Abstract

DESCRIPTION (provided by applicant): Malaria remains a major health problem worldwide. According to the World Health Organization in 2008 there were approximately 850,000 deaths related to malaria, with over 89% occurring in Africa. The tragedy is that technologies exist that can prevent, diagnose and even cure malaria. Preventative technologies that have been shown to be effective in clinical trials include the use of insecticide-treated mosquito nets (ITNs), intermittent preventive treatment during pregnancy (IPT) and prompt and effective treatment of malaria using artemisinin combination therapy (ACT). Despite the fact that most people in Sub-Saharan Africa are aware of the existence of these technologies, a large number of individuals do not adopt them. ITNs, IPT, and ACT are relatively new and their benefits may not be widely evident to the general population because individuals need to continuously experience these technologies to ascertain their effectiveness. When facing choices under uncertainty, individuals have incentives to learn from the actions and outcomes of their neighbors. The action of neighbors may also create peer pressure to engage in certain behaviors. The objective of this study is to determine the importance of these social interactions in the adoption and spread of ITNs, IPT, and ACT using data from all the Demographic Health Surveys (DHS), Malaria Indicator Surveys (MIS), and Multiple Indicator Cluster Surveys (MICS) between 1999 and 2010 for 34 Sub- Saharan countries. For each country we have multiple waves with information on ownership and usage of mosquito nets and ITN, usage of IPT and usage of ACT. Social interactions create a social spillover, where the effect of a government policy that encourages some individuals to adopt these technologies will also have an indirect effect through the influence of these individuals on the behavior of their neighbors. If social interactions are important, small changes in the determinants of malaria-preventative behaviors may lead to a high variation at the aggregate level. It is well known that the problems of identifying social interactions from other phenomena (that give rise to similar outcomes among peers) are immense. This study calculates the size of the social spillover by comparing the effects of an exogenous variable on the malaria preventive behavior at both the individual and group level, defining a group as a region or district of a country. In the presence of social spillovers, the ratio of these two effects will be significantly greater than one, implying that a social policy that convinces a small group of influential people to adopt the technology could have large effects at the community level.

Specific Aim

Malaria remains a major health problem worldwide. According to the 2009 World Malaria Report, in 2008 there were approximately 250 million episodes of malaria leading to 850,000 deaths, with over 89% occurring in Africa (WHO 2009). Malaria is particularly dangerous for pregnant women and children who have not yet developed partial immunity. In fact, 16% of all deaths among children under five are due to malaria (WHO 2009). The tragedy is that technologies exist and are available that can prevent, diagnose, and even cure malaria. Preventative measures that have been shown to be effective include the use of insecticide-treated mosquito nets (ITNs), indoor residual spraying (IRS) and intermittent preventive treatment during pregnancy (IPT). Prompt use of artemisinin combination therapy (ACT) has also been shown to be an effective response treatment. In 1998, the Roll Back Malaria Partnership (RBM) was created to coordinate global efforts against the disease. Among the main goals is achieving *full coverage of all people at risk of malaria in areas targeted for malaria prevention by the year 2015*. This full coverage includes universal use of ITNs, IPTs and ACT for vulnerable groups, especially children and pregnant women (RBM 2008).

Despite these recommendations and efforts by the RBM partnership, a large number of individuals do not follow these measures and the progress that has been made has not been uniform across countries (RBM 2010). ITNs, IPT, and ACT are relatively new technologies and their benefits may not be widely evident to the general population. When facing choices under uncertainty, individuals have incentives to learn from the actions and outcomes of their neighbors. The actions of neighbors may also create peer pressure to engage in certain behaviors. The aim of this study is to determine the importance of social interactions in the adoption and spread of ITNs, IPT, and ACT in Sub-Saharan Africa. Social interactions will create a social spillover, where the effect of a government policy that encourages individuals to adopt these malaria-preventive technologies will also have an indirect effect through the influence of these individuals on the behavior of their neighbors. If social interactions are important, small changes in the determinants of malaria-preventative behavior may lead to a high variation at the aggregate level. We will concentrate on the malaria-preventative behaviors affecting children under 5 and those taken by pregnant women. Understanding the dynamics of preventative behaviors of these vulnerable groups is crucial if Sub-Saharan Africa is to achieve the UN Millennium Development Goals 4, 5, and 6.

