreover, compared with treated households in rural areas, treated households in urban areas are located closer to health facilities (the average distance between the central point of a DHS cluster and the closest health facility hosting a CU is 8.88 km in urban areas and 13.22 km in rural areas).

TABLE 2: *Summary statistics of rural and urban households*

Variables	Rural areas *Mean non-treated*	Rural areas *Mean treated*	Rural areas *Diff*	Urban areas *Mean non-treated*	Urban areas *Mean treated*	Urban areas *Diff*
Sex household head (dummy)	0.70	0.69	-0.01	0.71	0.72	0.01
Age household head (years)	29.00	28.92	-0.08	28.28	28.07	-0.22
Age of child (years)	2.01	2.01	-0.01	2.01	2.00	-0.02
Household size (#)	6.14	6.18	0.04	5.72	5.08	-0.64***
Poverty headcount (%)	57.37	52.41	-4.97***	45.04	39.05	-5.99***
Logpop	9.16	9.69	0.53***	9.97	10.51	0.55***
HIV rate (%)	7.07	8.61	1.54***	6.47	9.45	2.97***
Stunted children (%)	31.14	31.10	-0.05	29.97	30.03	0.06
Malarious month(dummy)	0.30	0.40	0.10***	0.30	0.38	0.08***
Seasonal (dummy)	0.44	0.25	-0.19***	0.40	0.20	-0.20***
Epidemic (dummy)	0.26	0.20	-0.06***	0.22	0.13	-0.09***
Endemic (dummy)	0.19	0.38	0.19***	0.20	0.37	0.17***
Low-malarious areas (dummy)	0.11	0.17	0.05***	0.18	0.30	0.12***
Community Units						
# CUs in a location	-	2.07	-	-	3.94	-
# years a location has had CUs	-	4.05	-	-	4.17	-
Health facilities & Distance						
# health facilities	1.09	2.40	1.31***	2.44	5.43	2.99***
Distance DHS cluster to closest CU (km)	-	13.22			8.88	-
Observations used for PSM						
# observations within 5 km of closest CU	10902	2659	-	4022	2510	-
# observations within 25 km of closest CU	7248	6313	-	3098	3434	-

Notes: Malarious month index is a dummy equal to 1 if households in a particular cluster were interviewed in a malarious month and 0 otherwise. *Low-malaria* areas are those with little to no malaria transmission; *seasonal* are those areas that experience short periods of intense malaria transmission during the rainy seasons; *epidemic* are those areas where malaria transmission is seasonal with considerable year-to-year variation and endemic are those with transmission occurring all year round. Robust standard errors used and p-values are *** p<0.01, ** p<0.05,* p<0.1.

Finally, Table 2 also shows the number of households in each of our PSM treatments. Of the 20,093 households in our sample that have children under age 5, 5,169 are located within 5 km of the closest CU (2,659 of them are in rural areas and 2,510 are in urban areas) and 9,747 are located within 25 km of the closest CU (6,313 of them are in rural areas and 3,434 are in urban areas). Moreover, in relative terms, about 70% of the rural treated households are located within 25 km of the closest CU, while the corresponding share of urban treated households is 58%.

The differences between treated and non-treated areas clearly point to the importance of taking into account pre-treatment characteristics affecting the probability of receiving treatment when comparing health outcomes between treated and non-treated households. Regarding the factors affecting the probability of being exposed to CHWs, Table 3 reports the estimates of the logit regression where the binary outcome takes a value of 1 if households are exposed to CHWs and 0 otherwise for households located in rural and urban areas. Note that we do not include the number of health facilities in this regression, as it is highly correlated with the treatment itself since CHWs can only be introduced in locations where there is at least one health facility that can host a CU.

A large number of variables are significantly correlated with exposure to CHWs, and given the discussion above, they are generally unsurprising. For rural areas, Table 3 shows that households in locations with large populations and high HIV rates and households in endemic malaria areas were more likely to be exposed to CHWs. In urban areas, households in locations with high poverty, large populations, and high HIV rates were more likely to be exposed to CHWs. Thus far, we have seen that our treated and non-treated households differ across various pre-treatment characteristics, and for any meaningful comparison to be made between them, we first need to make them comparable.

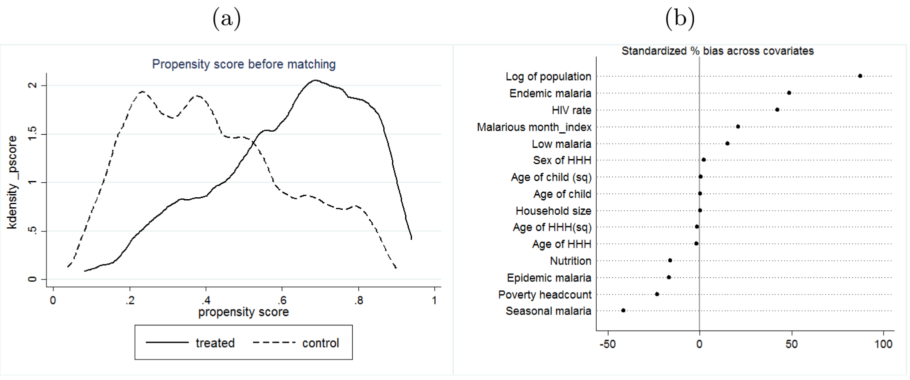
Table 3: *Logit regression coefficients for exposure to CHWs*

	Rural		**Urban**	
Variables	**5km**	**25km**	**5km**	**25km**
	Coef.	Coef.	Coef.	Coef.
Sex of HHH	-0.033	0.030	-0.014	-0.050
	(0.080)	(0.070)	(0.083)	(0.091)
Age of respondent	0.001	-0.003	0.018***	0.011*
	(0.005)	(0.004)	(0.006)	(0.006)
Age of child	-0.008	-0.003	-0.033*	-0.029*
	(0.014)	(0.012)	(0.018)	(0.018)
Household size	0.000	0.018	-0.079***	-0.050**
	(0.017)	(0.017)	(0.024)	(0.024)
Poverty headcount	-0.014**	-0.005	-0.005	0.008
	(0.006)	(0.004)	(0.008)	(0.009)
Logpop	0.426***	1.081***	0.766***	0.844***
	(0.148)	(0.143)	(0.177)	(0.199)
HIV rate	0.050**	0.040*	0.092***	0.158***
	(0.021)	(0.022)	(0.035)	(0.037)
Stunted children	0.052	0.006	0.035	0.096**
	(0.043)	(0.036)	(0.039)	(0.042)
Malarious month	0.159	-0.180	-0.091	-0.321
	(0.207)	(0.187)	(0.307)	(0.290)
Seasonal malaria	-1.127***	-0.088	-0.005	-0.470
	(0.329)	(0.262)	(0.452)	(0.437)
Epidemic malaria	-0.683**	-0.571**	-0.316	-1.191**
	(0.288)	(0.248)	(0.474)	(0.480)
Endemic malaria	-0.296	0.424	0.386	-0.193
	(0.298)	(0.284)	(0.455)	(0.470)
Constant	-6.316***	-10.467***	-10.042***	-12.472***
	(2.181)	(1.924)	(2.560)	(2.873)
Observations	13,561	13,561	6,532	6,532

The malaria zones are compared with the low-risk malaria zones. Standard errors in parentheses are adjusted to account for clustering at location level, and *p*-values are *** p<0.01, ** p<0.05,* p<0.1.

Before going into the matching algorithm, we assess the comparability of the two groups by looking at the distribution of confounders across treated and control groups. Figure 3 panel (a) and (b) shows the distribution of propensity scores for treated and control households. Crucially, as shown in panel (a), these distributions do not overlap perfectly and there is a clear lack of common support at the extremes of the propensity score distribution, implying that there are substantial differences in covariate distribution between the treatment arms, which may lead to a bias in estimated coefficients and imprecise statistical inferences. Panel (b) displays the standardized differences for comparing means across treated and control households before matching. We find that there is a bias between the treated and control households across covariates, and it is both positive and negative across covariates for both groups. These figures suggest the need for adjustment in confounders of both treatment and control households so we can have controls with characteristics similar to those of treated households.

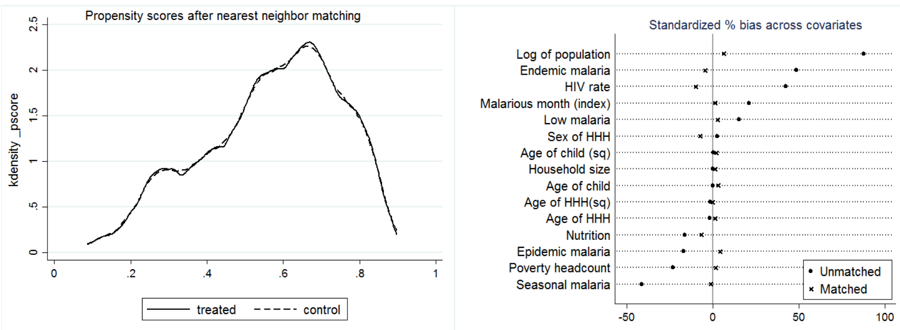
Figure 3: Propensity score and covariate balance before matching



We use the nearest neighbor (NN) matching as our matching algorithm to give us a suitable control group for our treated group. Panel (a) of Figure 4 shows that the propensity score overlap between the treated and control households has improved following nearest neighbor matching. In addition, panel (b) shows that the bias for all covariates has decreased and that most variables achieve a near zero bias. For example, before matching, our sample consisted of 19,908 households with children under age 5. After matching, the number was 19,834 implying that 74 treated households fell outside the region of common support.[17]

Figure 4: Propensity score and covariate balance after NN matching

(a) (b)



5 Results

This section presents two sets of results concerning the impact of CHWs. We first show estimates of the effect of CHWs on child malaria fever, health care utilization behavior, and anthropometric measures of child nutrition for the sub-samples of rural and urban households (Section 5.1). The arid regions of the country contain DHS clusters with mostly non-treated households. In section 5.2, we exclude these clusters and re-estimate the impact of the CHW program.

5.1 Child health and health care outcomes

Table 4 reports the results of the OLS and PSM regressions. A first look at the results indicates that, with a few exceptions, the CHW program had very little impact on child health and health care outcomes over

[17] This number differs from the 20,093 previously reported because some households with children under age 5 were not eligible for analysis because the children in those households were not de facto members of the households.

the studied period. Moreover, the limited evidence of effects is mostly concentrated to rural areas.

As shown in Table 4, the CHW program has not had a statistically significant impact on child health outcomes such as malaria fever, stunting and wasting. Similarly, households in the treated locations do not seem to differ significantly from households in the control locations when it comes to health care behavior such as bed net ownership and usage (though the PSM estimates suggest that the program seems to have marginally increased bed net ownership in rural treated households and utilization of nets in urban households located within 25 km of the closest CU).

When it comes to the outcomes for which we observe more robust effects, we find that, conditional on malaria fever, treated households in rural areas were more likely to have children tested for malaria than non treated households. This result holds in both the OLS and the PSM specifications, though the statistical significance is larger for the OLS estimates. Furthermore, the magnitude of the effect is larger for the PSM estimates of households located within 5 km of the closest CU. For instance, OLS estimates indicate that children in treated rural locations were 7 percentage points more likely to have been tested for malaria in 2014 (regardless of the distance to the closest CU). The PSM estimates indicate that children in rural households located within 5 km of the closest CU were 8 percentage points more likely to have been tested for malaria. Furthermore, children in rural households located within 25 km of the closest CU were only 5 percentage points more likely to have been tested for malaria.

