Social Interactions and Malaria Preventive Behaviors*

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Abstract

In this study we analyze whether social interactions are important determinants of health preventive behaviors in Sub-Saharan Africa specifically on malaria preventive behaviors for children under five and prenatal care for pregnant women. Malaria still is the major cause of mortality in Sub-saharan Africa for children under five, fortunately technologies exist that can prevent and cure malaria. Among these technologies sleeping under a insecticide treated net (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.

Keywords: Social interactions, social multiplier, malaria preventive behaviors, ITN, IPT.

J*EL classification*: I12

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1 Introduction

It is well known that social interactions are important in explaining large variations across time and space for many variables when measured at an aggregate level that cannot be explain from estimates of standard econometrics models (Glaeser and Sheinkman 2001, 2002). The main reason is that social interactions can lead to a large social-multiplier effect, where an individual's adoption of a technology or a small change in the fundamentals behind an action creates a social spillover that produces a much larger effect at the aggregate level. Social interactions has been shown to be significant in explaining a wide range of actions and/or behaviors including crime (Glaeser, Sacerdote and Sheinkman 1996), labor force participation (Bernheim 1994), out-of-wedlock births (Young 1997), the S-shape curve of hybrid corn adoption (Ellison and Fudenberg 1993), fertility in developing countries (Bloom et al., 2008), obesity (Auld 2011), among other behaviors.

In this study we analyze whether social interactions are important determinants of health preventive behaviors in Sub-Saharan Africa specifically on malaria preventive behaviors for children under five and prenatal care for pregnant women. Malaria still is the major cause of mortality in Sub-saharan Africa for children under five, fortunately technologies exist that can prevent and cure malaria. Among these technologies sleeping under a insecticide treated net (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).

Social interaction may be important determinants of adoption of ITN due to several reasons. First, individuals learn about the benefits of ITNs from the experiences of their neighbors either through conversations or direct observation (social learning). Second, it is possible that there peer effects or social influences from the usage of ITNs by a few sophisticated agents to the rest of the group. Third, outside factors such as public campaigns may encourage the usage of ITN to become the new social norm. Fourth, as more individuals sleep under an ITN, the individual risk of contracting malaria decreases causing a negative social interaction effect.

As comprenhesively discussed in Manski (1993) and more recently in Blume et al. (2011), 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), Bloom et al. (2008), Auld (2011) 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 come from 29 sub-saharan countries; 78 surveys (37 Demographic Health Surveys (DHS), 5 Malaria Indicator Surveys (MIS), 29 Multiple Indicator Cluster Surveys (MICS), 3 AIDS Indicator Survey (AIS), 2 special DHS) between 1999 and 2011. There are 326 regions and 572,939 children. We find that social multiplier is positive and significant, but small.

2 A Model of Social Interactions an Preventive Behaviors

Our goal is to explain the health preventive choices of an individual i who lives in a village g at time t of size n_{gt}, we denote this choice P_{igt} and it could represent sleeping under an ITN or any other preventive behavior. Each individual observes the average actions of his/her peers or reference group, $\widetilde{P}_{-igt} = \frac{1}{n_{gt}-1}\sum_{j\neq i} P_{jgt}$, it is subject to a taste shock given by $\digamma_{igt}$ and then chooses the optimal level, P_{igt}. Most empirical studies in the social interaction literature assume that the choice set is continuous, the real line, and a quadratic utility given by:

$$U\left(P_{igt}, \widetilde{P}_{-igt}, \digamma_{igt}\right) = \digamma_{igt}P_{igt} - \frac{1-\gamma}{2}P_{igt}^2 - \frac{\gamma}{2}\left(P_{igt} - \widetilde{P}_{-igt}\right)^2 \tag{1}$$

where $\gamma \in (0,1)$ is the conformity parameter, $g = 1, ..., G$ and $t = 1, \ldots, T^g$. We assume the "taste shock" can be decomposed as

$$\digamma_{igt} \equiv \alpha + X_{igt}\beta + \widetilde{X}_{-igt}\delta + A_{gt}\theta + v_{gt} + \varepsilon_{igt} \tag{2}$$

