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# Social Interactions and Malaria Preventive Behaviors in Sub-Saharan Africa

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## ABSTRACT

This paper examines the existence of social interactions in malaria preventive behaviors in Sub-Saharan Africa, i.e. whether an individual's social environment has an influence on the individual's preventive behaviors. We focus on the two population groups which are the most vulnerable to malaria (children under 5 and pregnant women) and on two preventive behaviors (sleeping under a bednet and taking intermittent preventive treatment during pregnancy). We define the social environment of the individual as people living in the same region. To detect social interactions, we calculate the size of the social multiplier by comparing the effects of an exogenous variable at the individual level and at the regional level. Our data come from 92 surveys for 29 Sub-Saharan countries between 1999 and 2012, and they cover approximately 660,000 children and 95,000 women. Our results indicate that social interactions are important in malaria preventive behaviors, since the social multipliers for women's education and household wealth are greater than one - which means that education and wealth generates larger effects on preventive behaviors in the long run than we would expect from the individual-level specifications, once we account for social interactions.

Key words: social interactions, social multiplier, malaria preventive behavior

JEL Classification: I12

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## 1. INTRODUCTION

Malaria is transmitted to people through the bites of infected anopheles mosquitoes. The World Malaria Report estimates that 660,000 individuals died of malaria in 2010. Over 80% of these deaths occurred in 14 countries in Sub-Saharan Africa and 86% of them occurred in children under 5 (WHO, 2012). Young children and pregnant women are particularly at risk because they do not have functional immunity against the disease or they temporarily lose their immunity. Fortunately, technologies exist that can prevent and cure malaria. Among these technologies, sleeping under an 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 net. This not only prevents the bite, but also reduces the mosquito population (RBM, 2010). In a comprehensive review of the literature, Lengeler (2004) concludes that widespread use of ITNs could reduce child mortality by 20%. ITNs have also been shown to be cost effective compared to other preventive measures (Binka et al., 1996; Goodman and Mills, 1999; Wiseman et al., 2003). For pregnant women, taking an intermittent preventive treatment (IPTp) during the gestation period has been found very effective in protecting mother and unborn baby from malaria.

In this paper, we empirically analyze the importance of social interactions on these two malaria preventive behaviors (bednet usage and preventive treatment during pregnancy) for children under 5 and pregnant women in Sub-Saharan Africa. Social interactions refer to the influence of the neighbors' preventive behaviors on the individual's preventive behaviors (endogenous social interactions) and to the effect of the neighbors' characteristics on the individual's preventive behavior (exogenous social interactions). Previous studies show that social interactions are important determinants of a wide range of behaviors, including crime (Glaeser et al., 1996), labor force participation (Bernheim, 1994), hybrid corn adoption (Ellison and Fudenberg, 1993), new agricultural technologies adoption (Conley and Udry, 2010), obesity (Auld, 2011), and fertility in developing countries (Canning et al., 2013). But to our knowledge, there is no empirical evidence regarding the existence of social interactions for malaria preventive behaviors. Yet, social interactions

may be important determinants of the adoption of malaria preventive methods for two reasons. First, mothers and pregnant women may learn about the benefits of malaria preventive behaviors from their neighbors' experiences with bednets or preventive treatments during pregnancy, either through conversation or direct observation (social learning). Second, it is possible that there are social influences from a few sophisticated agents to the rest of the group through explicit or implicit group pressures, where for example sleeping under a bednet becomes the new social norm.<sup>1</sup>

As originally discussed by Manski (1993) and more recently by Blume et al. (2011), it is impossible to identify endogenous and exogenous social interactions separately without longitudinal data containing detailed information on both the individual sources of information and their social networks. Our goal is more modest: we try to identify the existence of social interactions and to calculate the magnitude of the social multiplier implied by these social interactions. The existence of social interactions and the size of the social multiplier have important health policy implications. If there are social interactions, then policies that successfully convince an individual to adopt a technology (such as ITNs) will have a much larger effect in the long run than in the absence of social spillovers. In addition, knowledge about the size of the social multipliers associated with particular explanatory variables will allow policy makers to use resources more efficiently.

To estimate the social multiplier, we follow the strategy developed by Glaeser and Scheinkman (2002), Graham and Hahn (2005), Auld (2011), and Canning et al. (2013). Specifically, we define the neighbors of an individual as the individuals living in his region, and we calculate the size of the social multiplier by comparing the effect of a factor on preventive behaviors at the individual level, with the effect of (the mean of) the factor on (the average) preventive behaviors at the regional level. In the absence of social interactions, the effect of the factor on preventive behaviors at the individual level should be equal to the effect at the regional level. In contrast, we can conclude that there are social interactions if the effect of the factor on preventive behaviors at the regional level

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<sup>1</sup>The previous economic literature on malaria preventive behaviors studies the role of free distribution and cost sharing on bednets demand and usage (Dupas and Cohen, 2008), tests whether the demand for bednets varies with the framing of the marketing message in Kenya (Dupas, 2009), and quantifies the elasticity of bednet usage with respect to malaria prevalence in Sub-Saharan Africa (Picone et al., 2013).

is greater than at the individual level.

Our method requires repeated cross-sectional data and a large sample size. Our data come from 29 Sub-Saharan countries and 92 surveys (Demographic Health Surveys, Malaria Indicator Surveys, Multiple Indicator Cluster Surveys and AIDS Indicator Survey) between 1999 and 2012.

We find that the effects of women's education and household wealth on preventive behaviors at the regional level are significantly greater than at the individual level. The results provide support for the hypothesis that social interactions play an important role in explaining malaria preventive behaviors. In addition, policies that increase the level of education and wealth are likely to generate larger spillovers than policies that only concentrate on net distribution and preventive treatment uptake.