Social interactions have been shown to be important determinants of fertility decisions (Montgomery and Casterline, 1993; Bloom et al., 2008), prenatal care (Aizer and Currie, 2004), criminal behavior (Glaeser et al., 1996), the use of fertilizer (Conley and Udry, 2010) and other behaviors and decisions. The problems of identifying social interactions from other phenomena (that give rise to similar outcomes among peers) are immense (Manski, 1993, 2000). Manski emphasizes two problems when estimating social interaction effects. The first is the reflection problem, where the group influences the individual but the individual also influences the group. The second is distinguishing the effects of social interactions from unobserved factors that may affect everyone in the group.

In this study we will follow the approach of Glaeser and Scheinkman (2002), Graham and Hahn (2005), and Bloom et al. (2008), which calculates the size of the social spillover by comparing the effects of an exogenous variable at the aggregate level to the effects at the individual level. If social interaction effects are important, the effect of an exogenous variable on the preventative behaviors using aggregate data is much larger than when using individual data. Our method requires repeated cross-sectional data and a large sample size. Our data will come from all the Demographic Health Surveys (DHS), Malaria Indicator Surveys (MIS), and Multiple Indicator Cluster Surveys (MICS) between 1999 and 2010 for 34 Sub-Saharan Countries. For each country we have multiple waves with information on malaria-preventive behaviors including ownership and usage of mosquito nets and ITNs, usage of IPT and usage of ACT. We anticipate writing three papers related to this study; one for ITN, one for IPT, and one for ACT.

Research Strategy

a) Significance

Malaria is historically one of the major causes of mortality worldwide. This is why the World Health Organization (WHO) launched the Global Malaria Eradication Campaign in 1955. Mostly through the use of insecticide spraying, malaria was eradicated from 37 countries by 1973 and the campaign was terminated. However, in the 1980s the prevalence of malaria started to rise again which led to a renewed interest and the creation of the Roll Back Malaria (RBM) Partnership in 1998. Malaria control then became an important component of the Millennium Development Goals of the United Nations. The main policy recommendations by the Roll Back Malaria Partnership to control malaria in endemic areas are the use of insecticide treated nets (ITNs) by all populations at risk, indoor residual spraying (IRS), use of intermittent preventive treatment during pregnancy (IPT), and prompt and effective treatment of malaria using artemisinin combination therapy (ACT). These technologies have been shown to be both efficient and effective. Sleeping under an ITN is considered one of most effective ways to prevent malaria, since the mosquito dies immediately when it comes into contact with the mosquito net. This not only prevents the bite, but also reduces the mosquito population. In Africa, malaria-infected mosquitoes usually bite indoors at night and rest indoors after feeding; this makes ITNs highly effective (RBM 2010). In a comprehensive review of the literature, Lengeler (2004) concluded that widespread use of ITNs can reduce child mortality by 20%, uncomplicated malaria episodes by 50%, and severe malaria episodes by 45%. It also reduces the number of low birth weights when used by pregnant women. ITNs have also shown to be cost effective compared to other preventive measures (Binka et al., 1996; Goodman et al., 2000; Goodman and Mills, 1999; Wiseman et al., 2003). However, the RBM recommendation of widespread usage of ITNs is not without criticism. In malaria-endemic areas, use of ITNs may preclude the development of immunity, leading a greater risk of severe malaria (Snow et al., 1997; Modiano et al., 1998).

Despite the evidence on the benefits and the increase in ownership, many households still do not use an ITN. Several studies have analyzed individual and household characteristics that may affect this ownership and usage. Khan et al. (2008) found that in over 30% of households, the youngest child did not sleep under an ITN even though the household owned at least one. Cohen and Dupas (2010) and Dupas (2009) show that ownership is highly price-sensitive, but usage of an ITN does not depend on the price paid for the mosquito net. These studies use experimental data from Kenya and conclude that free distribution of nets is preferable to cost-sharing. Cruz et al. (2006) use data from Ghana and find that knowledge of malaria risks does not translate into ITN usage. Factors like perceived vulnerability appear far more important. ITNs also have external benefits to those who are not using the ITN due to the mosquito mortality. Gimning et al. (2003) and Hawley et al. (2003) find a decrease in the number of malaria vectors in control houses that are close to intervention villages compared to those that are more distant.