According to the OLS estimates, children in rural and urban treated locations were also about 5 percentage points more likely to have received a dose of vitamin A in the six months prior to the DHS survey, yet this effect remains marginally significant only in the case of PSM estimates for rural households located within 25km of the closest CU. OLS estimates also indicate that households in urban treated areas were more likely to seek formal treatment for malaria fever than households in the control locations. However, this result is not robust to the PSM specification, suggesting that the evidence of an effect is connected to the larger availability of formal health facilities in urban areas. Finally, the PSM estimates for urban areas indicate that treated households were less likely than non-treated households to seek any form of treatment conditional on malaria fever. This result is puzzling yet only marginally significant. A possible explanation for this result is that the urban poor may be less likely to seek any form of health care due to liquidity constraints, which have often been cited in the literature as constraints to health care access (see e.g. Cohen and Dupas, 2010).

All in all, we can conclude that our estimates provide evidence of an effect for two outcomes: malaria testing and intake of vitamin A, while the evidence of an effect for the remaining outcomes under study is statistically insignificant or non-robust.

Table 4: *CHW program impact on child health and health utilization behavior*

	RURAL						URBAN					
	OLS			PSM			OLS			PSM		
Dependent variables	**N**	**5km**	**25km**	**N**	**5km**	**25km**	**N**	**5km**	**25km**	**N**	**5km**	**25km**
Panel A												
Child had malaria fever in the last 2 weeks	13,452	-0.007	-0.008	13,433	-0.007	-0.020	6,456	0.006	0.006	6,401	-0.025	-0.018
		(0.011)	(0.011)		(0.017)	(0.016)		(0.018)	(0.018)		(0.022)	(0.017)
Panel B												
Bed net ownership	13,225	0.020	0.019	13,206	0.039*	0.045*	6,118	0.005	0.024	6,067	0.021	0.012
		(0.020)	(0.020)		(0.022)	(0.023)		(0.005)	(0.024)		(0.019)	(0.030)
Child slept under bed net last night	8,989	0.024	0.023	8,957	0.029	0.022	4,853	0.018	0.017	4,815	0.024*	0.019
		(0.017)	(0.017)		(0.017)	(0.017)		(0.016)	(0.016)		(0.013)	(0.018)
Child tested for malaria	3,258	0.072***	0.071***	3,224	0.083**	0.049*	1,484	-0.022	-0.023	1,465	-0.026	-0.038
		(0.022)	(0.021)		(0.035)	(0.028)		(0.037)	(0.037)		(0.041)	(0.034)
Treatment sought	3,240	0.027	0.026	3,203	-0.021	0.030	1,476	-0.037	-0.037	1,450	-0.055*	-0.083**
		(0.020)	(0.020)		(0.030)	(0.023)		(0.031)	(0.031)		(0.033)	(0.032)
Formal treatment	2,332	0.022	0.022	2,305	0.046	0.001	1,104	0.065**	0.063**	1,075	0.041	0.041
		(0.019)	(0.019)		(0.304)	(0.032)		(0.025)	(0.025)		(0.032)	(0.028)
Panel C												
Wasting	12,698	-0.009	-0.009	12,680	-0.005	-0.004	5,822	-0.006	-0.006	5,774	0.013*	0.003
		0.006	0.006		0.006	0.007		0.006	0.006		(0.007)	(0.006)
Stunted	12,698	-0.011	-0.012	12,680	-0.001	0.007	5,822	0.003	0.003	5,774	-0.017	-0.015
		(0.011)	(0.011)		(0.015)	(0.013)		(0.015)	(0.015)		(0.021)	(0.020)
Child received Vitamin A	13,423	0.048***	0.049***	13,418	0.027	0.033*	6,427	0.046**	0.047**	6,372	0.018	0.033
		(0.016)	(0.016)		(0.019)	(0.018)		(0.019)	(0.019)		(0.026)	(0.020)

Notes: The control variables used for the OLS regression are the same as control variables used for propensity score matching. OLS estimates are calculated as $\alpha_1 + \alpha_2 Dist_i$ as shown in Equation 1. Standard errors are adjusted to account for clustering at location level, and p-values are *** p<0.01, ** p<0.05,* p<0.1.

5.2 Restricting sample to non-arid areas

Table 5 reports the results of the OLS and PSM regressions for the sample of households that excludes arid areas. Figure A.3 of the Appendix shows the reamining areas for analysis. Since 80% of the households in the arid areas are included in the control group (vs. 47% for the overall sample), we therefore drop these areas because they might reduce the quality of the matching. However, Table 5 shows that excluding arid areas has minor effects on the significance of the results and that it might even reduce the significance of some PSM estimates.

This is for example the case for malaria testing and intake of vitamin A by rural households located within 25 km of the closest CU. Since the mean values of these outcome variables are much lower in arid areas, when excluding arid areas from the analysis the average value of these variables for the control group increases, turning the difference between the average values of treated and control households statistically insignificant.[18] A similar argument applies to the bed net ownership variable, which becomes insignificant for both specifications.

Furthermore, for some outcomes we observe that the effect becomes significant in the expected direction because the mean value of the outcomes for treated households in arid areas was also very low (and in some cases, not statistically different from the mean outcome of the control). By dropping arid areas from the analysis, the average value of the outcome variables for the treated group increases, turning the difference between the average values of treated and control households statistically significant. This is for instance the case for formal treatment for rural/urban households located within 5 km of the closest CU, for stunted children in urban areas located within 5 km of the closest CU, and for the intake of vitamin A in rural households located within 25 km of the closest CU.

[18] For instance, the share of non-treated rural households (located within 25 km of the closest CU) that were given a vitamin A dose in the last 6 months corresponds to 57.33% in arid areas vs. 66.75% in the overall sample.

Thus, our findings indicate that the evidence of an effect is sensitive to the choice of control group. Nevertheless, we find that the results from the previous section remain essentially the same in most cases.

Table 5: *CHW program impact on child health and health utilization behavior*

	RURAL						URBAN					
	OLS			PSM			OLS			PSM		
Dependent variables	**N**	**5km**	**25km**	**N**	**5km**	**25km**	**N**	**5km**	**25km**	**N**	**5km**	**25km**
Panel A												
Child had malaria fever in the last 2 weeks	10,486	-0.018	-0.018	10428	-0.006	-0.022	5,247	-0.023	-0.022	5144	-0.041*	-0.021
		(0.013)	(0.013)		(0.018)	(0.017)		(0.019)	(0.019)		(0.024)	(0.020)
Panel B												
Bed net ownership	10,307	0.002	0.001	10250	0.029	0.033	4,959	-0.015	-0.016	4865	0.024	0.021
		(0.021)	(0.021)		(0.020)	(0.025)		(0.022)	(0.022)		(0.018)	(0.032)
Child slept under bed net last night	7,548	0.006	0.005	7483	0.019	-0.002	3,989	0.020	0.020	3888	0.018	0.004
		(0.017)	(0.017)		(0.016)	(0.018)		(0.018)	(0.018)		(0.015)	(0.016)
Child tested for malaria	2,783	0.083***	0.082***	2748	0.101***	0.048	1,298	0.020	0.019	1266	-0.009	-0.016
		(0.024)	(0.024)		(0.035)	(0.030)		(0.039)	(0.039)		(0.043)	(0.034)
Treatment sought	2,769	0.016	0.016	2734	-0.017	0.012	1,294	-0.027	-0.026	1265	-0.049	-0.083***
		(0.021)	(0.021)		(0.031)	(0.025)	n	(0.031)	(0.031)		(0.034)	(0.031)
Formal treatment	2,008	0.034	0.034	1979	0.054*	0.003	966	0.025	0.022	952	0.066*	0.053
		(0.021)	(0.021)		(0.031)	(0.025)		(0.028)	(0.028)		(0.036)	(0.033)
Panel C												
Wasting	9,940	0.001	0.001	9868	0.003	-0.001	4,745	0.003	0.003	4636	0.012	0.004
		(0.005)	(0.005)		(0.006)	(0.007)		(0.005)	(0.005)		(0.008)	(0.005)
Stunted	9,940	-0.013	-0.014	9868	-0.001	0.017	4,745	-0.011	-0.011	4636	-0.034	-0.038*
		(0.012)	(0.012)		(0.016)	(0.013)		(0.017)	(0.017)		(0.022)	(0.022)
Child received vitamin A	10,459	0.020	0.021	10400	0.033*	0.022	5,225	0.014	0.015	5127	-0.001	0.010
		(0.017)	(0.017)		(0.020)	(0.019)		(0.018)	(0.018)		(0.027)	(0.019)

Notes: Control variables used for the OLS regression are the same as control variables used for propensity score matching. OLS estimates are calculated as $\alpha_1 + \alpha_2 Dist_i$ as shown in Equation 1. Standard errors are adjusted to account for clustering at location level, and p-values are *** p<0.01, ** p<0.05,* p<0.1.

6 Discussion and Conclusion

In countries such as Kenya, access to healthcare is challenged by a scarcity of health workers and health facilities. Using community members to render certain basic health services within their home communities has been identified as a key strategy for addressing the shortage of health workers. In this paper, we evaluate the effects of the CHW program implemented in Kenya in 2005. We use the geographic variation in program rollout by October 2014 to compare child health outcomes and health care behavior of households that were exposed to CHWs with households that were not exposed. We utilize propensity score matching to estimate the treatment effect of CHWs in a cross-sectional sample of Kenyan households while controlling for the selection bias due to the endogenous placement of CHWs.

Studied outcomes include malaria fever, health care utilization behavior related to malaria (e.g., bed net ownership and usage, testing for malaria, and whether households sought any treatment for malaria fever and if they sought it in the formal health care sector), and anthropometric measures of child nutrition (including stunting, wasting, and vitamin A intake). We chose these outcome variables since malaria and poor nutrition contribute to a large share of under age-5 child deaths and comprise important focus areas of the CHWs.

Our findings indicate that the CHW program had a very limited impact on the studied child health and health care outcomes. More specifically, our results provide evidence of an effect for the outcomes malaria testing and vitamin A intake in rural areas, while the evidence of an effect for the remaining outcomes is statistically insignificant or non-robust.

In contrast to our study of a nationwide non-randomized intervention, most (yet not all) studies providing evidence of effects of CHW interventions in sub-Saharan Africa represent evaluations of relatively small randomized control trials. A key lesson that can be learned from our analysis is that upscaling CHW interventions may be challenging due to institutional and budget constraints that can affect implementation and achievement of outcomes. Analyzing the reasons behind the limited effect of the CHW program is beyond the scope of this study. However, existing evidence points to the lack of monitoring and accountability of CHWs, and to the lack of personal financial incentives, as important factors. Moreover, the evidence suggests that CHWs may be performing some tasks more than others which may explain the difference in observed outcomes.

Our study shows that, instead of implementing the CHW program nationwide in Kenya, greater effectiveness may be achieved by targeting only the rural and urban areas with the greatest need for primary health care. Furthermore, relying on local communities to implement this intervention might lead to a great deal of variation in the timing of the roll-out. Unfortunately, the households in greatest need of assistance might be the last ones to access this intervention.