The paper is organized as follows. Section 2 presents a model of social interactions for malaria preventive behaviors. Section 3 contains the econometric strategy. Section 4 presents the data used in the analysis. Section 5 contains the empirical specification. Section 6 presents our results on the role of social interactions in malaria preventive behaviors, whereas Section 7 contains robustness checks and additional results. Lastly, Section 8 offers some concluding remarks.

## 2. A MODEL OF SOCIAL INTERACTIONS AND PREVENTIVE BEHAVIORS

This section presents a simple model of social interactions for malaria preventive behaviors based on Glaeser and Scheinkman (2001) and Blume et al. (2011). Although in our empirical study we analyze both sleeping under a bednet and taking an antimalarial drug during pregnancy, in the theoretical model we only focus on sleeping under a bednet to simplify the exposition.

For each time period  $t$ , assume that the population is arranged in  $G$  non-overlapping groups ( $g = 1, \dots, G$ ). We consider a mother of a child that is identified with an integer  $i$  and who belongs to group  $g$  at time  $t$ . The number of children in the group at time  $t$  is denoted  $n_{gt}$ . We assume that the utility enjoyed by the mother depends on her child preventive behaviors ( $P_{igt}$ ), the expected average preventive behaviors of the other

children in the group at time  $t$  ( $P_{-igt}$ ), and a “taste shock” ( $\Theta_{igt}$ ). Moreover, we assume that the mother’s utility is quadratic:

$$U(P_{igt}, P_{-igt}, \Theta_{igt}) = \Theta_{igt}P_{igt} - \frac{1-\gamma}{2}P_{igt}^2 - \frac{\gamma}{2}(P_{igt} - P_{-igt})^2 \quad (1)$$

where  $0 \leq \gamma < 1$  measures the taste for conformity. We also assume that the “taste shock” can be decomposed as:

$$\Theta_{igt} \equiv \alpha + X_{igt}\beta + X_{-igt}\delta + v_{gt} + \varepsilon_{igt} \quad (2)$$

where  $X_{igt}$  denotes the child-mother characteristics, such as the child age, gender, or the mother’s education, and  $X_{-igt}$  represents the average characteristics of the other children-mothers in the group at time  $t$ .

The mother chooses the continuous level of preventive behavior for the child that maximizes equation (1) subject to the average preventive behaviors of the other children in the group and her “taste shock.” The solution to the maximization of the utility function produces the standard linear-in-means model:

$$P_{igt} = \alpha + P_{-igt}\gamma + X_{igt}\beta + X_{-igt}\delta + v_{gt} + \varepsilon_{igt} \quad (3)$$

where the taste for conformity,  $\gamma$ , measures endogenous social interactions and  $\delta$  gives exogenous (contextual) social interactions.<sup>2</sup> Endogenous social interactions reflect the influence of the other children’s preventive behaviors on child  $i$ ’s preventive behavior. In our application, endogenous social interactions may arise when mothers are uncertain about the benefits of bednet usage for their children and their expectations of these benefits are a function of the group preventive behavior. Exogenous social interactions arise when the characteristics of the other children and mothers in the group,  $X_{-igt}$ , affect child  $i$  preventive behaviors through social pressure. For example, a group with a large percentage of highly educated mothers may make sleeping under a bednet the social norm

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<sup>2</sup>The model described by equations (1) and (2) is convenient to solve, but imposes unrealistic assumptions. In particular, it assumes that  $P_{igt}$  is a continuous variable and that there are no cross products between  $P_{-igt}$  and  $X_{-igt}$ . We interpret equation (3) as a linearization of some unknown non-linear function that represents the solution of the true model.

for all children in the group.

We assume that  $v_{gt}$  represents the group effect at time  $t$  that is observable to all mothers in the group at time  $t$ , but unobservable to us. We allow  $v_{gt}$  to be correlated with  $X_{igt}$  and  $X_{-igt}$ . Finally,  $\varepsilon_{igt}$  is the individual idiosyncratic component. We assume that  $E(\varepsilon_{igt}|X_{igt}, X_{-igt}, v_{gt}) = 0$  and that  $\varepsilon_{igt}$  is uncorrelated with  $\varepsilon_{i'g't'}$  for each  $i \neq i'$  or  $g \neq g'$  or  $t \neq t'$ .

Taking the expected value at the group-time level on both sides of equation (3) and solving for  $P_{-igt}$  leads to the social equilibrium for the group:

$$P_{-igt} = \frac{\alpha}{1-\gamma} + X_{-igt} \left( \frac{\beta + \delta}{1-\gamma} \right) + \frac{v_{gt}}{1-\gamma} \quad (4)$$

Substituting (4) into (3) and replacing  $X_{-igt}$  with its sample counterpart  $\bar{X}_{gt} = \frac{1}{m_{gt}} \sum_i X_{igt}$  leads to the following individual-level equation:<sup>3</sup>

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

where

$$\varepsilon_{igt}^* = \varepsilon_{igt} + \left( \frac{\gamma\beta + \delta}{1-\gamma} \right) (X_{-igt} - \bar{X}_{gt})$$

Taking sample group-time averages in (3) and solving for  $\bar{P}_{gt} = \frac{1}{m_{gt}} \sum_i X_{igt}$  leads to the group-level equation:

$$\bar{P}_{gt} = \frac{\alpha}{1-\gamma} + \bar{X}_{gt} \left( \frac{\beta + \delta}{1-\gamma} \right) + \frac{v_{gt}}{1-\gamma} + \bar{\varepsilon}'_{gt} \quad (6)$$

where

$$\bar{\varepsilon}'_{gt} = \frac{\gamma(P_{-igt} - \bar{P}_{gt}) + \delta(X_{-igt} - \bar{X}_{gt}) + \bar{\varepsilon}_{gt}}{1-\gamma}$$