where X_{igt} are the exogenous individual level covariates like age, gender, education, and wealth. $\widetilde{X}_{-igt} = \frac{1}{n_{gt}-1}\sum_{j\neq i} X_{jgt}$ measure the contextual social interactions. A_{gt} are observable area characteristic variables that affect all individuals' malaria-preventive behavior in the group at the same time like rain and temperature. The solution to the maximization of this utility function produces the standard linear-in-mean model:

$$P_{igt} = \alpha + \widetilde{P}_{-igt}\gamma + X_{igt}\beta + \widetilde{X}_{-igt}\delta + A_{gt}\theta + v_{gt} + \varepsilon_{igt} \tag{3}$$

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 (to the researcher) 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.

Glaeser and Sheinkman (2001) and Blume et al. (2011) show that the Bayes-Nash equilibrium for the above model exist and it is unique. The equilibrium solution leads to the following reduced form equation:

$$P_{igt} = \frac{\alpha}{1-\gamma} + X_{igt}\beta + \widetilde{X}_{gt}\left(\frac{\gamma\beta+\delta}{1-\gamma}\right) + A_{gt}\frac{\theta}{1-\gamma} + \frac{v_{gt}}{1-\gamma} + \varepsilon_{igt} \tag{4}$$

where $\widetilde{X}_{gt} = \frac{1}{n_{gt}}\sum_i X_{igt}$ is the group mean of individual characteristics. From equation (4) we can calculate the group level equilibrium:

$$\widetilde{P}_{gt} = \frac{\alpha}{1-\gamma} + \widetilde{X}_{gt}\left(\frac{\beta+\delta}{1-\gamma}\right) + A_{gt}\frac{\theta}{1-\gamma} + \frac{v_{gt}}{1-\gamma} + \widetilde{\varepsilon}_{gt} \tag{5}$$

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 control for the spurious unobserved group effect. We interpret this social multiplier as the steady state or long run effect of the exogenous variable that accounts not only for the direct effect of the exogenous variable but all of the indirect effects caused by the social interactions.

3 Econometrics Strategy

If we assume that there are no unobserved correlated group effects ($v_{gt} = 0$) and we have data in all individuals in the group it is straightforward to estimate $\left(\frac{\gamma\beta+\delta}{1-\gamma}\right)$ and β from the reduced form equation (4) using standard regression methods. Unfortunately, we can not rule out unobserved correlated group effects and we only observed a sample $m_{gt} < n_{gt}$ of individuals from each group g at time t. The first approach that we use to measure social interactions is to compare the variances at the individual and aggregate level. Assuming no contextual effects ($\delta = 0$), Glaeser and Scheinkman (2001) showed that:

$$\alpha = \frac{Var_{agg} - Var_{ind}}{Var_{agg} + Var_{ind}} \tag{6}$$

The second approach to estimate the social interaction is developed in Glaeser and Scheinkman (2001) and Glaeser et al. (2003) and it involves calculating the ratio of aggregate $(\frac{\beta+\delta}{1-\gamma})$ and individual (β) coefficients for the exogenous regressors. See Graham and Hahn (2005), Bloom et al. (2008) and Auld (2011) for applications of this method.

Note that we can estimate β from equation (4) applying the fixed effect estimator to the following equation:

$$P_{igt} = \alpha + X_{igt}\beta + w_{gt} + \varepsilon_{igt} \tag{7}$$

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 $E_g\left(X_{igt}\right)$ and A_{gt}, because they are invariant to time-specific group effects.

Finally, assume 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, we can obtain a consistent estimator of $\left(\frac{\beta+\delta}{1-\gamma}\right)$ using the between-group variation accross time:

$$\overline{P}_{gt} = \frac{\alpha}{1-\gamma} + \overline{X}_{gt}\left(\frac{\beta+\delta}{1-\gamma}\right) + A_{gt}\frac{\theta}{1-\gamma} + \frac{v_g}{1-\gamma} + \frac{\eta_t}{1-\gamma} + \overline{\varepsilon}^*_{gt} \tag{8}$$

where $\overline{\varepsilon}^*_{gt} = \left[\widetilde{X}_{gt} - \overline{X}_{gt}\right]\left(\frac{\gamma\beta+\delta}{1-\gamma}\right) + \widetilde{\varepsilon}_{gt}$. We can estimate this equation using time and group fixed effects. However, $\overline{X}_{gt}$ will be correlated with the disturbance in equation (8) 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: $\overline{X}_{1gt}$ and $\overline{X}_{2gt}$. We then use one set as an instrument for the other. Because of the random assignment into both groups, this estimator is consistent.