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A Appendix

TABLE A.1: *CHW program rollout by year of implementation*

Year	**# of CUs**
2005	17
2006	26
2007	91
2008	176
2009	421
2010	358
2011	894
2012	421
2013	145
2014	21

Figure A.1: Percent of individuals below the poverty line in Kenya

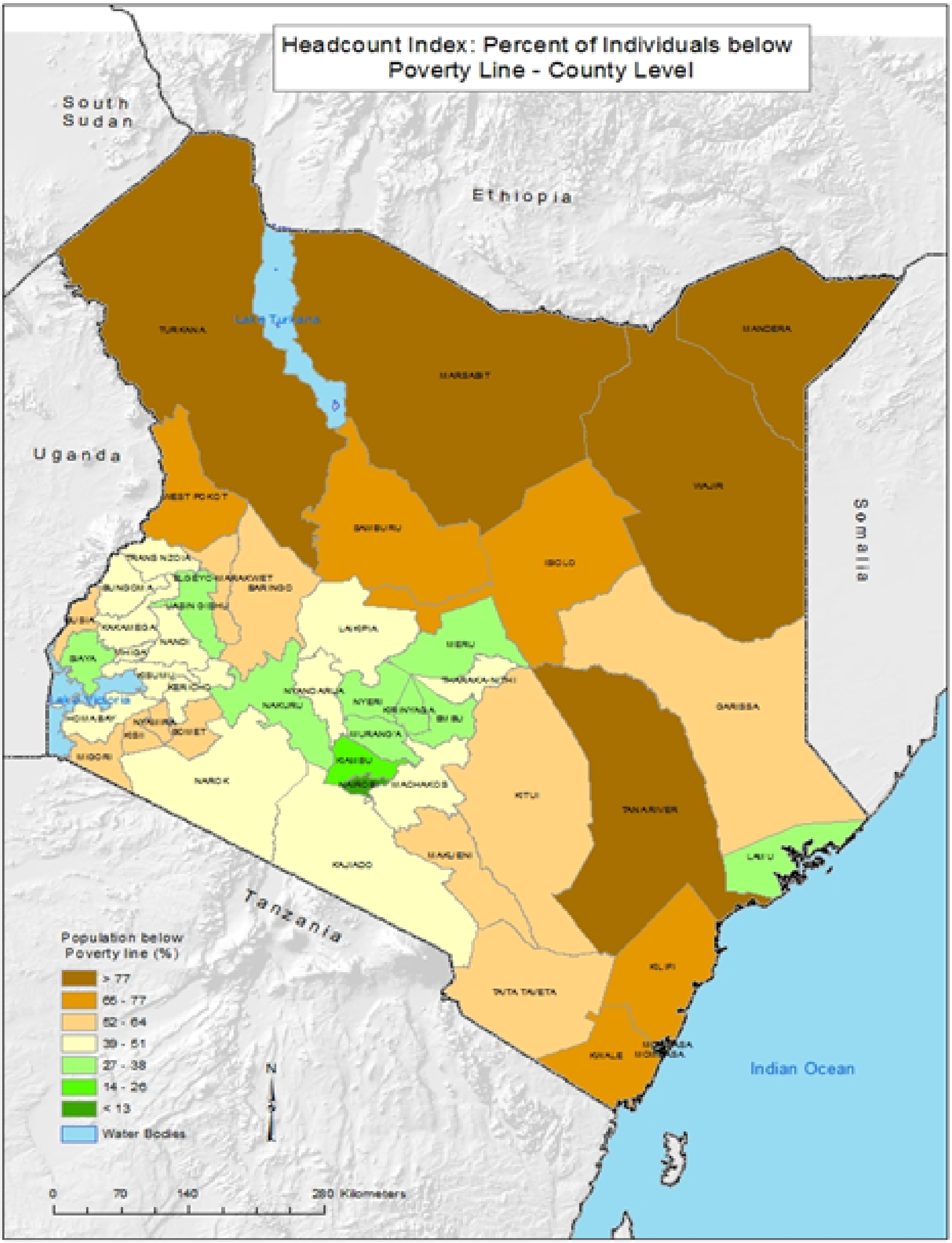

Figure A.2: Distance between DHS cluster and closest CU

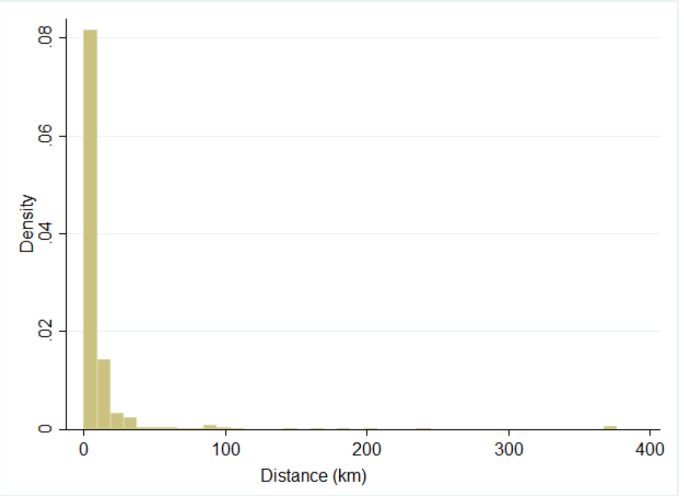

Figure A.3: DHS clusters excluding arid areas of Kenya

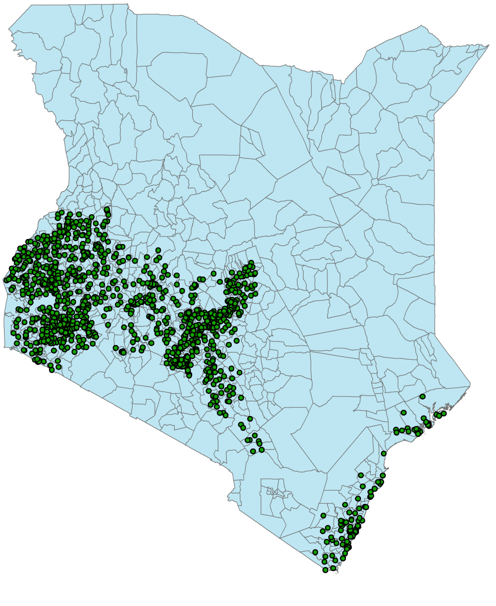

TABLE A.2: *Summary statistics for treated and non treated households*

	Non treated			Treated			
Variables	**Mean**	**SD**	**N**	**Mean**	**SD**	**N**	**Diff**
Sex of hhh	0.70	0.46	9,565	0.70	0.46	10,528	0.000
Age of hhh	28.80	6.55	9,565	28.61	6.55	10,528	-0.192**
Age of child	2.01	1.40	9,565	2.01	1.41	10,528	-0.004
Household size	6.03	2.50	9,565	5.80	2.42	10,528	-0.233***
Poverty headcount	53.72	22.84	9,565	48.10	18.86	10,528	-5.621***
Logpop	9.36	0.84	9,565	9.97	0.81	10,528	0.603***
HIV rate	6.65	3.92	9,565	8.97	4.93	10,528	2.313***
Stunted children	30.76	3.36	9,565	30.76	3.16	10,528	-0.003
Malarious month(dummy)	0.29	0.46	9,565	0.39	0.49	10,528	0.095***
Seasonal(dummy)	0.44	0.50	9,565	0.24	0.43	10,528	-0.198***
Epidemic(dummy)	0.25	0.43	9,565	0.18	0.38	10,528	-0.076***
Endemic(dummy)	0.18	0.38	9,565	0.37	0.48	10,528	0.196***
Low malarious areas (dummy)	0.13	0.34	9,565	0.21	0.41	10,528	0.078***
Urban	0.30	0.46	9,565	0.34	0.48	10,528	0.039***
Community Units							
# CUs in a location	-	-	-	2.69	2.05	10,528	-
# years a location has had CUs	-	-	-	4.06	1.71	10528	-
Health facilities & Distance							
# health facilities	1.39	1.97	9,565	3.42	4.06	10,528	2.033***
Distance DHS cluster to closest and CU	-	-	-	11.73	32.27	10528	-
Observations used for PSM							
# observations within 5 km of closest CU	-	-	14,924	-	-	5,169	
# observations within 25 km of closest CU	-	-	10,346	-	-	9,747	

Notes: Malarious month index is a dummy equal to 1 if households in a particular cluster were interviewed in a malarious month and 0 otherwise. *Low malaria* areas are those with little to no malaria transmission; *seasonal* are those areas that experience short periods of intense malaria transmission during the rainy seasons; *epidemic* are those areas where malaria transmission is seasonal with considerable year-to-year variation and endemic are those with transmission occurring all year round. Robust standard errors used and p-values are *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Chapter III

Information and Cooperation in Preventive Health Behavior: A Case Study of Bed Net Use*

Josephine G. Gatua†

Abstract

This paper assesses whether providing people with information on the public benefits of bed net use, and on other people's bed net use, changes their bed net use behavior. I use a survey experiment from rural Kenya, where randomly selected households are provided with information on the public benefits generated by bed net use, and on the consequences of an individual's own bed net use on the health of the immediate neighbor. The results show that information increased willingness to use bed nets, and that people are more willing to use bed nets when they know other people are using them as well. Results are robust to the inclusion of a broad set of controls, including risk aversion; number of household members to have suffered from malaria in the past 12 months; and number of children in the household who are below five years age. Overall, these results suggest that in addition to free distribution of bed nets, informing people on the private and public benefits of bed net use could potentially save many more lives.

Keywords: Bed nets, Malaria, Cooperation.

JEL Codes: C93, I12, I18

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1 Introduction

Developing countries have the highest proportion of infectious diseases such as malaria. For instance: in 2016, an estimated 216 million cases of malaria occurred worldwide, with 80% of the global malaria burden being in sub-Saharan Africa (WHO, 2017).[1] But malaria could be prevented by use of preventive technologies such as Insecticide Treated Bed Nets (ITNs). The use of ITNs confers two types of benefits: first, a private benefit, which is that the individual using an ITN is protected against the risk of malaria infection; and second, a public benefit, by which the individual using an ITN protects others from the risk of infection by reducing the number of infective mosquitoes in the surrounding environment.[2] The ability of ITNs to generate positive externalities coupled with the high elasticity of demand for ITNs in developing countries prompted the international community to advocate for free distribution or extensive subsidization of ITNs (Sachs, 2005; WHO, 2007). Since then, sub-Saharan Africa has been the greatest beneficiary of the free distribution initiative. However, increased access to ITNs has not been matched by the increase in utilization of ITNs (Cohen and Dupas, 2010). Moreover, in 2015, of the population at risk of malaria who had access to ITNs, only 53% slept under them (WHO, 2016).

How to increase access to and utilization of bed nets remains of interest to academics, because of the trade-off involved in the cost of prevention and treatment of malaria. The cost of preventing malaria is arguably lower than that of treatment. As an example, the median cost of protecting one person for one year, using an ITN, is about USD 2.20; that of diagnosing a case of malaria is USD 4.32; that of treating an episode of uncomplicated malaria is USD 5.84, and that of treating an episode of severe malaria is USD 30.26 (White et al., 2011). A look at these costs further justifies the need for free distribution of or high subsidies for ITNs. However, if ITNs are freely provided, and yet at the same time

[1]Malaria is an infectious disease caused by the plasmodium parasite and transmitted to humans by female anopheles mosquitoes. Mosquitoes breed in places that are humid, have high temperatures and water.

[2]The terms 'ITN' and 'bed net' will be used interchangeably throughout the text.

are not fully utilized, the burden of disease from malaria will increase; leading to additional treatment costs, which would make this health financing strategy unsustainable. Why is there a mismatch between access to and utilization of bed nets in developing countries? This remains an open question.

I use survey experiment from rural Kenya, collected between February and March 2016, to test whether informing people about the public benefits of using ITNs, and whether others are using bed nets, affects peoples' bed net use decisions. The survey experiment included three treatments. In the first treatment, a set of households were given existing information on the private benefits of using bed nets. In the second treatment, a different set of households were given additional information on the public benefits of using bed nets. Information on the public benefits of bed net use has not previously been provided in advertisements and health campaigns, and is therefore not in the public domain. In the third treatment, the last set of households was given additional information on how an individual's bed net also affects their immediate neighbor. In each treatment, participants were required to indicate their willingness to use bed nets for different levels of bed net use in their village. The positive externality generated by using bed nets is therefore a public good, because the reduction in malaria due to the use of ITNs is non-exclusive and non-rival in consumption, and the use of ITNs by an individual is similar to an individual deciding how much to contribute to a public good.[3]

I find that individuals who received information on the public benefits of bed net use, as well as those who received information on the *public benefits* of bed net use together with how own use affects the health of their neighbors, are more willing to use bed nets than individuals who were only given information on the private benefits of bed net use. This effect is observed across all levels of bed net use (by the village) that are presented to the households. The impact is stronger for the group that received the *public benefits* message together with how their own

[3]See Bronchetti et al. (2015), who argue that vaccination against influenza is a public good.

use affects other households located close to them. I also find that the willingness of households in the control group to use bed nets is independent of whether more or fewer people in the village are using bed nets. Households in the *public benefit* and the *public benefit + how personal use affects immediate neighbors* treatment respond to information on the level of bed net use in the village. That is if they know more people in the village are using bed nets, they are willing to increase their own use of bed nets. The observed behavior is consistent with people being conditionally cooperative in decisions involving bed net use.