Following Glaeser and Scheinkman (2001), Glaeser et al. (2003), Auld (2011), and Canning et al. (2013), the social multiplier is the ratio of the effect of characteristic  $X$  on preventive behaviors at the group level over its effect on preventive behaviors at the

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<sup>3</sup>We only observe a sample  $m_{gt} < n_{gt}$  of individuals from each group  $g$  at time  $t$ . This creates a measurement error for variables based on sample averages.



individual level. In other words, the social multiplier is the ratio of  $\frac{\beta+\delta}{1-\gamma}$  from equation (6) and  $\beta$  from equation (5), that is:

$$\text{Social Multiplier} = \frac{\frac{\beta+\delta}{1-\gamma}}{\beta}$$

In the absence of social interactions ( $\gamma = 0$  and  $\delta = 0$ ), the social multiplier equals 1 because the effect of any characteristic on preventive behaviors is the same at the individual level and at the group level. In contrast, in the presence of endogenous social interactions ( $0 < \gamma < 1$ ) and assuming no exogenous social interactions ( $\delta = 0$ ), the social multiplier equals  $\frac{1}{1-\gamma}$  and is thus greater than one. Symmetrically, when there is no endogenous social interaction ( $\gamma = 0$ ) and only exogenous social interactions ( $\delta \neq 0$ ), and provided that  $\beta$  and  $\delta$  have the same sign, the social multiplier is also greater than one. Finally, when there are both endogenous and exogenous social interactions ( $0 < \gamma < 1$  and  $\delta \neq 0$ ), and provided that  $\beta$  and  $\delta$  have the same sign, the social multiplier is also greater than one.

### 3. IDENTIFICATION AND ESTIMATION STRATEGY

This section is divided into four subsections. First, we define our reference group and discuss the implications of this choice. Second, we present the contextual effects we focus on in this study. Third, we examine the identification of the individual-level model. Fourth, we discuss the identification of the regional-level model.

#### 3.1. Reference Group

We define an individual's reference group as all the individuals who live in the same region, split into its urban and rural parts. This is the most precise level of disaggregation we can use in our data, as the (split) region is the smallest geographical entity that we can follow over time. The construction of the geographical regions is presented in details in Section 4.

Note that all of our survey samples are collected from geographical clusters which are smaller and more precise than regions. However, we do not use the cluster as our

reference group for two reasons. First, within any country, the clusters selected change in each survey. It is therefore impossible to apply cluster fixed effects in our group-level regressions. Second, the number of children under 5 and pregnant women within each cluster is small, and so measurement error in calculating group averages would be large.

In this paper, we measure the social interactions that occur within (split) regions. However, there might also be social interactions across urban and rural areas within the same region, or across regions, or even across countries. We expect the social multiplier to increase with the level of aggregation. As a consequence, we interpret our results on the social multiplier within (split) regions as lower bounds.

In addition to larger geographical areas (the unsplit region, the country, a set of countries), the reference group could also be defined by cultural traits such as ethnicity, local dialect, or religion. In the future, researchers may be interested in investigating social interactions using these alternative definitions of the group.

### **3.2. Explanatory Variables and Exogenous Social Interactions**

Our models of bednet usage include the following list of explanatory variables: the child's age and gender, the mother's age and education, household size, and household wealth. In our analysis of preventive treatment during pregnancy, we control for the woman's age and education, household size, and household wealth.

When we examine the social multipliers, we focus on the mother or woman's education and on household wealth, because these variables can be influenced by governmental policies on the one hand, and because they are likely to generate exogenous social interactions on the other hand. We expect educated and wealthy women to be more likely to use preventive methods (because they understand their benefits) and to be respected and imitated by their neighbors. Consequently, we expect education and wealth to generate exogenous social interactions, meaning that a woman's decision regarding prevention will be positively influenced by the average education and wealth level in her group.

### 3.3. Individual-Level Model

We use the individual-level model in equation (5) to identify the denominator of the social multiplier,  $\beta$ . We estimate this equation including cluster fixed effects, which are time variant. The inclusion of these cluster fixed effects perfectly control for unobserved factors that affect malaria preventive behaviors for everyone in the cluster at time  $t$  such as malaria campaigns, weather, and earning prospects. Unfortunately in equation (5), the inclusion of cluster fixed effects captures any characteristic that is region-time specific. Consequently, the inclusion of these fixed effects does not allow us to identify the coefficients on  $\bar{X}_{gt}$ .

### 3.4. Aggregate-Level Model

We use the aggregate-level equation (6) to identify the numerator of the social multiplier,  $\frac{\beta+\delta}{1-\gamma}$ .

#### 3.4.1. Main Model

In our main model, we decompose  $v_{gt}$  into three effects: (i) a time-invariant group-specific effect  $v_g$ , (ii) a vector of country ( $c$ ) specific time-variant controls  $Z_{1ct}$ , and (iii) a vector of region-specific time-variant controls  $Z_{2gt}$ .<sup>4</sup>

$$\begin{aligned} \bar{P}_{gt} = & \frac{\alpha}{1-\gamma} + \bar{X}_{gt} \left( \frac{\beta+\delta}{1-\gamma} \right) + \frac{v_g}{1-\gamma} \\ & + \frac{\theta_1 Z_{1ct}}{1-\gamma} + \frac{\theta_2 Z_{2gt}}{1-\gamma} + \bar{\varepsilon}'_{gt}, \end{aligned} \quad (7)$$

$v_g$  controls for omitted factors that are time invariant and affect the malaria preventive behaviors for everyone in the group (for instance, the level of malaria prevalence or the ethnic composition of the group). Moreover,  $Z_{1ct}$  controls for time-variant omitted factors that affect the malaria preventive behaviors of everyone in the country.  $Z_{1ct}$  includes a survey (i.e. country-time) dummy and country-specific time trends and their squares. Finally,  $Z_{2gt}$  captures omitted factors that affect high malaria prevalence regions differently,