4 Data

The data for this analysis will come from the Demographic and Health Surveys (DHS), Malaria Indicator Surveys (MIS), AIDS Indicator Surveys (AIS) and Multiple Indicator Cluster Surveys (MICS) for countries in Sub-Saharan Africa. These surveys are large and nationally representative for a number of Sub-Saharan Countries. 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 (MIS) and AIDS Indicator Survey (AIS) are also part of the MEASURE DHS project. Fortunately, DHS, AIS 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/AIS, but comparable measures of malaria prevention between MICS and DHS/MIS/AIS can still be obtained.

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. Instead we use regions.

We conduct separate analysis for children under 5 and women that were pregnant during the last five years before the survey the two most vulnerable groups to malaria. We restrict our data to Sub-Saharan African countries at least two usable DHS/MIS/AIS/MICS surveys containing comparable information on malaria prevention between 1999 and 2011. Table 1 describes our data. There are 29 countries; 78 surveys (37 DHS, 29 MICS, 5 MIS, 3 AIS, and 2 special DHS), 326 regions, and 572,939 children under 5.

5 Empirical Specification

Overview: We estimate equations (4) and (6) for both samples: children under 5 and pregnant women. In the estimation of equation (4) we use individual data, while in the estimation of equation (6) we aggregate the dependent and explanatory variables at the regional level.

Dependent Variables: We study the following dependent variables for children under five: 1) Whether a child slept under a mosquito net the nigth before the survey, 2) whether the child slept under an ITN the nigth before the survey. We are able to create consistent information on this measure for all surveys with malaria preventive behavoirs modules. Sleeping under an ITN is considered the main tool in the RBM parthership arsenal to figth malaria. 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.

Explanatory Variables: We divide the explanatory variables into the following categories: individual level, household level, area level, region fixed effects, and time fixed effects. Below we discuss these categories in more detailed for both the children and women/pregnant analysis.

Individual level variables for the children sample include: age, gender, mother's education, and relation to the head of the household. We expect age to have a negative effect on the probability of sleeping under a mosquito net because the risk of malaria decreases with age. Mother's education will be defined as a binary indicating whether the mother has secondary education or higher and we expect this variable to have a positive effect on the probability of sleeping under the net because educated mothers are more likely to understand the advantages of nets. In rural areas in Africa the head of the household decides who uses the mosquito net every nigth, we include binaries indicating wheter the child is a son/daughter of the head of the household and whether the child is a grandson/granddaughter of the head of the household to test whether priority is given to the closest kin to the head of the household. For the woman/pregnant analysis we will include age, education, time between the survey and the birth of the baby, whether the head of the household was a parent of the child.

Household level variables include household size, number of children under 5 in the household, and household wealth. We expect household size and number of children in the household to have a negative effect because they measure higher competition for resources. On the hand household wealth should have a positive effect on the dependent variables because it implies more resources. Household wealth is measured by ...

Area level variables include cluster fixed effects in the estimation of equation (4) and the percentage living in urban areas in equation (6) .... Including cluster fixed effects controls for factors that affect the dependent variables for all individuals in the area equally at the time of the survey. [Area characteristics include whether the interview was conducted during the malaria season, average rainfall, and average temperature.]

We also include regional fixed effects in equation (6) and time fixed effects in equations (4) and (6). 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.

6 Results

6.1 Evaluating social interactions using excess variance across regions

We first identify whether there are social interactions in preventive behaviors by examining the variance in prevention across regions. Indeed, social interactions imply high levels of variance across space.