During intermittent preventive treatment (IPT), a full therapeutic dose of an anti-malaria drug is administered to pregnant women after the second trimester. IPT is recommended for all countries with stable malaria transmission. Sulfadoxinr-pyrimethamine (SP) is easier to administer and preferred to cheprophylaxis with chloroquine because the emergence of chloroquine-resistant malaria. The treatment consists of at least two full doses that can be given during an antenatal visit. Clinical trials in Kenya and Malawi have shown IPT-SP to be beneficial to maternal anemia and healthy birth weight (Greenwood et al., 2004). Previous studies such as Launiala and Honkasalo (2007) and van Eijk (2004) have also investigated the factors affecting compliance to IPT-SP: unclear directives about IPT with SP by nurses, periodic shortages of SP, women's limited understanding of IPT-SP, tendency for late enrollment and nurses' under-performance. Other studies found that pregnant women may be concerned about side effects (see Enato and Okhamafe, 2005).

Immediate malaria treatment within 24 hours of fever onset is recommended to prevent life-threatening complications for children under 5. The main challenge is distinguishing fever caused by malaria from fever related to something else which needs an alternative treatment. It is recommended that before administering ACT, a rapid diagnostic test for malaria be conducted. Currently, ACT is recommended for the plasmodium falciparum, which is the mosquito that most commonly transmits malaria in Sub-Saharan Africa (WHO, 2010). Since 2003, most malaria drug policies of Sub-Saharan countries recommend the use of ACT as the first line drug.

Although full ownership of ITNs and availability of IPT-SP and other drugs are a prerequisite to achieve the Millennium Development Goals, populations at risk must use these technologies consistently to achieve the desired results. An ITN stored in a shelf will be of little help. Our study will contribute to the current literature by analyzing and estimating the importance of social interactions in determining the adoption and spread of ITNs, IPT-SP and ACT. Social interactions can lead to a large social-multiplier effect, where an individual's adoption of a technology creates a social spillover that produces a much larger effect at the aggregate level. Social interaction may be due to social learning, where individuals learn about the benefits of ITNs, IPT-SP and ACT from the experiences of their neighbors either through conversations or direct observation. Social interaction may also be due to social influence or peer effects where usage of the technology becomes the social norm.

As discussed in Manski (1993), identifying social interactions is very difficult without longitudinal data containing detailed information on both the individual source of information and their social networks. First, an individual's use of a technology like ITN depends on the ITN usage of his/her neighbors, but his/her ITN usage also affects the neighbors' ITN usage. This is the "reflection problem." Second, unobserved neighborhood characteristics like the number of mosquitoes in the area will influence the ITN usage of the individual and his/her neighbors. This will create a spurious correlation between the average neighborhood ITN usage and the individual ITN usage. Third, we cannot distinguish between endogenous and exogenous social interactions. An endogenous interaction is when the *average ITN use* of the group influences the individual ITN use, while exogenous interaction occurs when the *average characteristics* of the group (such as the group average education) affect the individual's ITN usage.

We follow the strategy of Glaeser and Scheinkman (2002), Graham and Hahn (2005), and Bloom et al. (2008), which calculates the size of the social spillover by comparing the effects at the individual level and at the aggregate level. Our method requires repeated cross-sectional data and a large sample size. Our data will come from all the Demographic Health Surveys (DHS), Malaria Indicator Surveys (MIS) and Multiple Indicator Cluster Surveys (MICS) between 1999 and 2010 for 34 Sub-Saharan Countries.

b) Innovation

We expect our study to produce several innovations in the analysis of adoption of newer malaria-preventative technologies like ITNs, IPT, and ACT.

First, we will create an aggregate longitudinal data set for Sub-Saharan Africa based on the average group behavior of different geographical areas to study malaria using all of the available information from DHS/MIS/MICS surveys. Our groups will be regions within countries and, when we have more precise geographical identifiers, we will also aggregate at smaller areas such as districts.

Second, our study will be the first to determine and measure the importance of social interactions in the adoption of ITNs, IPT and ACT for a large number of Sub-Saharan Countries. The size of the social spillover will have important policy implications since policies that successfully convince an individual to adopt a technology (such as using an ITN) will have a much larger effect than in the absence of social spillovers.