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<sup>4</sup>Controlling for region-time fixed effects is not an option because they are perfectly correlated with  $\bar{X}_{gt}$ .

and it controls for time-variant weather-related factors that affect the malaria preventive behaviors of everyone in the region depending on whether the interview is conducted during the rainy or malaria seasons. Specifically,  $Z_{2gt}$  includes an interaction between a time-invariant region-specific malaria ecology index and a time trend, an interaction between the malaria ecology index and a time trend square, and the precipitation and temperature deviations. The precipitation (or temperature) deviation equals the difference between the month of the interview precipitation (or temperature) in the region and the annual average precipitation (or temperature) in the region. The precipitation and temperature deviations are used in the analysis of bednet usage only.

Although the empirical model given in equation (7) controls for many potential omitted factors that might be correlated with  $\bar{X}_{gt}$ , it does not control for all possible region-time variant factors that might cause an omitted variable bias. This could happen in two situations in particular. First, it is possible that between surveys there are migrations into a region within a country from people of different ethnic backgrounds. This is likely to change the region aggregate levels of education, wealth, and malaria preventive behaviors. Second, it is also possible that national authorities target regions with low education and/or wealth for mass net or IPTp campaigns.<sup>5</sup>

In sum, in our main model, we estimate  $\beta$  in equation (5) under weaker assumptions than  $\frac{\beta+\delta}{1-\gamma}$  in equation (7) because we control for cluster fixed effects in equation (5), but we only control for survey fixed effects, region fixed effects, country-specific time trends, trends that depend on the level of malaria ecology in the region, and precipitation and temperature deviations in equation (7). To assess the importance of controlling for cluster omitted variable biases, we also estimate equation (5) without cluster fixed effects and including the same controls as in equation (7).

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<sup>5</sup>We conducted research on the policies of many of the countries in our sample and found that net distribution campaigns tend to be national, without targeting a particular region. For example, in Madagascar (with the exception of three districts in the Vakinankaratra province, which is dropped in our sample) campaigns have been offering ITNs free of charge across the whole country, starting in 2004 (Snow et al., 2012), whereas in Benin, treated nets have continuously been distributed nation-wide for pregnant women and children after malaria was declared the most important disease for children under 5 in 2007 (Damien et al., 2010).

### 3.4.2. Measurement Error and Split-Sample IV Model

Another potential source of bias when estimating equation (7) is measurement error in the explanatory and dependent variables, since we use the sample averages instead of the true population averages ( $\bar{\varepsilon}'_{gt} = (\gamma (P_{-igt} - \bar{P}_{gt}) + \delta (X_{-igt} - \bar{X}_{gt}) + \bar{\varepsilon}_{gt}) / (1 - \gamma)$  in equation (7)).

Measurement error in the explanatory variables is likely to lead to an attenuation bias as in the classical error-in-variables model. Following Graham and Hahn (2005), Canning et al. (2013), and Auld (2011), we correct for measurement error in the explanatory variables using the split-sample IV method proposed by Angrist and Krueger (1995). In this method, we randomly split the sample within each (split) region and year into two subgroups 1 and 2, and we calculate the means of the characteristics for the subgroups,  $\bar{X}_{(1)gt}$  and  $\bar{X}_{(2)gt}$ . Because of the random assignment into the subgroups, measurement errors in  $\bar{X}_{(2)gt}$  are uncorrelated with measurement errors in  $\bar{X}_{(1)gt}$ . We can then use  $\bar{X}_{(2)gt}$  as instruments for  $\bar{X}_{(1)gt}$  to get consistent estimates of the regional means.

Measurement error in the dependent variable may create a bias if women in regions with high levels of education and wealth misreport/overstate their preventive behaviors due to social pressure. We assume that the potential bias due to correlations between the measurement error in the dependent variable and the explanatory variables is small and can be ignored.

## 4. DATA

The data 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. DHS, MIS, and AIS are part of the MEASURE DHS project, which is partially funded by USAID. The goal of the DHS project is to monitor the population and health situations of the target countries. DHS/MIS/AIS data contain detailed information on health and preventive health behaviors for children, women, and men. MICS is funded by UNICEF and it is used to monitor the situation of children and women.

Starting in 1999-2000, DHS/MIS/AIS and MICS began collecting information on the use of mosquito nets, whether the nets are ITNs, and intermittent preventive treatments for past pregnancies (IPTp). Because malaria eradication was not a health policy priority before the creation of the Roll Back Malaria Partnership, DHS/MIS/AIS and MICS do not include questions related to malaria prevention before 1999-2000. Fortunately, DHS, MIS, and AIS 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/AIS/MICS samples are drawn from geographical clusters. These clusters are obtained from the previous census enumeration areas (EAs) and they are nationally representative. 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.

For each individual, the data contain information on his region of residence, his cluster of residence, and whether his cluster is in a urban or rural setting. Our aggregate geographical group is the region of residence split into rural and urban clusters. Thus, we create two groups per region. One group is made of all urban clusters in the region and the other group is composed of all rural clusters in the region.

For some countries, the boundaries of some regions have changed between surveys conducted in different years. In these instances, we combine regions using maps provided in the public report of each survey. We drop groups with less than 100 observations, because small cells would lead to unreliable group estimates.

We restrict our data to countries for which we have at least two usable DHS/MIS/AIS/MICS surveys containing comparable information on malaria prevention between 1999 and 2012. Table I describes our data. We use 92 surveys (mainly DHS and MICS) covering 29 countries. Malaria is endemic in all the countries we use in our analysis, according to the Roll Back Malaria website.<sup>6</sup> The number of surveys per country ranges from two (for

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<sup>6</sup>See [www.rollbackmalaria.org/endemiccountries.html](http://www.rollbackmalaria.org/endemiccountries.html)

11 countries) to five (for Malawi, Nigeria, Rwanda, and Senegal).