If there is no social interaction and if people are randomly distributed across regions, the variance of mean preventive behaviors among regions should be equal to the variance of preventive behaviors among individuals. In contrast, if the variance of the mean preventive behaviors among regions is larger than the variance of preventive behaviors among individuals, there is either social interactions and/or sorting of individuals across regions.

In a first step, we do not address the sorting of individuals. We compare the variances computed at the individual and regional level, without any control. The implied social multipliers are heavily biased in favor of finding social interactions.

In a second step, we want to isolate social interactions from the sorting of individuals across regions. We assume that sorting across regions depends on a number of fundamentals (individual observed characteristics and/or country fixed unobserved characteristics). We re-estimate the variances at the individual and regional levels, controlling for these characteristics. This time, the comparison of the variance at the individual and regional levels is informative of social interactions alone.

Table 3 displays the estimates of the variance at the individual and regional levels, α and the social multiplier, for sleeping under a bednet and under an ITN.

[Insert Table 3 here]

The estimates in Panel A do not control for any observed characteristic and are thus biased in favor of finding social interactions. In this case, we find an α value of 0.986 for both sleeping under a net and an ITN. The implied social multiplier is 71.42. Panel B shows the results when we calculated the individual and aggregate variance controlling for individual observed characteristics, to address the sorting of individuals. Both the individual and aggregate variance slightly decline and the estimates of α also decrease to 0.987 and 0.983. These estimates still represent very large levels of social interactions. Panel C displays the results when we control for country fixed effects in addition to individual characteristics. Country fixed effects control for any unobserved variable affecting bednet and ITN usage. As expected, individual and aggregate variances decrease substantially. The overall value of α declines to 0.974 and 0.959, which markedly decreases the implied social multipliers to 38.46 and 24.39. These estimates are roughly half as large as in Panel A when we did not correct for observable and unobservable influences on bednet and ITN usage.

To sum up, bednet and ITN usage do not display sizeable excess variation across regions, when we control for observed and unobserved influences on usage. Sleeping under an ITN display more unexplained variation across regions than sleeping under a bednet.

6.2 Evaluating social interactions using regressions

The second method we use to quantify social interactions is the comparison between the predictors of prevention at the individual level and the predictors of prevention at the region levels.

Table 4 displays the regression results for sleeping under any type of bednets, in columns (1) and (2), and an ITN, in columns (3) and (4). Columns (1) and (3) give the results for the individual (child)-level regression, whereas columns (2) and (4) give the results for the region-level regressions.

[Insert Table 4 here]

The child level regressions in columns (1) and (3) indicate that as children grow older, from birth to 4 years of age, the probability that he sleeps under any type of bednet and under an ITN significantly decreases. The probability that a child aged 0 sleeps under any type of bednet is 2.63 percentage points larger than for a child aged 3-4; but the probability that a child aged 1-2 sleeps under any type of bednet is only 0.11 percentage points larger than for a child aged 3-4. We also observe a quick decrease in the probability of sleeping under an ITN with age. Interestingly, the age pattern is reversed in regional-level regressions in columns (2) and (4). At the regional level, children ages 0 are less likely than older children to sleep under a bednet or an ITN.

Similarly, we find that the effect of the child gender is different at the individual and regional levels. At the individual level, male and female children are as likely to sleep under a bednet or an ITN. In contrast, at the regional level, boys have a significantly larger likelihood of sleeping under a bednet or an ITN than girls.

The effect of household size on bednet and ITN usage is negative in the four models and significant in models (1) to (3). This finding is consistent with competition for resources within households: for a given number of bednets and ITNs within a household, the likelihood that the bednet is attributed to a child decreases with the number of household members.

The bottom of Table 4 displays the social multipliers. The social multiplier for sleeping under any type of bednet and an ITN are 1.036 and 1.012. These results suggest first that the multipliers for malaria prevention are rather small, compared to the multipliers for fertility for instance (Bloom et al., 2008). Second, these results imply that social interactions are larger for sleeping under any type of bednet than for sleeping under an ITN.

Table 5 reports the estimates for whether the woman received prenatal care by a skilled provider (a doctor or a nurse) and took IPT, during her last pregnancy.