This paper contributes to two strands of literature. The first is related to the literature on health information provision and behavior. Although there are few studies available, most of the evidence for developing countries shows that health information could have some effect on behavior. Using a randomized prospective design in India, Jalan and Somanathan (2008) show that informing households that their drinking water is contaminated increases the probability that they will start purifying their water. In Bangladesh, using data from a controlled experiment, Madajewicz et al. (2007) find that informing households that their well water has an unsafe concentration of arsenic raises the probability that they will switch to another well. In Kenya, using a randomized field experiment, Dupas (2011) finds that providing teenagers with information on the relative risk of HIV infection according to partner age led to a decrease in teenage pregnancy. I add to this literature by informing households of how their personal health behavior affects their health and that of others; and at the same time, of what others are doing, which has not been studied previously.[4]

The second strand is related to the literature on the provision of public goods. On average, empirical findings from both lab and field exper-

[4] A strand of recent literature explores the role of information on vaccination decisions (Betsch et al., 2013; Vietri et al., 2012). The disease dynamics and decision-making involving protective measures such as vaccines are different, and have different consequences from those involving protective measures such as the use of ITNs. Therefore, research on vaccination may not apply when making decisions on ITN usage (see Gersovitz and Hammer, 2004; Toxvaerd, 2010, for a detailed account of important differences between diseases addressed by vaccination, and vector-borne diseases such as malaria).

iments show that contributions to public goods exceed the zero-level contribution, which is the predicted contribution for a selfish individual (e.g. Zelmer, 2003). A large number of people will cooperate by contributing to the public good if they believe that others are also cooperating, implying that people are conditional cooperators (Fischbacher and Gächter, 2010; Fischbacher et al., 2001; Frey and Meier, 2004; Martin and Randal, 2008; Muller et al., 2008; Shang and Croson, 2009), and that 'partners' as opposed to 'strangers' tend to contribute more to a public good (Keser and Van Winden, 2000). In line with the literature, this study treats the number of days an individual is willing to sleep under a bed net as being equivalent to contributing to a public good. Although conditional cooperation in a public good setting has been tested, it has not been tested in an infectious disease setting, which I aim to do in this paper.

Taken together, the study findings suggest that behavioral decisions respond to information on how actions affect the larger society, and that people tend to follow the behavioral decisions of others. The implications of these findings are that providing information on the private benefits of using bed nets in additional to information on the external benefits generated by the use of bed nets could potentially save money that would have otherwise been used for treatment. However, one should be careful about providing social information about what others do, especially in an infectious disease setting, and perhaps rethink how it is presented. A statement along the lines of "more people in the village are using bed nets" will encourage people to use more as opposed to a statement like "fewer people in the village are using bed nets", which discourages people from using bed nets.

The remainder of the paper is organized as follows: Section 2 describes the externalities, hypotheses and the survey experiment. Section 3 presents the setting and descriptive statistics. The estimation strategy and results are presented in section 4. Section 5 concludes.

2 Experiment and Hypotheses

2.1 Externalities and public goods

As stated previously, malaria is preventable, and its spread can be effectively controlled by the use of preventive measures such as ITNs.[5] This is because ITNs repel mosquitoes, thereby reducing the human-vector contact by acting as a physical barrier and shortening the length of life of the mosquitoes. Additionally, the insecticides that are used for treating bed nets kill mosquitoes, leading to a reduction in the number of mosquitoes in the environment. The ability of ITNs to reduce the number of infective mosquitoes in the surrounding environment generates positive externalities (Bradley et al., 1986). These positive externalities are therefore a public good. Successful malaria prevention will thus depend on the degree of public good generated by the use of ITNs. Hence, cooperation among individuals in the sustained use of ITNs becomes key in the control of malaria, due to the associated positive externalities. This type of externality is referred to as a pure prevention externality.[6]

In the externality context, Cohen and Dupas (2010) show that the use of ITNs by pregnant women and children not only benefits them, through reduced mortality for infants and reduced maternal anemia for pregnant women, but also benefits non-users in surrounding areas, if there is a large proportion of bed net users. Concerning child mortality, Hawley et al. (2003) report the protective effect of ITNs on compounds lacking ITNs located within 300 meters of compounds with ITNs. Moreover, Hawley et al. (2003) show that ITNs have no protective effect when their use in a village is less than 25%. However, protective effects are observed when coverage exceeds 50%. Similarly, another study shows that if the usage rate is 65%, malaria prevalence is 2%; but if usage falls

[5] Other methods such as Indoor Residual Spraying (IRS) and environmental management can also be used, but ITNs are the most effective (Eisele and Steketee, 2011).

[6] Gersovitz and Hammer (2004) describe pure prevention externalities as the preventive actions of one individual that may directly affect the probability that other people become infected, whether or not preventive action prevents infection of the individual undertaking it.

to 50%, the prevalence rate increases to 5%. A further fall in usage to 35% leads to a prevalence rate of 18%.[7] Therefore, in order to achieve the maximum effect in a community, ITN coverage should be as high as possible, with a target of complete coverage (Teklehaimanot et al., 2007; WHO, 2007). This ability of an ITN to protect not only the user but also others creates the 'public good' aspect of ITNs.

2.2 Survey experiment

The survey experiment took place in two rural divisions of the Nyanza and Rift valley regions of Kenya, and involved a total of 822 households. Among them, 275 were randomly chosen to receive the private benefit message that is currently being provided by the government in the entire country. Therefore, these households act as the control group. Another, 273 households were chosen to receive Treatment 1, which provided information on the *public benefits* of using bed nets. Lastly, 274 households were chosen to receive Treatment 2 ('*strengthened*' *public benefit*), which provided the public benefit message together with information on how a person's bed net use affects their immediate neighbor. A more detailed description of the study setting is provided in the next section.

Due to the low literacy and numeracy skills in rural areas in developing countries, participants were first interacted with to check their understanding of probability and proportions.[8] When the enumerator was satisfied with the respondents' understanding of the concepts, they were then given the opportunity to participate in the survey experiment. Each of the participants was presented with a hypothetical scenario in which they had to imagine that their village was made up of 1,000 people (including men, women, and children), and that about 400 people in the village were regularly sleeping under an ITN every day (this being the status quo). The control group received the *private benefit* informa-

[7] `news.harvard.edu/gazette/story/2013/04/progress-puzzles-in-halting-malaria/`

[8] I follow Delavande and Kohler (2009), who use interactive methods to elicit subjective expectations in developing countries.

tion where reference is made only to the private benefit of using ITNs. Thereafter, one of the two experimental treatments was presented to each participant. The experimental treatments given were: (1) a treatment in which both the *private* and the *public benefits* of using ITNs were presented and (2) a treatment in which *private* and *public benefits* were presented, as well as information on how an individual's bed net use affects his or her *neighbor*. 'Being a neighbor' is closely related to the proximity of one household to another: I therefore refer to the second treatment as the *public benefits* + *social proximity* treatment. More detailed information about the information content of these treatments is provided below.

The protective effects of bed nets are seen when a large number of people are using bed nets, as described in the previous section. I use this information to create four hypothetical levels of village bed net use, from low levels (less protection) to high levels (more protection) of bed net use in the community; maximum protection is achieved when everybody is using them. The participants in each of the treatment types were required to state the number of days they would be willing to sleep under an ITN, for each of the four levels of bed net use in the village. The order in which average ITN use in the village was presented to the participants was randomized.

Control group: *Private benefit*

Respondents were given the factual information normally given by the Ministry of Health through campaigns and advertisements. This information explains how malaria is transmitted, how malaria infection differs from person to person and the benefits of ITNs to a user. In addition, they were given the average bed net use in the village in a year. Thereafter, the respondents were asked to indicate how many days in a week they would use a bed net, for each level of hypothetical average bed net use in the village. The four average levels of village bed net use provided were: when nobody (0), 250, 800, and 1,000 people in the village are using bed nets. The group is viewed as a benchmark group, because it contains only information that already exists in the public domain. Examples of existing advertisements are shown in Figure A.1 in the Appendix.

Treatment 1: Public benefit treatment

In this treatment, respondents were first provided with information similar to that given to the control group on the private benefit of using ITNs. Then they were provided with additional information on how the use of ITNs generates positive externalities to others in the village. In particular, it was explained that if more people in the village sleep under a bed net every day, fewer people will get malaria; and if fewer people in the village sleep under a bed net, more will get malaria, regardless of whether they themselves are using a bed net. In this treatment, no reference is made to how the participant's own use affects others. Following the presentation of this information, the respondents were asked to indicate how many days in a week they would use a bed net, for each hypothetical village average bed net use given.

Treatment 2: Public benefit + social proximity treatment

In this treatment, participants were provided with both the private and the public benefits of ITN use. This was followed by extra information which made the effects of the participants' actions on others salient to the participants. One mechanism for creating salience was information on how one's own bed net use can affect others. Another was the use of the word *neighbor* to signify someone known to and within close proximity to the participant; here, the message was framed to make the participant's own actions and consequences salient by explicitly stating that if an individual uses a bed net, they protect both themselves and their neighbors, and vice versa. The term *neighbor* was used to create a sense of social closeness for the respondent, as opposed the term 'others' in the village. Similarly to the respondents receiving the other treatment and the control group, respondents were asked to indicate the number of days in a week they would be willing to sleep under a bed net for each hypothetical village average level of bed net use. Table 1 shows the characteristics of the treatment groups. A summary of the actual experimental treatments that were given to the respondents is shown in the Appendix.

TABLE 1: *Characteristics of the control group and treatments*

Characteristic	**Private benefit**	**Public benefit**	**Public benefit + social proximity**
Cause of malaria	Yes	Yes	Yes
Private benefit	Yes	Yes	Yes
Village ITN use	400	400	400
Public benefit	No	Yes	Yes
Public benefit + social proximity	No	No	Yes
ITN use range (days)	0 to 7	0 to 7	0 to 7
Village bed net use levels	0, 250, 800, 1000	0, 250, 800, 1000	0, 250, 800, 1000

The experiment elicits stated preferences of bed net use. It does not involve documenting actual bed net use. Due to budget and logistical constraints, premised by the short period of the survey, it was not possible to observe actual bed net use in this study. The approach used in this study may raise concerns, such as those of hypothetical bias and social desirability bias. For example, in willingness to pay (WTP) studies, although there is no widely accepted theory of how people respond to questions about their WTP when the situation is hypothetical (Murphy et al., 2005), most findings suggest that respondents overstate hypothetical WTP relative to their actual WTP (Alpizar et al., 2008; Harrison, 2006; List and Gallet, 2001; Murphy et al., 2005). To mitigate the hypothetical bias, participants were informed that their responses were confidential, and would be used purely for research purposes. In addition, a follow-up question was asked, in order to infer what each participant took into consideration while answering the questions posed; the responses will be analyzed in the results section. Moreover, while usage levels may be inflated by social desirability bias, it is not obvious that this bias would invalidate my test for conditional cooperation.