[Insert Table I here]

We merge the DHS/MIS/AIS/MICS regions with monthly precipitation and temperature data from 1999 to 2012 based on weather station observations and interpolations from the Climatic Research Unit (CRU), available at [www.cru.uea.ac.uk](http://www.cru.uea.ac.uk).

We also merge the DHS/MIS/AIS/MICS regions with a measure of malaria prevalence ( $\text{PfPR}_{2-10}$ ) for 2010 obtained from the Malaria Atlas Project (MAP) databases which are publicly available at [www.map.ox.ac.uk](http://www.map.ox.ac.uk).  $\text{PfPR}_{2-10}$  captures the percentage of children ages 2 to 10 who have detectable levels of the *Plasmodium falciparum* parasite in their peripheral blood.  $\text{PfPR}_{2-10}$  is constructed from parasite surveys that are periodically carried out in areas known to have malaria. Then, using Bayesian geostatistical algorithms with adjustments for climatic and environmental factors, MAP made projections in time and space to create a continuous display of  $\text{PfPR}_{2-10}$ , called the Malaria Endemicity map, for all of Africa in 2010. Gething et al. (2011) provide details on the construction of  $\text{PfPR}_{2-10}$ .

## 5. EMPIRICAL SPECIFICATION

**Overview:** We estimate equations (5) and (7) separately for children under 5 and for women who gave birth over the two years preceding the interview. When estimating equation (5), we use individual-level variables, whereas for equation (7), we use the averages of the variables in the group.<sup>7</sup>

We do not use sample weights because when the model is correctly specified, ordinary least squares results are consistent (Deaton, 1997; Solon et al., 2013). In addition, weights should be based on the population in each region and survey, but we do not have the true populations for all regions and surveys in our data.

**Dependent Variables:** For children under 5, we study the following dependent variables: (i) whether the child slept under any type of mosquito net the night before

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<sup>7</sup>An overview of the variables is given in Appendix A.

the survey, and (ii) whether the child slept under an ITN the night before the survey. Sleeping under an ITN is considered to be the main tool to fight malaria in the RBM partnership arsenal.

For women who gave birth over the two years preceding the interview, we use the following dependent variables: (i) whether the woman took at least one dose of Fansidar during her last pregnancy, and (ii) whether the woman took at least two doses on Fansidar during her last pregnancy. WHO recommendation is that women take two doses of Fansidar. In that case, it is considered that they complete the IPTp treatment.

**Explanatory Variables:** In the children models, we control for the mother’s education, household wealth, child age, whether the child is a male, the mother’s age, and household size. In the women analysis, we include controls for the woman’s education, household wealth, the woman’s age, and household size. The mother or woman’s education is a binary indicating whether the mother or woman has secondary education or higher. The wealth variable is a dummy for whether the household has an improved source of drinking water or improved sanitation facilities.<sup>8</sup>

Our specifications also include controls for cluster fixed effects (equation (5)), survey fixed effects (equation (7)), region fixed effects (equation (7)), country-specific trends (equation (7)), trends interacted with malaria ecology (equation (7)), and precipitation and temperature deviations (equation (7), children sample).

The malaria ecology index captures the variation in malaria prevalence in the region that is explained by climatic factors. We construct the malaria ecology index using PfPR<sub>2-10</sub> for 2010, the average precipitation and temperature data, the average maximum precipitation and temperature, and the average minimum precipitation and temperature. The average precipitation (temperature) is the mean precipitation (temperature) between 2000 and 2010. To quantify the average maximum precipitation (temperature), we find the month with the highest average precipitation (temperature) in the region for each year and then average over all the years. Using the same procedure, we find the average

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<sup>8</sup>The DHS/MIS/AIS contain an index of wealth reported in quintiles. This index is calculated based on questions related to the possession of assets such as a radio or a bicycle. We do not use this measure, because it is not comparable across surveys.



minimum precipitation (temperature). We then take the squares, cubes, and quartics of each of the six climate variables, leaving us with 24 climate variables.

We then regress malaria prevalence (PfPR<sub>2-10</sub> in 2010) on our 24 climate variables. The fit of the resulting prediction, with an  $R^2$  of 0.63, is very high (see Appendix B). Our malaria ecology index is the prediction of malaria prevalence from this regression.

When estimating equation (7) for the children sample, we control for precipitation and temperature deviations. The precipitation (respectively temperature) deviation variable captures the difference between the month of the interview precipitation (temperature) and the annual average precipitation (temperature) in the region. These deviations are calculated as follows. We begin by taking the level of precipitation (temperature) for each region in each month from 1999 to 2012. We then take the average over the 12 months preceding the interview to get the annual average precipitation (temperature) for a region. The deviation is just the month of the interview precipitation (temperature) minus the annual average precipitation (temperature) for each region.

## 6. MAIN RESULTS

### 6.1. Descriptive Statistics

Descriptive statistics are reported in Table II. In column (1), we show the descriptive statistics for the individual-level data, whereas in columns (2) to (4), we present the descriptives for the regional-level data. While column (2) contains the descriptives for the whole period 1999-2012, columns (3) and (4) present them for the sub-periods 1999-2005 and 2006-2012.

Column (1) shows that only 29% of children under 5 slept under a bednet the night before the survey and only 21% slept under an ITN. The percentage of women who took at least one dose of Fansidar is 34%, but the percentage who took at least two doses of Fansidar is only 18%. The mean child age is 2 years and the mean mother or women's age is around 27 years. Only 13-15% of mothers or women have secondary education and the average household size is approximately 8 members.