[Insert Table 5 here]

Both the individual and region-levels regressions indicate that women with a secondary education are more likely to attend prenatal care and take IPT than women with no education or primary education only. This is an expected result, since women with a higher education are more likely to be aware of the benefits of prenatal care interventions and antimalarial drugs for their own health and neonatal mortality.

Women's age also matters, at the individual level. The probability that a pregnant woman attends prenatal care decreases with her age but the probability that she takes IPT increases with age. As a woman age, she is more likely to have had a greater number of pregnancies. So the negative effect of woman's age on the probability of attending prenatal care simply means that a woman with more experience in childbearing finds it less useful to attend prenatal care than a woman with less experience.

There is no social multiplier for prenatal care. This result was expected: indeed, the share of women atending prenatal care is very high, and might be close to its long-run equilibrium level. As a consequence, the absence of social interaction is expected.

7 Conclusion

Prevention against malaria is inadequate in most sub-Saharan countries. The paper examines whether social interactions explain prevention against malaria in sub-Saharan Africa and thus could help reach adequate levels of prevention. We use several methods to quantify social multipliers, each with different strength and weaknesses. Taken together, our results suggest that social multipliers in prevention are small in these countries.

Social interactions imply excess variation in prevention across regions. For this reason, our first method is to examine whether there is excess variation in prevention across regions. The results suggest that excess variation is not apparent in the data and that social multipliers are probably small. Social multipliers in ITN usage appear to be larger than social multipliers in bednet usage and antenatal care.

The second empirical strategy infers social multipliers from comparison of estimates of individual and region-levels regressions. We find small but significant social spillovers in bednet and ITN usage, but no positive social multiplier in antenatal care.

Our analysis faces a number of limitations. First, it is possible that our aggregate results are biased because we cannot control for malaria control policies that affect usage and were implemented at different times for different regions of the same country. Our individual results control for these differences using cluster fixed effects. Second, we assume a linear-in-mean model of social interactions and do not take advantage of the binary nature of our dependent variables. Future work will address these problems.

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Table 1: Data sources

Country	No. waves	No. regions	No. children	Surveys
Angola	3	17	16,927	MICS01, MIS06, MIS07
Benin	2	6	21,504	DHS01, DHS06
Burkina Faso	2	13	15,564	DHS03, MICS06
Burundi	2	17	10,222	MICS00, MICS05
Cameroon	3	12	18,061	MICS00, DHS04, MICS06
CAR	2	17	22,431	MICS00, MICS06
Chad	2	8	10,340	MICS01, DHS04
Côte d'Ivoire	3	11	20,238	MICS00, AIS05, MICS06
DRC	2	11	18,995	MICS01, DHS07
Ethiopia				DHS00, DHS05
Gambia	2	8	10,061	MICS00, MICS05
Ghana	3	10	13,673	DHS03, MICS06, DHS08
Guinea	2			
Kenya	3	8	18,997	MICS00, DHS03, DHS08
Lesotho				
Liberia				
Madagascar	3	6	21,375	MICS01, DHS03, DHS08
Malawi	4	26	59,871	DHS00, DHS04, MICS06, DHS09
Mali	3	9	27,513	DHS01, DHS06, SP10
Mozambique	2	11	14,265	DHS03, AIS09
Namibia	2	12	8,757	DHS00, DHS07
Niger	2	8	14,218	MICS01, DHS06
Nigeria	4	36	55,859	DHS03, MICS06, DHS08, MIS10
Rwanda	5	12	32,050	DHS00, MICS01, DHS05, DHS(I)08, DHS10
Senegal	4	10	41,744	MICS01, DHS05, MIS06, MIS08
Sierra Leone	3	4	14,807	MIC01, MICS06, DHS08
Swaziland	2	4	6,400	MICS01, DHS06
Tanzania	3	21	24,916	DHS04, AIS07, DHS10
Togo	2	6	7,229	MICS01, MICS06
Uganda	3	4	18,017	DHS01, DHS06, MIS10
Zambia	3	9	19,212	MICS01, DHS02, DHS07
Zimbabwe	2	10	9,693	DHS99, DHS05
Total	78	326	572,939	

Notes. DHS stands for standard Demographic and Health Survey, DHS(I) for interim DHS, SP for special DHS, MICS for Multiple Indicator Cluster Survey and MIS for Malaria Indicator Survey.