2.3 Hypotheses

In this study, subjects were asked to state the number of nights per week they are willing to use bed nets, conditional on different levels of bed net use by other village members. Laboratory and field experiments conducted in both developed and developing countries suggest that some people are conditionally cooperative. Public good experiments have been used to measure cooperative preferences, and a stylized fact from these public goods experiments is that people contribute substantially more than predicted theoretically. For example, Frey and Meier (2004) find that the more others cooperated, the more their subjects are inclined to cooperate as well. However, they also show that not all subjects were sensitive to the behavior of others. Fischbacher et al. (2001) find that in a one-shot public good game, about 50% of their participants increase their contribution if others do so as well, while one third are free-riders. Moreover, Chaudhuri (2011) demonstrates that conditional cooperators are often willing to engage in punishment of free-riders, even when such punishment is personally costly and confers no long-term benefit. That individuals tend to voluntarily contribute a significant share of their endowment to an efficiency-enhancing public good despite the free-rider problem suggests that some individuals have other-regarding preferences such as altruism, reciprocity and commitment (e.g. Andreoni, 1990; Croson, 2007; Falk and Fischbacher, 2006; Fehr and Schmidt, 1999). Therefore, my first hypothesis is:

Hypothesis 1: *People in the private benefit, public benefit, and public benefit plus social proximity treatment will increase their bed net use as the bed net use of the other village members increases.*

The premise of my analysis is that individuals make the best decisions, as they see them, from the options available to them and subject to the information they have. When people are given information about the social desirability of their actions, they respond by improving on their actions. For example, Gersovitz and Hammer (2004) argue that if people already have general information – such as about the existence of a disease, how it is and is not transmitted, and whether preventive options are available – then providing this information over and over is unlikely to change how people behave. But providing information on whether the individual is infected or infectious, and on the risks in the immediate environment such as disease vectors, can be a real constraint on decisions. This is because the new information has aspects that involve the public; these aspects were not evident in the previous general information that people had. Hence, I expect information on the public benefits of bed net use to affect bed net use decisions, for each level of average bed net use in the village. My working hypothesis for the second research question is:

Hypothesis 2: *Average bed net use in the public benefit treatment and public benefit plus social proximity treatment is greater than the average bed net use in the private benefit treatment for each level of average bed net use of a village.*

Empirical evidence shows that people's willingness to pay for an intervention that improves the health and safety of others is a substantial fraction of the amount they are willing to pay to obtain the same benefits for themselves. For example, Smith (2007) finds that average willingness to contribute to the treatment of another person is equal to about half of one's willingness to pay for one's own treatment. This shows that people do care for the welfare of others. In the *public benefit + social proximity* treatment, in addition to being provided with information on the public benefits of bed net use, individuals are informed of how their actions would affect themselves and their neighbors by the explicit use of the words *you* and *neighbor*. Therefore, my third hypothesis is:

Hypothesis 3: *Average bed net use in the public benefit plus social proximity treatment is greater than average bed net use in the public benefit treatment, for each level of average bed net use in the village.*

3 Setting and Descriptive Statistics

3.1 Field setting

The experiment was part of a larger survey on malaria and Community Health Workers (CHWs) in rural Kenya. The survey and experiment were designed by the author, and fielded between February and March

2016. The experiment was conducted in Kisumu and Kericho counties in Kenya, which are located in the Nyanza and Rift Valley regions, respectively (see map, Figure A.2 in the Appendix). Each of the selected counties has a distinct risk of malaria infection. In Kisumu, malaria transmission occurs all year round (endemic). In Kericho, malaria does not occur all year, peaking during rainy seasons or when temperatures spike beyond a certain level (epidemic). Kisumu county has a 47.6 percent rural population while Kericho county has 61.3 percent, compared to a national average of about 67.7 percent (KNBS, 2014). The poverty incidence in Kisumu is 39.9 percent while that of Kericho is 39.3 percent, compared to a national average of 45 percent. The dependency ratio of both Kisumu and Kericho is 0.9, compared to a national average of 0.87 (Ngugi et al., 2013).[9]

For the survey/experiment, two divisions: one from each county were selected as the study population. These were Nyando division in Kisumu and Soin division in Kericho, which border each other. A total of 41 villages were then randomly selected from the two divisions. Details on the sampling strategy are provided in Table A.1 in the Appendix. A list of households from each of the sampled villages was taken from the chiefs (local leaders), and about 20 households were randomly selected from each village list. A total of 822 households from 41 villages were interviewed over the survey period. I sought to interview the household members who are most involved in the health issues of their households, and are therefore most suited to responding to a health-related questionnaire. In most cases these people were women; thus, in my sample only 27% of the respondents are male.

A team of 13 enumerators underwent a three-day training, including multiple group sessions, to ensure consistency in administering the survey and experiment(s), as well as in the interpretation of responses. In order to gain the confidence of the respondents, before administering each survey and experiment the enumerators identified themselves as researchers affiliated with the Ministry of Public Health and Sanitation,

[9]Calculation: number of people below 15 and above 64, divided by the number of people between 15 and 64.

Kenya Institute of Public Policy Research and Analysis (KIPPRA) and the University of Nairobi, and explained that the survey was solely for research purposes. Respondents were informed that their responses would be combined with responses from all other households to be surveyed, and that a report would be generated thereafter. Once this information was given to a respondent, the enumerator(s) sought consent for participation from the respondent, after which the survey proceeded. None of the respondents refused to participate in the survey. Because the respondents were familiar with this type of activity from the government, they were at ease with participating in the survey and experiment. Moreover, the experiment involved malaria, which is a well-known disease, and respondents were comfortable with answering malaria-related questions.

The implementation of the survey and experiments comprised two steps. In the first step, enumerators administered a household survey to collect information on socio-economic, demographic and health characteristics. In the middle of this survey, the experimental treatment was presented. Thereafter, the rest of the survey was completed. Households and treatments were randomly assigned to each of the enumerators. This meant that each household received only one type of treatment. The second step, which was conducted one week after the survey, involved conducting incentivized risk experiments with the household heads who had responded to the survey and experiments.[10] The survey and experiments were conducted in local languages.[11]

When visiting a household, the enumerator would administer the survey and experimental treatments to the respondent in private. The responses

[10] The respondents' risk-aversion levels were obtained from an incentivized experiment in which individuals completed a series of 20 ordered choices between playing a lottery with a 50% chance of winning (risk), or accepting a sure amount. An individual who chose the lottery could win a constant amount of money (Ksh200) by betting on the color of a ball drawn blindly from a bag containing 10 balls. An individual could opt for the sure amount of money at any point in the series. The amount that could be won was kept constant, while the sure amount increased monotonically from Ksh10 to Ksh200.

[11] Kipsigis is the language spoken in Kericho while Dholuo is the language spoken in Kisumu.

given by the respondent were recorded on paper. The interviewer was also required to indicate whether they thought the respondent was being truthful during the interview. The average length of each interview was 1.5 hours, with about 65 households being interviewed in a day. Stated preference studies show that respondents may be sensitive to the order in which tasks are presented to them, which creates a bias in their responses (e.g. Clark and Friesen, 2008; DeShazo, 2002; Herriges and Shogren, 1996). To avoid potential systematic changes along the sequence of responses provided by a respondent, the order in which the average bed net use in the village was presented to the respondents was randomly assigned. For example, some respondents first received high levels of village bed net use followed by low levels of village use; others first received low levels followed by high levels; while others received a mix of both.

3.2 Descriptive statistics

All 822 respondents agreed to participate in the experiment and answer the survey questions. Table 2 shows the variable definitions, and Table 3 provides summary statistics for the sample of participants on which the analysis is based. On average, 85% of household members had suffered from malaria the previous year. Bed net ownership in these regions is very high due to the government's free net distribution program. According to the data, 99% of the households have at least one bed net; but not every household member has a bed net, which implies that they must share. The reported mean usage of bed nets by household heads was about 3.6 days in the past week prior to the survey. The average household size was 5, and the majority of participants were female (73%). On average, participants had spent seven years in school (primary school level), and had an average wealth calculated as the sum of the value of assets of USD 9,670 (median USD 5,446), reflecting a skewed distribution.[12,13] On average, 97% of respondents reported

[12]Including: land, mobile phone, bicycle, cart, radio, television, motorbike, house, motor vehicle, solar panel, poultry, donkey and livestock.

[13]USD 1 = Kenya Shilling (Ksh) 102.

that at least one member of their household had suffered from malaria at least once in their lifetime, while on average three household members were reported to have suffered from malaria in the past year. With treatments having been randomly assigned to individuals, the average observable and unobservable characteristics of the households should be similar across the experimental groups. The mean values of the key variables were compared across treatment groups and the null hypotheses (that the differences in means are not statistically different from zero) were tested. No variables, except for 'Catholic' and 'Care for others' in the control group and treatment 1, were statistically different. This confirms that the treatments were administered to groups that are similar. The difference in religion (Catholic) and care for others is minor, and is not expected to bias the results.

TABLE 2: *Variable Description*

Variables	Variable Definition
Outcome variable	
# ITN in 7 days	Number of days in a week a respondent will use a bed net
Key explanatory variables	
Treatment (T)	Control group (private benefit), public benefit, and public benefit + social proximity treatment
Level (L)	Average bed net use in the village: L0, L250, L800 and L1,000
Socioeconomic variables	
Age	Age of the respondent in years
Sex	1 if respondent is male, 0 otherwise
Education	Respondent's years of schooling
Household size	Number of household members
Married	1 if respondent is married, 0 otherwise
Catholic	1 if religion is Catholic, 0 otherwise
Protestant	1 if religion is Protestant, 0 otherwise
Seventh Day Adventist	1 if religion is Seventh Day Adventist, 0 otherwise
Traditional/ No religion	1 if religion is traditional/No religion, 0 otherwise
Wealth (USD)	Total value of household assets
pc ITN	Per capita bed net ownership
Health variables	
# of children	Number of children in the household under 5 years
# of elderly	Number of elderly in the household above 55 years
# ITN last week	Number of days respondent slept under ITN last week
Ever had malaria	1 if any household member has ever had malaria, and 0 otherwise
# malaria	Number of household members who suffered from malaria in the past year
# chronic illness	Number of household members with chronic illness
Alcohol	1 if respondent consumes alcohol, 0 otherwise
Perceived effectiveness of bed net	Originally ranging from 0 to 10, with 10 indicating high effectiveness of bed net and 0 indicating no bed net effectiveness (rescaled to 1 if greater than or equal to 8, and 0 otherwise, implying 0 = not effective, and 1 = very effective)
Consequence of actions	Whether respondent sometimes acts spontaneously rather than thinking too much about the consequences of his actions. Originally ranging from 1 to 4, with 1 indicating 'strongly agree' and 4 'strongly disagree' (rescaled to 1 if respondent indicated 'strongly agree' or 'agree', and 0 otherwise)
Risk Aversion	Incentivized measure of risk attitude where $\theta < 0.5$: risk-loving, $\theta > 0.5$: risk-averse, and $\theta = 0.5$: risk-neutral