Third, we will not only study the size of the average social spillover in a geographical area, but we will also explore whether social spillovers are larger within homogeneous cultural and linguistic groups.

c) Approach

c.1) Methodology

Following Bloom et al. (2008), assume that in our data we have *G* non-overlapping groups of individuals (*g=1,…,G*). For each group *g* at time *t* (*t=1,…,*T^g) we have a sample of M^{gt} individuals (*i=1,…,* M^{gt}). We assume that the malaria-preventative behavior (e.g. sleeping under an ITN) of an individual i follows a linear-in-means specification such as:

$$P_{igt} = \alpha + E_g(P_{igt})\gamma + X_{igt}\beta + E_g(X_{igt})\delta + A_{gt}\theta + v_{gt} + \varepsilon_{igt} \quad (1)$$

where P_{igt} is the preventive behavior of person *i* in group *g* at time *t*. X_{igt} are the exogenous individual level covariates like age, gender, education, and wealth. A_{gt} are area characteristic variables that affect all individuals' malaria-preventive behavior in the group at the same time like rain and temperature. $E_g(.)$ denotes the expectation with respect to the *g*th group. Social interactions can be endogenous and/or exogenous. The endogenous social interaction effect is given by *γ* and measures the effect of the group's *malaria-preventive behavior* on the individual's malaria- preventive behavior. The exogenous (contextual) social interaction effect is given by *δ* and measures instead the effects of the average characteristics of the group on the dependent variable. (For example, a more educated group may encourage malaria-preventive behavior on children through social pressure). v_{gt} is the unobserved correlated group effects that influence the malaria-preventive behavior of both the individual and the group, like the mosquito prevalence at time *t*. Both types of social interactions produce a spillover effect, but the unobserved correlated group effect does not have social spillovers. Finally, ε_{igt} is the idiosyncratic component.

$E_g(P_{igt})$ is correlated with the disturbances in equation (1) for two reasons. First, the individual's malaria-preventive behavior will also affect $E_g(P_{igt})$ (the reflection problem). Second, the unobserved correlated group effect (v_{gt}) will create a spurious correlation between $E_g(P_{igt})$ *and* P_{igt}. To estimate the social interaction effects we will follow the approach of Glaeser and Scheinkman (2002), Graham and Hahn (2005), and Bloom et al. (2008). The approach is based on first obtaining a consistent estimate of β. We first take the group expectations in equation (1) and solve for the social equilibrium (Manski 1993):

$$E_g(P_{igt}) = \frac{\alpha}{1-\gamma} + E_g(X_{igt})\left(\frac{\beta+\delta}{1-\gamma}\right) + A_{gt}\frac{\theta}{1-\gamma} + \frac{v_{gt}}{1-\gamma} \quad (2)$$

We then assume that each group is in social equilibrium. If we substitute the social equilibrium into equation (1) we obtain the following reduced form equation:

$$P_{igt} = \frac{\alpha}{1-\gamma} + X_{igt}\beta + E_g(X_{igt})\left(\frac{\gamma\beta+\delta}{1-\gamma}\right) + A_{gt}\frac{\theta}{1-\gamma} + \frac{v_{gt}}{1-\gamma} + \varepsilon_{igt} \quad (3)$$

We can estimate β from equation (3) using two alternatives. The first alternative is to apply the fixed effect estimator to the following equation:

$$P_{igt} = \alpha + X_{igt}\beta + w_{gt} + \varepsilon_{igt} \quad (4)$$

where w_{gt} is a time-specific group fixed effect. This specification provides a consistent estimator of β under weak statistical assumptions, but this specification does not allow us to estimate the impact of $E_g(X_{igt})$ *and* A_{gt}, because they are invariant to time-specific group effects.