Column (2) contains the regional-level statistics for 1999-2012. Note that as expected the means at the regional level in column (2) are different from the means at the individual level in column (1). However, the differences between columns (1) and (2) are generally small, because the regions are rather homogenous, implying that the means of the variables are rather similar across regions. By contrast, for women's preventive behaviors, the means in column (2) are different from those in column (1): this is due to the heterogeneity in preventive treatment between regions (with some regions where preventive treatment is common and others where it is rare), and to the fact that regions have different sample sizes.

When we break up the 1999-2012 period into two sub-periods, 1999-2005 in column (3) and 2006-2012 in column (4), we see that the regional means of all four preventive behaviors increase over time, but the increase is substantially stronger for sleeping under an ITN and taking two doses of Fansidar. Similarly, among the explanatory variables, the share of educated mothers and of wealthy households also improve over time.

The sample size for the individual-level models varies from 88,316 observations for taking two doses of Fansidar to 662,105 observations for sleeping under any type of bednet. For the regional-level regressions, the sample size ranges from 356 to 1,436 observations.

[Insert Table II here]

## 6.2. Main Model

Table III displays the regression results of our main model, for sleeping under any type of bednet in Panel A and for sleeping under an ITN in Panel B. Columns (1) to (3) give the results of the individual-level regressions, whereas column (4) gives the results of the regional-level regression. Column (1) presents the results without controlling for any fixed effect, column (2) controls for the exact same fixed effects as in the regional-level model in column (4), and column (3) controls for cluster fixed effects.

[Insert Table III here]

In both Panels A and B, the coefficients on children's and women's demographics in column (1) are somewhat different from those in models that do control for fixed effects

in columns (2) and (3). This highlights that adequately controlling for unobserved factors is necessary for our study. As a consequence, we will not comment on the results from column (1).

In Panel A, individual models in columns (2) and (3) show that the mother’s secondary education increases the probability that the child sleeps under any type of bednet by 6.7 and 5.6 percentage points. In the regional model in column (4), the coefficient on the mother’s secondary education is larger than in individual-level models, since maternal education increases the probability that the child sleeps under any type of bednet by 12.7 percentage points. Moreover, individual-level models in columns (2) to (3) show that household wealth increases the probability that the child sleeps under any type of bednet by 3.2 and 2.2 percentage points. Again, the effect of wealth in the regional-level model is greater, since wealth increases the probability that the child sleeps under any type of bednet by 4.4 percentage points. However, the coefficient on wealth is not significant.

In Panel B, we find that the coefficient on the mother’s education is greater in the regional-level model in column (4) than in the individual-level models in columns (2) and (3). However, the coefficients on education and wealth are not significant in the regional-level model. Our specification includes country-specific time trends that together with (split) region fixed effects explain most of the variation in ITN usage at the group level.

All models indicate that sleeping under any type of bednet or under an ITN does not depend on the child gender, since the coefficient for the child being a male is generally small and is never significant. The effect of household size on bednet and ITN usage is negative in our models, but the coefficient is significant in individual-level models only. This finding is consistent with competition for resources within households: for a given number of bednets and ITNs within a household, the likelihood that a bednet is allocated to a child decreases with the number of household members.

Table IV reports the estimates for the preventive outcomes for women. Panel A contains the results for taking at least one dose of Fansidar, whereas Panel B reports the coefficients for taking two doses of Fansidar, which corresponds to the WHO recommendation for pregnant women.

[Insert Table IV here]

In Panel A, specifications in columns (2) to (4) indicate that women with secondary education are significantly more likely to adopt preventive behaviors 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 antimalarial drugs. We also find that the coefficient on education in the regional-level regression in column (4) is much larger than the coefficient in individual-level regressions in columns (2) and (3). Similarly, the coefficient on household wealth is positive, significant, and greater in the regional-level model than in the individual-level models. Results in Panel B are consistent with those in Panel A, but the coefficients on education and wealth in the regional-level models are not significant.

In both Tables III and IV, the estimated parameters in columns (2) and (3) are rather similar, but they are different from the parameters in column (1). This suggests that our decomposition of the unmeasured group effect,  $v_{gt}$  (into survey fixed effects, region fixed effects, different time trends, and precipitation and temperature deviations) is sufficient to control for the omitted variable bias.

The social multipliers associated with education and wealth are reported in Table V.

[Insert Table V here]

The social multipliers for the mother's or woman's secondary education are computed by dividing the coefficients on the mother's or woman's secondary education from the regional-level regression in Tables III and IV, column (4), by the coefficients on the mother's or woman's secondary education from the individual-level regressions, in Tables III and IV, column (3). We use the same procedure to calculate the social multipliers for wealth. We use bootstrap methods to calculate the 95% confidence intervals of the social multipliers (Li and Maddala, 1999): 1,000 bootstrap samples are taken with randomization at the country and regional level respectively (to maintain the panel structure of the data). Note that the 95% confidence intervals of the multipliers are not symmetric; symmetry of the confidence interval for a ratio only occurs in very large samples.

The social multipliers for education and wealth are significantly greater than one for sleeping under any type of bednet, taking one dose of Fansidar or more, and taking two doses of Fansidar or more. This suggests that the decision to adopt preventive behaviors does not only depend on women’s education or household wealth, but also on the average women’s education and household wealth in the region, and that there are spillovers between households.

In addition, while the multipliers associated with sleeping under any type of bednet are rather modest, those for antimalarial treatments during pregnancy are large. At first sight, these large multipliers may seem implausible. However, the large social multipliers for women’s preventive behaviors could also really capture the existence of strong social interactions. In particular, that social interactions matter more for women’s treatment uptake than for children’s bednet usage makes sense, since getting preventive treatment is a public/social activity, whereas using a bednet is more private. It is easier for a woman to observe her neighbor going to a health facility to get preventive treatment, than to observe her neighbors’ child using a bednet at night. As a consequence, knowledge about the neighbors’ preventive treatment uptake is more widespread, which should increase the level of social interactions.