Table 3: *Summary statistics and mean comparisons between treatment groups*

		All		Private (0)		Public(1)		public + social proximity(2)		[0-1]	[0-2]	[1-2]
Variables	**Obs**	**Mean**	**SD**	**Mean**	**SD.**	**Mean**	**SD.**	**Mean**	**SD.**	**Diff**	**Diff**	**Diff**
Male	822	0.27		0.24		0.29		0.28		-0.05	-0.04	0.01
Age	822	42.21	15.46	42.11	15.97	42.03	14.74	42.48	15.70	0.08	-0.37	-0.45
Education (in years)	822	6.78	3.49	6.73	3.48	6.96	3.54	6.65	3.45	-0.23	0.08	0.31
Household size	822	5.39	2.14	5.29	2.22	5.42	2.10	5.47	2.09	-0.13	-0.18	-0.05
# of children (<5yrs)	822	0.96	0.92	0.93	0.92	1.00	0.94	0.95	0.91	-0.08	-0.03	0.05
# of elderly (>55yrs)	822	0.44	0.69	0.42	0.68	0.45	0.69	0.45	0.70	-0.03	-0.03	-0.01
Catholic	822	0.15		0.13		0.19		0.14		-0.06*	-0.01	0.05
Protestant	822	0.60		0.63		0.57		0.60		0.06	0.03	-0.03
SDA	822	0.10		0.10		0.09		0.10		0.01	-0.00	-0.01
Traditional	822	0.15		0.14		0.15		0.16		-0.01	-0.02	-0.01
Married (1=Yes)	822	0.79		0.77		0.80		0.78		-0.03	-0.01	0.02
pc ITN ownership	822	0.71	0.38	0.73	0.36	0.70	0.41	0.70	0.36	0.03	0.02	-0.01
Ever had malaria (1=Yes)	822	0.97		0.97		0.98		0.97		-0.01	-0.03	-0.01
Hhold malaria (last year)	822	2.98	2.21	2.79	2.18	3.05	2.30	3.09	2.15	-0.27	-0.04	0.01
# of days used ITN last week	822	3.63	2.02	3.63	1.95	3.67	2.00	3.59	2.11	-0.04	0.03	0.08
Chronic illness	822	0.12		0.13		0.12		0.10		0.01	0.03	0.02
Smoking	822	0.03		0.03		0.04		0.03		-0.01	-0.00	0.01
Alcohol	822	0.07		0.06		0.10		0.06		-0.04	-0.00	0.04
Risk aversion	806	0.47	0.23	0.46	0.24	0.47	0.23	0.48	0.23	-0.01	-0.02	-0.01
Effectiveness of ITNs	822	0.74		0.72		0.76		0.74		-0.04	-0.02	0.02
Consequences of ones actions	822	0.29		0.31		0.30		0.25		0.02	0.06	0.04
Wealth (USD)	822	9670	20550	9069	14603	9894	14899	10050	28883	-825	-981	-155

Robust standard errors used in computing difference in means across treatments; Exchange rate: USD1= Ksh102; *** p<0.01, ** p<0.05, * p<0.1

4 Empirical Strategy and Results

This paper assumes that public benefit and social proximity information is an exogenous determinant of bed net usage. In this section I describe the approach used to estimate the impact of *public benefit* and *public benefit + social proximity* information on bed net use. I compare the number of days in a week individuals are willing to sleep under a bed net, given different average levels of bed net use in the village. Because of the random assignment of respondents to treatments, the impact can be identified by simple mean comparison across the treatment groups. I estimate this impact using Ordinary Least Square regression; and I add controls that predict variation in bed net usage, to improve the efficiency of the estimation.

I estimate these effects using Equation 1 below, where, Y is the number of days of bed net use in a week for individual i in village j.

$$Y_{ij} = \delta_0 + \sum_{k=2}^{3} \delta_{1k} T_{ki} + \sum_{l=2}^{4} \delta_{2l} L_{li} + \sum_{k=2}^{3} \sum_{l=2}^{4} \delta_{3kl} T_{ki} L_{li} + \sum_{k=2}^{3} \delta_{4k} T_{ki} (\mathbf{X}_i - \bar{\mathbf{x}}) + \sum_{l=2}^{4} \delta_{5l} L_{li} (\mathbf{X}_i - \bar{\mathbf{x}}) + \gamma_v + \epsilon_{ij} \tag{1}$$

T_{ki} is a dummy variable for treatment k for individual i, L_{li} is a dummy variable for level L for individual i; and T*L is the interaction term between treatment and levels. The $\mathbf{X}_i's$ are the control variables that interact with the treatment and levels variables, where each control variable in the interaction is centered at the mean. Mean-centering helps reduce the covariance between the constituent terms and the interaction terms, which lowers collinearity as well as facilitating the interpretation of the main effects as the expected difference between the groups at the average value(s) of the centered variables. The interactions are meant to explore whether the levels have a heterogeneous effect, depending on the treatment. γ_v represents the village fixed effects while ϵ is the error term. Following the estimation of the model with a complete set of interaction terms, I compute and report the averages of the effects of the control variables.

4.1 Non-parametric results

For each level of average bed net use in the village, Figure 1 – 4 show how the average bed net use changes as we move from the benchmark treatment (private benefit) to the *public benefit + social proximity* treatment. The graphs suggest a positive association between more extensive information and bed net use. In addition, as we move from the control group to the *public benefit + social proximity* treatment, the distribution of bed net use becomes negatively skewed.

Figure 1: Village bed net use: 0

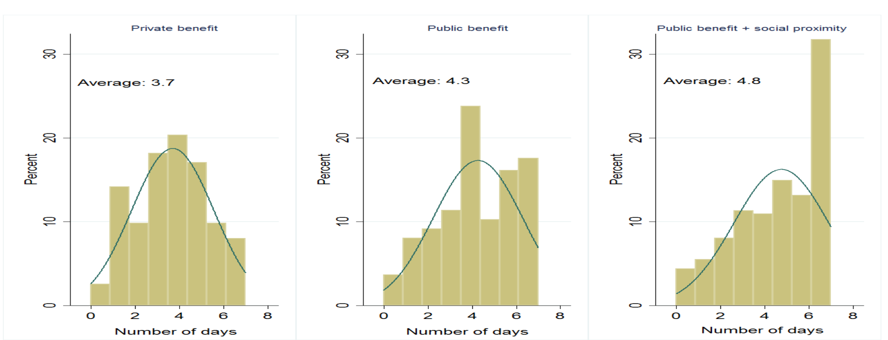


Figure 2: Village bed net use: 250

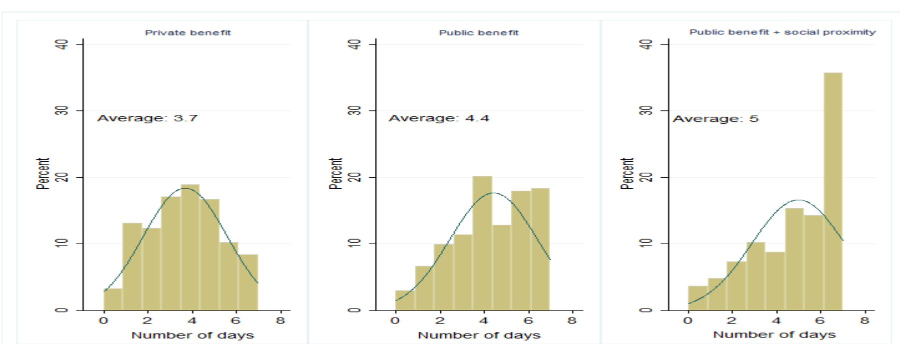


Figure 3: Village bed net use: 800

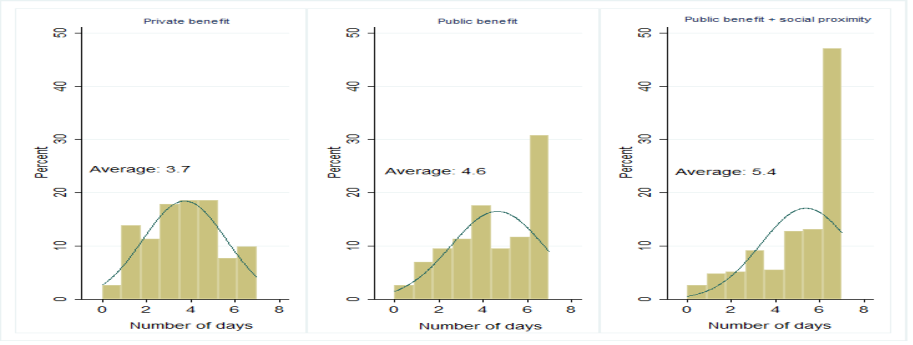
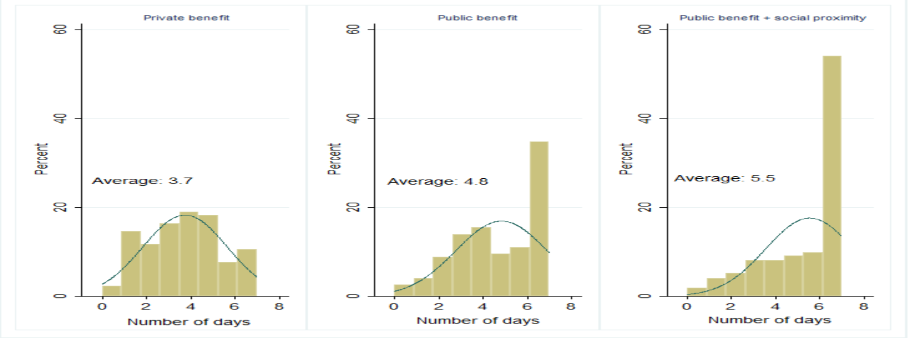


Figure 4: Village bed net use: 1000



A Mann-Whitney test to test for differences in mean bed net use across treatments shows that average bed net use in the *public benefit* and *public benefit + social proximity* treatments is significantly different at the 5% level, compared to the private benefit treatment. Similarly, I find that average bed net use in the *public benefit* treatment is significantly different at the 5% level from the average bed net use in the *public benefit + social proximity* treatment (see Table 4).[14]

[14]Similar results are obtained using the Wilcoxon test for medians.

Table 4: *Pairwise comparison of all key variables*

	mean (weekly)			p-values		
	(T0)	(T1)	(T2)			
Village bed net use	**Private benefit**	**Public benefit**	**Public benefit + social proximity**	**T0-T1**	**T0-T2**	**T1-T2**
0	3.7	4.3	4.8	0.001***	0.000***	0.000***
250	3.7	4.4	5.0	0.001***	0.002***	0.000***
800	3.7	4.6	5.4	0.000***	0.000***	0.000***
1,000	3.7	4.8	5.5	0.000***	0.000 ***	0.000***

Pairwise comparisons using Mann-Whitney rank-sum test

Table 5 provides a breakdown of the conventional contributor types by treatment (see Fischbacher et al., 2001). A participant is classified as a conditional cooperator if her own bed net use increases monotonically with the average level of bed net use by others. Free-riders are those who have 0 bed net use, irrespective of the average bed net use of others. A hump-shaped contributor has the same conditional contribution pattern as a conditional cooperator up to a certain maximum point, and then drops her contribution. A participant is an unconditional cooperator if the conditional cooperation is the same regardless of contribution by others. Conditional cooperators represent approximately 25% of participants, while 33% are unconditional cooperators and 1% are free-riders. The remaining participants are classified as unconditional cooperators, hump-shaped contributors, free-riders or others. These proportions do not resemble those obtained in previous studies; for example Fischbacher et al. (2001) find that conditional cooperators make up roughly 50%, 'hump-shaped' contributors roughly 14%, free riders are approximately 30%, while Herrmann and Thöni (2009) find that free-riders make up roughly 5%. The divergence of these results from those previously obtained in the literature may perhaps be explained by the nature of the public good studied. Unlike other public-good contexts which do not involve direct bodily harm, in the infectious disease setting an individual considers that there is a positive probability of being infected with malaria when deciding on bed net use.

Table 5: *Fractions of contributor type by treatment*

Type	**Private benefit**	**Public benefit**	**Public benefit + social proximity**	**Total**
Free riders	1	4	2	7
	0.00%	1.4%	0.7%	1%
Conditional cooperators	29	98	75	202
	11%	36%	27%	25%
Unconditional cooperators	117	109	47	273
	43%	40%	17%	33%
Hump shaped contributors	83	44	110	237
	30%	16%	40%	29%
Others	45	18	40	103
	16%	6.6%	15%	13%
Total	275	273	274	822
	100%	100%	100%	100%

I further examine whether bed net use changes as individuals move from low levels of village use to high levels of village use in each treatment. The Wilcoxon signed-rank test in Table 6 reports that in the control group, there are no statistically significant differences in bed net use as individuals move from low levels of village bed net use to high levels of bed net use. However, in the *public benefit* treatment, there is a difference in bed net use as individuals move from low levels of village bed net use to high levels of village bed net use. Similarly, in the *public benefit + social proximity* treatment, we see that there are significant differences in bed net usage as individuals move from low village levels of bed net use to high levels. But once individuals get to high levels of village bed net use, there is no statistically significant difference between the two high use levels. These results potentially point to the presence of conditional cooperation in the public benefit and *public benefit + social proximity* treatments, but not in the control group.