Alternatively, we can estimate the following observable reduced-equation derived from (3) under the additional assumption that we can decompose v_{gt} into two effects: a time- invariant group-specific effect v_g and group-invariant time-specific effect η_t

$$P_{igt} = \frac{\alpha}{1-\gamma} + X_{igt}\beta + \bar{X}_{gt}\left(\frac{\gamma\beta+\delta}{1-\gamma}\right) + A_{gt}\frac{\theta}{1-\gamma} + \frac{v_g}{1-\gamma} + \frac{\eta_t}{1-\gamma} + \varepsilon^*_{igt} \quad (5)$$

where ε^*_{igt}=$\left[E_g(X_{igt}) - \bar{X}_{gt}\right]\left(\frac{\gamma\beta+\delta}{1-\gamma}\right) + \varepsilon_{igt}$. We can estimate this equation using time and group fixed effects. However, $\bar{X}_{gt}$ will be correlated with the disturbance in equation (5) due to the classical error-in-variables problem. We plan to use the split-sample IV estimator proposed by

Angrist and Krueger (1995) to overcome this problem. The sample within each year and group is randomly split into two sets: $\bar{X}_{1gt}$ and $\bar{X}_{2gt}$. We then use one set as an instrument for the other. Because of the random assignment into both groups, this estimator is consistent.

The second part of the approach is to obtain a consistent estimator of $\left(\frac{\beta+\delta}{1-\gamma}\right)$ using the between-group variation. From equation (5) we calculate the group average:

$$\bar{P}_{gt} = \frac{\alpha}{1-\gamma} + \bar{X}_{gt}\left(\frac{\beta+\delta}{1-\gamma}\right) + A_{gt}\frac{\theta}{1-\gamma} + \frac{v_g}{1-\gamma} + \frac{\eta_t}{1-\gamma} + \bar{\varepsilon}^*_{gt} \qquad (6)$$

We then estimate $\left(\frac{\beta+\delta}{1-\gamma}\right)$ using group and time fixed effects combined with the split-sample IV approach described above.

We will define the social multiplier to be the ratio between $\left(\frac{\beta+\delta}{1-\gamma}\right)$ and β. If there are no social interactions this ratio will be one. However, if social interactions *do* exist, the ratio should be larger than one. We cannot distinguish between endogenous and exogenous social interactions, but we can control for the spurious unobserved group effect. As discussed by Bloom et al. (2008) this approach estimates the steady state or long run effect of the exogenous variable.

c.2) Data and Empirical Specification

The data for this analysis will come from the Demographic and Health Surveys (DHS), Malaria Indicator Surveys (MIS) and Multiple Indicator Cluster Surveys (MICS) for countries in Sub-Saharan Africa. These surveys are large and nationally representative. The Demographic and Health Survey's goal is to monitor the population and health situations of the target countries and it is part of the MEASURE DHS project which is partially funded by USAID. DHS data contain detailed information on health and preventive health behaviors for children, women and men. UNICEF is the main sponsor of the Multiple Indicator Cluster Survey which is used to monitor the situation of children and women. Starting in 2000, DHS and MICS began collecting information on the ownership and use of mosquito nets, whether the net is an ITN, intermittent preventive treatment (IPT) from past pregnancies and ACT treatment of fever for children. Because malaria eradication was not a health policy priority before the creation of RBM, DHS and MICS do not include questions related to malaria prevention before 1999/2000. The Malaria Indicator Survey is also part of the MEASURE DHS project and it began in response to the RBM needs of additional information on malaria prevention. Fortunately, DHS and MIS use the same basic malaria questions, making comparisons between and within countries using these surveys straightforward. MICS questionnaires are not identical to DHS/MIS, but comparable measures of malaria prevention between MICS and DHS/MIS can still be obtained.

We will select Sub-Saharan African countries with data from at least two usable DHS/MIS/MICS that contain comparable information on malaria prevention between 1999 and 2010. Table 1 describes our data. There are 34 countries with at least two surveys; 78 surveys are already available, and 33 surveys are ongoing. We expect that we will have three surveys for most countries by the time the project starts. All the surveys in Table 1 include information on ownership and usage of mosquito nets but not all surveys include information on IPT and ACT.

DHS/MIS/MICS samples are nationally representative of the population, but they are drawn from geographical clusters. Clusters vary in size and population but typically contain around 500 individuals. In rural areas a cluster is usually a village or group of villages and in urban areas it is about a city block. We do not use the cluster as our geographical group for two reasons. First, the clusters chosen vary between waves of each country. Thus, we cannot apply cluster fixed effects in equations (4) and (5). Second, because each cluster contains around 30 households, the measurement error of using sample group averages increases considerably.