For sleeping under an ITN, we do not find that the social multipliers of education and wealth are significantly greater than one. It is not clear whether this result reflects an absence of social interactions for ITN usage or a lack of statistical power in the regional-level model due to the lack of variation in our variables once we control for region fixed effects and several time trends.

### **6.3. Split-Sample IV Model**

Tables VI reports the results of the split-sample IV method that corrects for measurement error in education and wealth in the regional-level model (see Section 3.4.2).

Column (1) contains the estimates from the regional-level model estimated with OLS (from Tables III and IV), whereas column (2) reports the estimates when using SSIV. For all four dependent variables, the first-stage F-statistics and Kleibergen-Paap Wald F-statistics are large and we can reject the null hypothesis that the model is not identified.

The coefficients from the SSIV model are rather similar to the ones from the OLS model, which suggests that measurement error is small in our study and can be ignored.

[Insert Table VI here]

## 7. ROBUSTNESS CHECKS AND ADDITIONAL RESULTS

### 7.1. GMM/IV Model

We here relax the assumption that survey fixed effects, region fixed effects, country-specific time trends, malaria ecology interacted with time trends, and precipitation and temperature deviations completely address the endogeneity of  $\bar{X}_{gt}$  in equation (7). Our strategy is to take the first difference in equation (7) and then use lagged values of  $\bar{X}_{gt}$  as instruments, in a GMM/IV framework. Unfortunately, these instruments are weak and most of the coefficients are unreliable. The method and results are presented in Appendix C.

### 7.2. Controlling for Wealth Inequality

We re-estimate our models controlling for wealth inequality. We proxy wealth inequality with the standard deviation of wealth within the region for the year of the interview. The results are reported in the online Appendix D, Table D.I. Note that we control for wealth inequality in regional-level models, but not in individual-level models, because in individual-level models, cluster fixed effects already capture the impact of any variable that is fixed for any region-year.

In Table D.I, the individual-level estimates are thus the same as in Tables III and IV. In Panels A, C and D, the regional-level coefficients on education and wealth are generally comparable to those in Tables III and IV and they are greater than individual-level coefficients (note that in the regional-level model, the coefficient on household wealth for one dose of Fansidar or more is no longer significant though). Consequently, the social

multipliers on education and wealth will remain greater than one for sleeping under any type of bednet and taking one or two doses of Fansidar or more.<sup>9</sup>

### 7.3. East and West Africa

We also consider differences in social interactions between East and West Africa. We cannot detect any heterogeneity because of a lack of statistical power. The results of this analysis are reported in the online Appendix E.

### 7.4. Excess Variance Across Groups

We finally check the robustness of our findings on the presence of social interactions in malaria preventive behaviors by analyzing whether there is excess variance of preventive behaviors across groups. Glaeser, Sacerdote, and Scheinkman (1996) and Graham (2008) show that we can measure social interactions based on covariance restrictions of the disturbances. In particular, social interactions create excess variance across groups and these variances depend on the group size. Graham (2008) show that under the assumption of random assignment for the linear-in-means model, we can identify social interactions by using differences in the variance of outcomes of groups of different sizes. Unfortunately, we do not have information on the group sizes (e.g. the population of the split regions) and we cannot implement this method.

Our approach follows Auld (2011) and is based on comparing the actual estimated standard deviation of our outcome across groups:

$$S_{P_{group}} = \sqrt{\frac{1}{\#group} \sum_{gt=1}^{\#group} (\bar{P}_{gt} - \bar{P})^2}$$

where  $\bar{P} = \frac{1}{N} \sum_{i=1}^N P_{igt}$  and  $\bar{P}_{gt} = \frac{1}{N_{gt}} \sum_{i=1}^{N_{gt}} P_{igt}$ ; with the estimated standard deviation assuming that  $P_{igt}$  is i.i.d. with the same mean and standard deviation as in the actual data. If social interactions are present under the assumption of random assignment and

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<sup>9</sup>Note that other factors, such as the perception of the value of life, may have an impact on the decision to adopt preventive behaviors against malaria. Our data do not contain information on such perceptions though. If we assume that the perception of the value of life is the same for all individuals in any cluster, then our individual-level models with cluster fixed effects already control for the perception of the value of life. However, this might be a strong assumption. We leave this point for future research.

no unmeasured group effects, the group standard deviation using actual data will be larger than the group standard deviation using counterfactual data.

We consider two different group definitions: 1) cluster-time combinations of individuals, and 2) region-time combinations of individuals.

Because many differences in the group variances are caused by individual and group characteristics, we repeat the analysis but in a first stage we regress  $P_{igt}$  on individual characteristics, time trends and region fixed effects, and we then use the residuals to calculate the standard deviations.

In Appendix F, Table F.I, Panel A shows the results for the standard deviations based on the raw data. We find that there is an excess variance at the group level that becomes larger with the size of the group. In Panel B, we control for individual characteristics, time trends, and region fixed effects, and still find excess variance at the group level. We need to be cautious when interpreting these results because this method does not control for unmeasured heterogeneity across groups. However, the results are consistent with the existence of social interactions.

## 8. CONCLUSION

If the Millennium Development Goal of the United Nations of eliminating all avoidable deaths caused by malaria is to be achieved, the level of malaria prevention must not only increase substantially from current levels, but must also remain high and become the new social norm. This paper examines whether there is a social multiplier in the adoption of mosquito nets by children and preventive treatment during pregnancy by women. This social multiplier can be caused by either endogenous social interactions, exogenous social interactions, or both. In this paper, although we cannot examine the source of social interactions, we can identify their existence by quantifying the social multiplier. As far as we are aware, we are the first to investigate this topic.