TABLE 6: *Strength of cooperation across village use levels*

Average bed net use in the village	**z**	**Pr** Z(>**z**)
	Private benefit	
level 0 vs 250	0.32	0.749
level 250 vs 800	-0.76	0.448
level 800 vs 1000	-0.20	0.843
	Public benefit	
level 0 vs 250	-3.95	0.000***
level 250 vs 800	-6.53	0.000***
level 800 vs 1000	-6.25	0.000***
	Public benefit + social proximity	
level 0 vs 250	-3.63	0.000***
level 250 vs 800	-5.72	0.000***
level 800 vs 1000	-1.38	0.167

Differences tested using Wilcoxon signed-rank test

4.2 Regression results

Result 1:

A common result in public goods games is that there are non-zero contributions. An explanation for the non-zero contributions is that people are conditional cooperators, i.e. they will contribute to a public good if other people also do so (e.g. Fischbacher et al., 2001). To investigate whether people in different treatment groups are conditionally cooperative, I estimate Equation 1 with a set of controls and village fixed effects included. Standard errors are adjusted to take clustering at the individual level into account. Table 7 presents the regression results. The results of the *private benefit* treatment fail to support hypothesis 1, regarding people being conditionally cooperative. This is evidenced by the insignificance of the estimated coefficients when all levels of average bed net use are compared to the base category of level 0. This implies that if people do not have information about the public benefits of their actions, they are not affected by the actions of others.

In the *public benefit* treatment, we see that when people are told that more people in the village are using bed nets, their willingness to use bed nets also increases. This is seen in the positive and statistically significant coefficients of *public benefit* treatment interacted with the different levels of village bed net use. Individuals are willing to increase their bed net use by about 0.14 days in a week when they are told that 250 people in the village are using bed nets, relative to when nobody in the village is using bed nets, and this increase is statistically significant.[15] Similarly, giving individuals a village use level of 800 increases their willingness to use bed nets by 0.35 days in a week and by 0.55 days in a week when they are told that 1,000 people in the village are using a bed net, compared to when nobody in the village is using a bed net. This indicates the presence of conditional cooperation, and that the motive to conditionally cooperate in order to reciprocate outweighs that of free-riding. This result in the public benefits treatment is in favor of hypothesis 1.

Strengthening the public benefit information, by making salient how an individual's actions affect his or her neighbors, increases the willingness to use bed nets. Compared to the private benefits treatment, people in the *public benefit* and *social proximity* treatment are willing to increase their bed net use by 0.22 days when they are told that 250 people in the village are using bed nets, by 0.58 days when 800 people in the village are using bed nets, and by 0.71 days when everyone in the village is using a bed net. The results for the group exposed to public benefit and social proximity treatment can be interpreted in favor of hypothesis 1, and thus suggest that the motive to conditionally cooperate outweighs that of free-riding. At high levels of village use where the risk of malaria infection is relatively low, we see that people are more driven by the conditional cooperative motive than by free-riding.

[15] This result is obtained by adding the coefficient of the main effect at average village bed net use of 250 (-0.019) to the coefficient of the interaction of public benefit treatment at village bed net use level of 250 (0.154).

Result 2:

Next, I explore the effect of providing information on the public benefits of using bed nets on willingness to use bed nets.[16] Table 7 shows that when nobody in the village is using bed nets, individuals in the public benefit treatment are willing to increase their bed net use by 0.4 days in a week, compared to those in the private benefit treatment for the same level of village bed net use. Furthermore, if 250 people in the village are using bed nets, those in the public benefit treatment will increase their bed net use by 0.58 days in a week, compared to those in the control group for the same level of village bed net use.[17] A similar pattern is observed for higher levels of bed net use; and the observed increases are not only statistically significant, but also economically significant. For instance, we have seen that compared to the private benefit treatment, when people in the public benefit treatment are told that 250 people in the village are using bed nets, they are willing to increase their bed net use by 0.58 days, which is associated with an increase of 13.2% (with respect to the mean). The willingness to use bed nets at a village bed net use level of 800 is associated with a 16% increase, and that at village bed net use of 1,000 is associated with a 20% increase.[18] Result 2 on public benefits treatment finds evidence in favor of hypothesis 2.

Compared to the control group, where people have information on only the private benefits of bed net use, larger effects are observed on willingness to use bed nets when people are given information on the public benefits of using bed nets, combined with a message detailing how one's own personal use affects one's immediate neighbor. Compared to the control group, people in this treatment are willing to increase bed net use by 0.97 days in a week when nobody else in the village is using bed

[16] All treatments are jointly significant at all levels of village bed net use, as shown by the joint significance of F=23.96 and p>F=0.000.

[17] This is the total effect obtained by adding the coefficient of the main effect of public benefit treatment (0.427) to the coefficient of the interaction of public benefit treatment at level 250 (0.154).

[18] The magnitude and significance of coefficients does not change after controlling for religion (Catholic); which, as reported in the summary statistics, was significantly different between the private and public benefits treatments.

nets; by 1.2 days in a week when 250 people in the village are using bed nets; by 1.5 days per week when 800 people in the village are using bed nets; and by about 1.7 days per week when 1,000 people in the village are using bed nets. These increases are statistically significant. To put them into perspective, these effects represent a 20%, 22%, 24% and 30% increase respectively for each level of village bed net use, with respect to the mean. These results lend further support to hypothesis 2: that providing information on public benefits together with information on how an individual's own bed net use affects their neighbors matters for bed net use.[19]

[19]Similar results are obtained when using a Poisson regression, as shown in Table A.2 in the Appendix.

Table 7: *Effect of public-benefit information on bed net use*

Dependent variable: Number of days of bed net use in a week

Variables	Coef.
Base: Private benefit	
Public benefit	0.427***
	(0.140)
Public benefit + social proximity	0.970***
	(0.143)
Base: Level 0	
Level 250	-0.019
	(0.048)
Level 800	0.018
	(0.046)
Level 1000	0.020
	(0.072)
Public benefit*L250	0.154**
	(0.062)
Public benefit*L800	0.335***
	(0.065)
Public benefit*L1000	0.528***
	(0.094)
Public benefit + social proximity*L250	0.235***
	(0.081)
Public benefit + social proximity*L800	0.557***
	(0.113)
Public benefit + social proximity*L1000	0.694***
	(0.165)
Sex	0.190
	(0.156)
Age	0.006
	(0.007)
Education (in years)	0.030
	(0.019)
Married	-0.396**

Continues

Table 7 – *Continued*

Variables	**Coef.**
	(0.159)
Household size	-0.119***
	(0.035)
# under 5yrs	0.172**
	(0.072)
# over 55yrs	0.036
	(0.119)
pc ITN ownership	-0.091
	(0.162)
Household malaria	0.144***
	(0.030)
# of days ITN lastweek	0.026
	(0.028)
Risk aversion	2.367***
	(0.238)
Chronic illness	0.295*
	(0.161)
Alcohol	-0.329
	(0.233)
Effectiveness of ITNs	1.873***
	(0.145)
Consequences of ones actions	-0.097
	(0.130)
Log of wealth	-0.004
	(0.057)
Constant	3.178***
	(0.359)
Observations	3,224
Village fixed effects	Yes
R-squared	0.404

Notes: All 4 levels of bed net use in the village are jointly significant across the treatments (F=14.79 and P>F=0.000). Order effects are not observed. Standard errors in parentheses are adjusted to take into account clustering at individual level and p-values are *** p<0.01, ** p<0.05,* p<0.1.

Result 3:

Thus far, we have seen that individuals in both the *public benefit* treatment and *public benefit + social proximity* treatment are more likely to use bed nets compared to the control group that has only the private benefit information, at all levels of village bed net use. Next, I test whether there is a difference in willingness to use bed nets between individuals in the *public benefit* treatment and those in the *public benefit + social proximity* treatment. Table 8 below shows that people in the *public benefit* treatment are less willing to use bed nets at all levels of village bed net use provided, when compared to the *public benefit + social proximity* treatment group.[20] The observed differences signify the effect of providing the extra information on how an individual's actions affect their neighbors' welfare. This result supports hypothesis 3, that strengthening the information on the public benefits of bed net use with that of the effect of one's own behavior leads to a larger behavioral effect.

TABLE 8: *Differences between public benefit and public benefit + social proximity treatments*

Average bed net use in the village	**Coef.**
Public benefit (Level 0)	-0.544***
	(0.152)
Public benefit (Level 250)	-0.624***
	(0.150)
Public benefit (Level 800)	-0.766***
	(0.151)
Public benefit (Level 1000)	-0.710***
	(0.153)

After each participant had responded with their willingness to use bed nets for all four average bed net use levels in the village, they were asked a follow-up question, on the factors they had considered when giving their responses. In the control group, on average, people are more concerned with their own health, and their actions are independent of what others do. Examples of responses in this treatment are: '*I will*

[20]These results are obtained from Table 7 using the contrast command in Stata.

not copy what others do'; '*I want to be safe by sleeping under a net, no matter what others do*'; and '*I have to protect myself, despite the number of users*'. In the public benefit treatment, people seem to take into account what others do when making decisions. Examples of responses from this treatment group are: '*Depends on the users and the number of people using ITNs*'; '*The fact that I have to be among the large number who use ITNs so as to reduce malaria*'; and '*I go with the flow*'. In the public benefit *plus* social proximity treatment, people tend to respond more to the externality message. Examples of some of the responses in this treatment are: '*I am concerned about my health and about that of my people*'; '*I am looking at the health status of my neighbor, and my own*'; and '*I do not want to be responsible for infecting my neighbor*'.

Thus far, the evidence implies that giving information on the existence of public benefits when using bed nets matters; and more so when this type of information is combined with extra information on how an individual's bed net use can affect his or her neighbor. The results in Table 7 – which include interacted control variables, though only averages are reported – indicate that risk aversion is positively related to bed net use. The estimates concerning risk aversion suggest that a two-standard-deviation increase in the risk aversion of an average individual increases the number of days of bed net use by 1.09 days in a week, and that this effect is similar in magnitude to the effect of information obtained in the two treatments. Similarly, the average change in bed net use for an average individual who perceives bed nets to be effective increases by about two days in a week, compared to an average individual who does not perceive bed nets to be effective. Furthermore, the average change in bed net use per week when an average household includes a child under 5 years old, or has an additional member having suffered from malaria in the last 12 months, increases by about 0.17 and 0.14 days. The results therefore show that although providing people with information on the public benefits of bed net use has an effect on their willingness to change behavior, other observable characteristics also have an effect, and can therefore be taken into account when providing such information due to the existence of interaction effects, as observed.

5 Conclusion

In this paper I use a survey experiment to analyze the effect of providing information about the public benefits of using bed nets on a person's decision whether or not to use bed nets in rural Kenya. I study the role of information on the public benefits of bed net use, and the role of providing social information; i.e. what other people in the village do. I find that giving people information on the public benefits of using bed nets has significant effects compared to providing them with only the private benefits. These effects are greater when an individual knows the effect of his or her actions on his or her neighbors. In addition, I find that when people have information regarding the public benefits of bed net use, they tend to be conditionally cooperative such that if they find out that more people in the village are using bed nets, they will also be willing to use more, and vice versa. The findings are robust to the inclusion of numerous control variables.

An important challenge for governments around the world, and especially in sub-Saharan Africa, is how to convince people to do what is best for all. I recognize that these results represent rural Kenya, and may not hold true for all developing countries. But I also acknowledge that rural Kenya is very similar both in context and in human well-being to many rural areas in other developing countries, especially those in sub-Saharan Africa, and much can be inferred from the study. Moreover, this work provides some insights towards understanding the channels through which peoples' behavior can be influenced, which in turn provides a solution to the pressing issue of how to improve the health and economic outcomes of a population by controlling malaria.