We will experiment with two geographical measures as our group. First, we will define the group as the region. There are 403 regions and all surveys allow us to identify the region of

the country where the respondent lives. Second, some DHS/MIS/MICS collect the latitude and longitude of the center of each cluster. This information can be used to link the cluster to smaller geographical divisions such as districts. Our 34 countries potentially could be divided into 2,767 districts. Because we have over 700,000 households, the group sample measurement error should be small whether we use districts or regions.

Table 1: Panel Description

Country	Available Surveys	Ongoing Surveys
Angola	MIS06	MICS08, MIS10
Benin	DHS01, DHS06	
Burkina Faso	DHS03, MICS06	DHS10
Burundi	MICS00, MICS05	DHS10
CAR	MICS00, MICS06	MICS10
Cameroon	MICS00, DHS04, MICS06	
Chad	MICS00, DHS04	MICS10
Congo Republic	MICS01, DHS07	MICS10
Cote d'Ivoire	MICS00, AIS05, MICS06	DHS10
Ethiopia	DHS00, DHS05, MIS07	DHS10
Gambia	MICS00, MICS06	
Ghana	DHS03, MICS06, DHS08	
Guinea	DHS99, DHS05	
Guinea-Bissau	MICS00, MICS06	MICS10
Kenya	MICS00, DHS03, DHS08	MIS07, MIS10
Lesotho	DHS04	DHS09
Liberia	DHS07, MIS09	
Madagascar	MICS00, DHS03, DHS08	
Malawi	DHS00, DHS05, MICS06	DHS10
Mali	DHS01, DHS06	DH(S)10, MICS10
Mauritania	DHS00, DHS04(s), MICS06	MICS10
Mozambique	DHS03, MICS08	DHS10
Namibia	DHS00, DHS06	HIV10
Nigeria	DHS03, MICS07, DHS08	MIS10, MICS11
Rwanda	DHS00, DHS05, DH(I)07	DHS10
Sao Tome	MICS00, MICS06	MICS10
Senegal	MICS00, DHS05, MIS06, MIS08	DHS10
Sierra Leone	MICS00, MICS05, DHS08	MICS10
Swaziland	MICS00, DHS06	MICS10
Tanzania	DHS99, DHS04, MIS07	DHS09
Togo	MICS00, MICS06	MICS10
Uganda	DHS00, DHS06	MIS09
Zambia	MICS99, DHS01, DHS07	MIS06, MIS08
Zimbabwe	DHS99, DHS05	DHS10

We will merge each geographical group (region or cluster) to different sources of data. First, we will link environmental data on average rainfall and average temperature obtained from

the Intergovernmental Panel on Climate Change (IPCC). Malaria is more prevalent one to two months after peak rainfall. Second, we will link administrative boundary data obtained from the Mapping Malaria Risk in Africa (MARA, www.mara.org.za). Third, we will link data of the start and end of the transmission season from MARA. Fourth, we will link data on malaria endemicity obtained from the Malaria Atlas Project (MAP, www.map.ox.ac.uk).

We will study the following dependent variables related to mosquito nets and ITNs: 1) number of mosquito nets (including ITNs) owned by the household relative to the household size, 2) number of ITNs owned by the household relative to the household size, 3) mosquito nets (including ITNs) usage relative to household size, 4) ITN usage relative to household size, 5) ITN usage by children under 5, and 6) ITN usage by pregnant women. Our dependent variable associated with IPT usage will be whether a woman who delivered a baby during the last 5 years completed the IPT treatment. Finally, for the ACT analysis our dependent variables will be whether a child who had fever during the previous two weeks received any anti-malaria drugs and whether he/she received ACT treatment.

There are several potential explanatory variables in DHS/MIS/MICS. For the household-level analysis of mosquito net or ITN usage (dependent variables 1, 2, 3, and 4), we can calculate the share of children under 5 and pregnant women in the household, the household level of education, mothers' average age, household size, household exposure to public health messages of sleeping under an ITN, dwelling characteristics, and household wealth quintile. In the household ownership equations, we can also include availability of transportation and self-reported distance to a health facility. Area characteristics include whether the interview was conducted during the malaria season, average rainfall, and average temperature. Other potential variables include loss of a previous child and other preventive behaviors not related to malaria such as immunizations. A potential problem is that our decomposition of unobserved correlated group effects (v_{gt}) into a time-invariant group-specific effect (v_g) and a group-invariant time-specific effect (η_t) will be violated if there are factors that affect the ITN ownership and usage of everyone in the group (such as campaigns that distribute ITNs), but the timing of the campaign was not uniform across groups. This will not affect our estimates of equation (4), but it will affect our estimates in equations (5) and (6). To mitigate this problem we will interact time dummies with country fixed effects and region fixed effects in our district analysis.