Table 2: Summary statistics

		Standard deviation	
	Mean	Individual	Region
Children's preventive outcomes			
Sleeping under a bednet	.302	.459	.230
Sleeping under an ITN	.198	.398	.200
Women's preventive outcome			
Prenatal care doctor/nurse	.752	.431	.214
Children's demographics			
child aged 0	.231	.421	.027
child aged 1 or 2	.399	.489	.028
child is male	.503	.499	.023
mother's age	28.730	7.506	2.090
mother: secondary education	.145	.352	.161
mother's education missing	.021	.144	.101
household size	7.480	4.860	2.690
Women's demographics			
woman's age	27.420	6.824	1.224
woman: secondary education	.184	.387	.181
woman's education missing	.012	.112	.067
household size	7.246	4.935	2.835

Table 3: Aggregate variance and social interactions

	Var_{ind}	Var_{agg}	α	Social multiplier
A. Unadjusted				
Sleeping under a bednet	.207	31.358	.986	71.428
Sleeping under an ITN	.157	23.590	.986	71.428
B. Adjusted for individual covariates				
Sleeping under a bednet	.194	31.177	.987	76.923
Sleeping under an ITN	.137	16.404	.983	58.823
C. Adjusted for individual covariates and country fixed effects				
Sleeping under a bednet	.169	12.965	.974	38.461
Sleeping under an ITN	.123	5.984	.959	24.390

Table 4: Social multipliers in preventive behaviors for children

	Sleeping under a bednet		Sleeping under an ITN	
	Individual	Aggregate	Individual	Aggregate
	(1)	(2)	(3)	(4)
Age 0	0.0263***	-0.370**	0.0418***	-0.319*
	(0.00154)	(0.188)	(0.00139)	(0.165)
Ages 1-2	0.0110***	0.226	0.0249***	-0.0779
	(0.00132)	(0.168)	(0.00118)	(0.147)
Male	-0.00131	0.398***	-0.000943	0.388***
	(0.00114)	(0.105)	(0.00103)	(0.0908)
Hh size	-0.00367***	-0.0112**	-0.00370***	-0.00447
	(0.000141)	(0.00552)	(0.000126)	(0.00483)
Mother's education missing	-0.0156***	0.0409	0.0299***	0.178***
	(0.00481)	(0.0600)	(0.00418)	(0.0520)
Mother secondary education	0.0961***	-0.183**	0.0827***	0.0183
	(0.00181)	(0.0867)	(0.00161)	(0.0757)
Mother's age	0.000476***	-0.000529	0.000515***	0.00874*
	(8.24e-05)	(0.00514)	(7.40e-05)	(0.00445)
Observations	500,327	932	461,860	888
R-squared	0.226	0.842	0.232	0.852
Social multiplier	1.036		1.012	
	(.000)		(.000)	

Table 5: Social multipliers in preventive behaviors for women

	Prenatal care doctor/nurse		IPT	
	Individual	Aggregate	Individual	Aggregate
	(1)	(2)	(3)	(4)
Hh size	0.000292	-0.00941	0.000273	0.0178***
	(0.000233)	(0.00648)	(0.000206)	(0.00669)
Woman secondary education	0.0201***	0.125*	0.0805***	0.475***
	(0.00273)	(0.0749)	(0.00247)	(0.100)
Woman's education missing	-0.0230**	-0.0706	-0.683***	-3.618***
	(0.00896)	(0.0751)	(0.0237)	(0.821)
Woman's age	-0.000755***	0.000212	0.000530***	0.00704
	(0.000142)	(0.00409)	(0.000122)	(0.00710)
Observations	169,164	934	166,885	729
R-squared	0.191	0.657	0.467	0.925
Social multiplier	1.001		1.026	
	(.000)		(.000)	