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A Appendix

Control group (Private benefit)

Malaria is caused solely by mosquitoes. When a mosquito that has a certain parasite bites a human, it infects him or her with malaria. When you sleep under an Insecticide Treated Bed Net (ITN), you protect yourself from being bitten by infective mosquitoes that can cause malaria. However, the risk of malaria infection may differ from person to person, such that some may get malaria while others may not. Also it may be that you have malaria in you but you do not display the symptoms of malaria. What this means is that you could be spreading malaria without your knowledge. Now, I want you to imagine that in this village that you live in, there are about 1,000 people (including men, women and children), and currently an average (for both the dry and the rainy season) of 400 people are regularly sleeping under an ITN every night.

(Enumerator: 'Regular' means seven days a week)

I would like you to think, and tell me what you would do if your village had these different situations:

a) If the number of regular ITN users in your village (of 1,000 people) is 250 people, how many days would you sleep under an ITN in one week?[21] ..... days. b) What if everyone in the village is regularly sleeping under an ITN; how many days would you sleep under an ITN in one week? ..... days. c) If the number of regular ITN users in the village is 800 people, how many days would you sleep under an ITN in one week? ..... days. d) If nobody in the village is regularly sleeping under an ITN, how many days would you sleep under an ITN in one week? ..... days.

Follow-up question: What factor(s) did you consider when answering these questions?

....

[21] The enumerator asked the question in such a way that the respondent was responding to the hypothetical village of 1,000 people, and not their actual village.

Public benefit treatment

Malaria is caused solely by mosquitoes. When a mosquito that has a certain parasite bites a human, it infects him or her with malaria. When you sleep under an Insecticide Treated Bed Net (ITN), you protect yourself from being bitten by infective mosquitoes that can cause malaria. However, the risk of malaria infection may differ from person to person, such that some may get malaria while others may not. Also, it may be that you have malaria in you but you do not display the symptoms of malaria. What this means is that you could be spreading malaria without your knowledge. Now I want you to imagine that in this village that you live in, there are about 1,000 people (including men, women and children), and currently an average (for both the dry and the rainy season) of 400 people are regularly sleeping under an ITN every night. (Enumerator: 'Regular' means 7 days a week)

There is also other important and true information which I would like you to know: if more people in your village regularly sleep under ITNs, the risk of getting malaria infection in the village is lowered. This is because the number of infective mosquitoes in the neighborhood is reduced, thereby lowering the chance that people in the village will be bitten by an infective mosquito. In contrast, if fewer people in your village regularly sleep under ITNs, the risk of getting malaria is increased. This is because the number of infective mosquitoes in the neighborhood increases thereby increasing the chance that people in the village will be bitten by an infective mosquito.

I would like you to think, and tell me what you would do if your village had these different situations:

a) If the number of regular ITN users in your village (of 1,000 people) is 250 people, how many days would you sleep under an ITN in one week? ..... days. b) What if everyone in the village is regularly sleeping under an ITN; how many days would you sleep under an ITN in one week? ..... days. c) If the number of regular ITN users in the village is 800 people, how many days would you sleep under an ITN in one week? .....

days. d) If nobody in the village is regularly sleeping under an ITN; how many days would you sleep under an ITN in one week? ..... days.

Follow-up question: What factor(s) did you consider when answering these questions?

....

Public benefit + social proximity treatment

Malaria is caused solely by mosquitoes. When a mosquito that has a certain parasite bites a human, it infects him or her with malaria. When you sleep under an Insecticide Treated Bed Net (ITN), you protect yourself from being bitten by infective mosquitoes that can cause malaria. However, the risk of malaria infection may differ from person to person, such that some may get malaria while others may not. Also it may be that you, have malaria in you but you do not display the symptoms of malaria. What this means is that you could be spreading malaria without your knowledge. Now I want you to imagine that in this village that you live in, there are about 1,000 people (including men, women and children), and currently an average (for both the dry and the rainy season) of 400 people are regularly sleeping under an ITN every night.

(Enumerator: 'Regular' means seven days a week.)

There is also other important and true information which I would like you to know: if more people in your village regularly sleep under ITNs, the risk of getting malaria infection in the village is lowered. This is because the number of infective mosquitoes in the neighborhood is reduced, thereby lowering the chance that people in the village will be bitten by an infective mosquito. In contrast, if fewer people in your village regularly sleep under ITNs, the risk of getting malaria infection is increased. This is because the number of infective mosquitoes in the neighborhood increases, thereby increasing the chance that people in the village will be bitten by an infective mosquito.

Moreover, by regularly sleeping under an ITN, you not only protect yourself, but also your neighbor. This is because you reduce the number of infective mosquitoes in the neighborhood, thereby lowering the chance that both you and your neighbor will be bitten by an infective mosquito. On the other hand, if you don't regularly sleep under an ITN you may possibly be responsible for infecting your neighbor; because once infected, you increase the number of infective mosquitoes.

I would like you to think, and tell me what you would do if your village had these different situations:

a) If the number of regular ITN users in your village (of 1,000 people) is 250 people, how many days would you sleep under an ITN in one week? ..... days. b) What if everyone in the village is regularly sleeping under an ITN; how many days would you sleep under an ITN in one week? ..... days. c) If the number of regular ITN users in the village is 800 people, how many days would you sleep under an ITN in one week? ..... days. d) If nobody in the village is regularly sleeping under an ITN; how many days would you sleep under an ITN in one week? ..... days.

Follow-up question: What factor(s) did you consider when answering these questions?

....

Figure A.1: Advertisements on bed net use

Note: The text explains that sleeping under a bed net prevents malaria, that pregnant women and children are at higher risk of dying from malaria, and the average lifetime of bed net effectiveness.

Note: The text of this poster is written in one of the national languages (Kiswahili). The words mean that we sleep under a bed net and mosquitoes stay out.

A.1 Sampling

The selected divisions (Nyando and Soin) had a total of 127 villages. I excluded villages in urban areas, leaving a total of 109 villages in the rural areas (Nyando 47 and Soin 62). The mean number of households in Nyando was 100, with a standard deviation of 27.8, a minimum of 53, and a maximum of 186 households. In Soin division, one village had 435 households, making it distant from other villages in terms of number of households. I regarded this village as an outlier which could affect the mean; and I therefore excluded it from the sample, leaving a total of 61 villages. The mean number of households in Soin was 71.5, with a standard deviation of 19.8, and a minimum of 42 and a maximum of 151 households. I then included the villages with a number of households within one standard deviation from the mean, so as to avoid over- or under- representation of villages. Therefore, in Nyando, villages with fewer than 72 households and those with more than 128 were excluded from the sample of my study population; while in Soin, villages with fewer than 27 households and with more than 127 households were excluded from the sample of my study population In the end I had a total of 84 villages from the two divisions. I then randomly sampled 19 villages from Nyando and 22 villages from Soin. Table A.1 provides a summary.

TABLE A.1: *Sampling*

	Nyando	*Soin*
Total no. of villages	47	61
Mean number of households	100	71.5
Std. Deviation	27.8	19.8
Villages included	100 $\pm$27.8	71.5 $\pm$19.8
Total villages before sampling	38	46
Villages sampled	19	22

A.2 *Map of Study Area*

Figure A.2: Map of Study Area

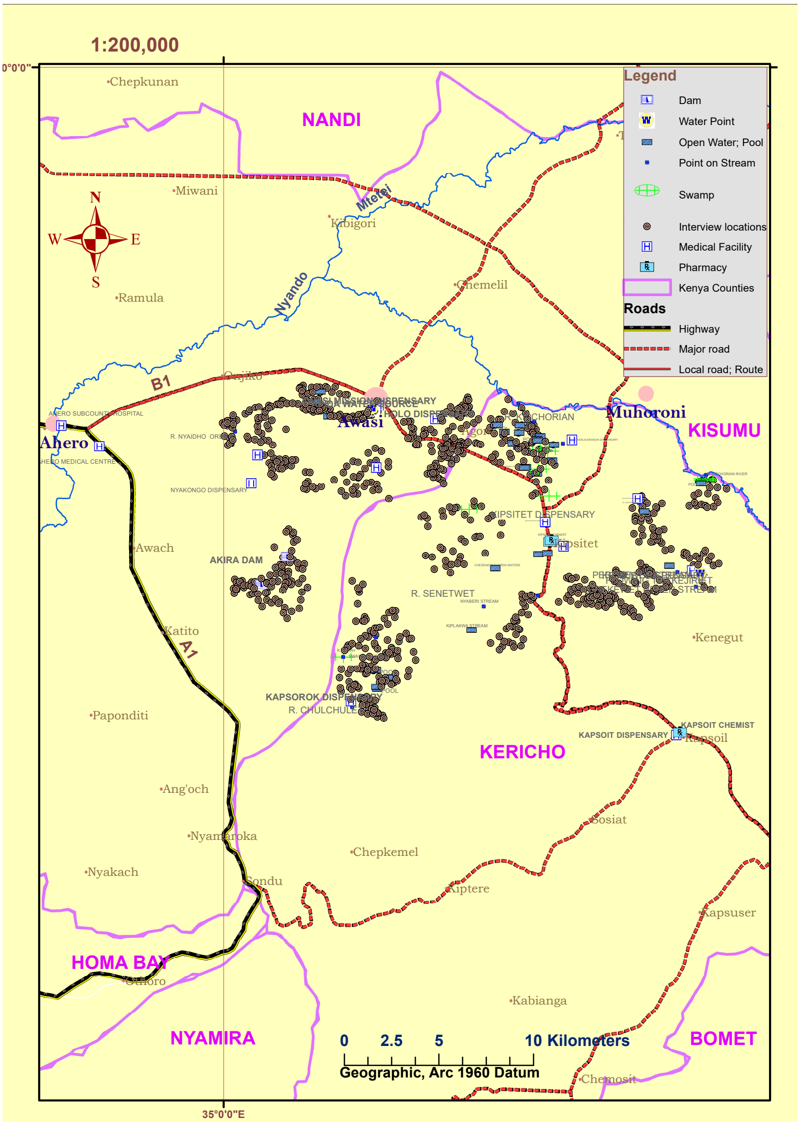

Table A.2: *Poisson effect of public-benefit information on bed net use*

Dependent variable: Number of days of bed net use in a week

Variables	**Marginal Effect**
Base: Private benefit	
Public benefit	0.555***
	(0.138)
Public benefit	1.089***
	(0.139)
Base: Level 0	
Level 250	-0.022
	(0.048)
Level 800	0.013
	(0.046)
Level 1000	0.033
	(0.069)
Public benefit*L250	0.137***
	(0.038)
Public benefit*L800	0.349***
	(0.043)
Public benefit*L1000	0.529***
	(0.059)
Public benefit + social proximity*L250	0.215***
	(0.064)
Public benefit + social proximity*L800	0.575***
	(0.099)
Public benefit + social proximity*L1000	0.719***
	(0.141)
Sex	0.204
	(0.156)
Age	0.005
	(0.006)
Education (in years)	0.029
	(0.019)
Married	-0.398**

Continues

Table A.2 – *Continued*

Variables	Marginal Effect
	(0.157)
Household size	-0.114***
	(0.036)
# under 5yrs	0.172**
	(0.071)
# Over 55yrs	0.067
	(0.118)
pc ITN ownership	-0.067
	(0.156)
Household malaria	0.146***
	(0.031)
# of days ITN last week	0.033
	(0.029)
Risk aversion	2.398***
	(0.239)
Chronic illness	0.274*
	(0.161)
Alcohol	-0.318
	(0.243)
Effectiveness of ITNs	2.153***
	(0.191)
Consequences of ones actions	-0.105
	(0.133)
Log of wealth	-0.008
	(0.057)
Observations	3,224
Village fixed effects	Yes

Notes: Order effects are not observed. Standard errors in parentheses are adjusted to take into account clustering at individual level and p-values are *** $p<0.01$, ** $p<0.05$,* $p<0.1$.

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