In the individual analysis of ITN usage, our exogenous variables will include age of the child, mother's education, whether a parent is the head of the household, dwelling characteristics, exposure to ITN messages, household size and wealth quintiles. In our analysis of IPT treatment for recent mothers, we will include the following explanatory variables: age, education, number of previous children, birth interval, household size, wealth quintile, availability of transportation and distance to health facilities. Finally in our analysis of ACT, our explanatory variables will include age of the child, mother's education, whether a parent is the head of the household, exposure to ACT messages, household size, wealth, availability of transportation and distance to health facilities.

In our basic model we assume that the social spillovers are geographic. It may be possible that social spillovers are larger and occur at a faster rate in regions that are culturally and linguistically more homogeneous. DHS/MIS/MICS collects information on ethnic group, language, and religion of the household. This information will allow us to divide our groups into homogeneous and less homogeneous groups. We will then test whether homogeneous groups have a higher social multiplier. Using the same approach we will also test whether malaria endemicity (e.g. stable vs. unstable) changes the size of the social multiplier.

If we find that social interactions are important, we will collect precise field data on social networks of individuals and their source of information to identify the characteristics of the individuals that are more likely to influence the group's behavior. This will allow policy makers to target these influential people through campaigns in order to take the greatest advantage of these potentially large spillover effects.

Picone –R03

Human Subjects Protection/Risks to Human Subjects

a. Human Subjects Involvement, Characteristics and Design

We will only use secondary data that is publically available. Currently, we have data on 680,000 households in 34 countries.

b. Sources of Materials

Only secondary data will be used with no individual identifiers. Date will be obtain from:

Demographic and Health Survey (DHS) multiple countries and years

Malaria Indicator Survey (MIS) multiple countries and years

Multiple Indicators Cluster Survey (MICS) multiple countries and years

c. Potential Risks

There are no risks to the subjects

d. Potential Benefits of the Proposed research to Human Subjects and others

The only benefits to the subjects are through the findings of the study which may lead to better policies.

Picone R03

Inclusion of Women and Minorities

Our primary sample will consist of children under age 5, pregnant women, and recent mothers. Our preliminary work with the data for selected countries (Ghana and Nigeria) suggests that the ratio of men to women (including children) will be about 4 to 7.

Our data will come from Sub-Saharan Africa and we expect the large majority of subjects to be black with less than 2% white. Hispanic participation is negligible.

Picone_R03

Targeted/Planned Enrollment Table

Hispanic or Latino	0.2%
Not Hispanic or Latino	99.8%
Ethnic Category:	
Racial Categories	
American Indian/Alaska native	0
Asian	0
Native Hawaiian or other Pacific Islander	0
Black	98%
White	2%

Children will not be excluded from the study and the primary sample will consist of children under age 5.

Data will come from Sub-Saharan Africa so the majority of subjects will be not Hispanic or Latino and the majority will be black with a small percentage of white and Hispanic.

Picone –R03

Inclusion of Children

Children under age 5 will be the main focus of the study. It is expected that children under age 5 will make up approximately 70% of the study population depending on the specification.

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UNIVERSITY OF CAPE COAST
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DEPARTMENT OF POPULATION AND HEALTH

UNIVERSITY POST OFFICE
CAPE COAST, GHANA

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LETTER OF SUPPORT – STUDY ON MALARIA IN GHANA

I write to indicate my interest in and willingness to participate in the proposed study on malaria in Ghana involving the University of Cape Coast and the University of South Florida. I have been working with Dr. Gabriel Picone and colleagues on aspects of Malaria in Ghana. My involvement in the proposed project will include providing local context and the necessary backstopping in Ghana.

I will be involved with my colleague, Mr. Daniel Amoako-Sekyi of the School of Medical Sciences, who is also involved in research in Malaria. As a major health problem in Ghana, a study on Malaria will contribute to the search for strategies which can be incorporated into policy and programs.

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