Our results are consistent with the possibility of large social multipliers associated with education and wealth for antimalarial drugs take up during pregnancy and more modest social multipliers for bednet usage. These results are plausible. In Africa, antimalarial



drugs during pregnancy are administered during visits to antenatal clinics. Everyone in a particular neighborhood can observe if a woman is pregnant and whether she attends the antenatal clinic as scheduled. In contrast, sleeping under a bednet is not easily observable for individuals outside the household. Thus, peer pressure and the opportunities for social interactions are likely to be larger for antimalarial drugs during pregnancy compared to bednet usage.

The existence of social multipliers suggests that the steady state or long-run effect of a policy that increases the use of bednets or antimalarial treatments during pregnancy (promotional campaigns or subsidies of bednets and treatments) will be larger than what we would have predicted using the individual-level coefficients, once all the indirect effects caused by social interactions are accounted for. Moreover, when combined with investments in education and infrastructure, these policies will generate large multiplier effects. Thus, the cost of achieving the Millennium Goals will be smaller than in the absence of spillovers.

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Table I. Data sources

Country	No. waves	No. regions	Surveys
Angola	3	17	MICS01, MIS06, MIS11
Benin	2	6	DHS01, DHS06
Burkina Faso	3	13	DHS03, MICS06, DHS10
Burundi	4	17	MICS00, MICS05, DHS10, DHS12
Cameroon	4	12	MICS00, DHS04, MICS06, DHS11
Central African Republic	2	17	MICS00, MICS06
Chad	2	8	MICS01, DHS04
Côte d'Ivoire	4	11	MICS00, AIS05, MICS06, DHS11
Democratic Republic of the Congo	3	11	MICS01, DHS07, MICS10
Gambia	2	8	MICS00, MICS05
Ghana	3	10	DHS03, MICS06, DHS08
Kenya	2	8	DHS03, DHS08
Liberia	2	15	MIS08, MIS11
Madagascar	4	6	MICS00, DHS03, DHS08, MIS11
Malawi	5	26	DHS00, DHS04, MICS06, DHS10, MIS12
Mali	2	9	DHS01, DHS06
Mozambique	2	10	DHS03, DHS11
Namibia	2	12	DHS00, DHS06
Niger	2	8	MICS00, DHS06
Nigeria	5	36	DHS03, MICS07, DHS08, MIS10, MICS11
Rwanda	5	12	DHS00, MICS00, DHS05, DHS(I)07, DHS10
Senegal	5	10	MICS00, DHS05, MIS06, MIS08, DHS10
Sierra Leone	4	4	MIC00, MICS05, DHS08, MICS10
Swaziland	3	4	MICS99, DHS06, MICS10
Tanzania	4	21	DHS04, AIS07, DHS09, AIS11
Togo	3	6	MICS00, MICS06, MICS10
Uganda	4	4	DHS00, DHS06, MIS09, DHS11
Zambia	3	9	MICS00, DHS01, DHS07
Zimbabwe	3	10	DHS99, DHS05, DHS10
Total	92 surveys	340*	

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

\*Each region will be divided in two (one rural, one urban) in the rest of the analysis and the regions with less than 100 observations will be dropped.

Table II. Summary statistics

	Individual level	Regional level	Regional level	
	1999-2012	1999-2012	1999-2005	2006-2012
	Mean (Std)	Mean (Std)	Mean (Std)	Mean (Std)
<i>Children's preventive outcomes</i>				
Sleeping under any type of bednet	0.296 (0.456)	0.289 (0.229)	0.192 (0.196)	0.349 (0.228)
Sleeping under an ITN	0.215 (0.411)	0.209 (0.221)	0.051 (0.074)	0.299 (0.226)
<i>Women's preventive outcomes</i>				
One dose of Fansidar or more	0.349 (0.476)	0.379 (0.329)	0.227 (0.290)	0.471 (0.312)
Two doses of Fansidar or more	0.187 (0.390)	0.199 (0.215)	0.071 (0.132)	0.290 (0.216)
<i>Children's demographics</i>				
Mother's secondary education	0.151 (0.358)	0.179 (0.179)	0.142 (0.165)	0.202 (0.207)
Household wealth	0.658 (0.474)	0.687 (0.240)	0.633 (0.246)	0.720 (0.230)
Child age	1.954 (1.419)	1.954 (0.108)	1.930 (0.103)	1.968 (0.109)
Child is male	0.502 (0.499)	0.502 (0.030)	0.500 (0.031)	0.503 (0.030)
Mother's age	26.996 (10.753)	27.055 (2.674)	27.676 (2.199)	26.668 (2.866)
Household size	7.740 (4.821)	7.549 (2.369)	7.736 (2.269)	7.432 (2.424)
<i>Women's demographics</i>				
Secondary education	0.134 (0.341)	0.154 (0.190)	0.154 (0.192)	0.158 (0.188)
Household wealth	0.639 (0.480)	0.658 (0.242)	0.616 (0.238)	0.703 (0.237)
Age	27.551 (6.852)	27.588 (1.238)	27.457 (1.373)	28.109 (1.050)
Household size	7.814 (5.296)	7.746 (3.029)	7.324 (2.612)	7.872 (3.129)
Obs. for Sleeping under any type of bednet	662,105	1,436	-	-
Obs. for Sleeping under an ITN	601,031	1,342	-	-
Obs. for One dose of Fansidar or more	95,555	388	-	-
Obs. for Two doses of Fansidar or more	88,316	356	-	-

Table III. Regressions for preventive behaviors for children (OLS)

	Individual Equation (5) OLS (1)	Individual Equation (5) OLS (2)	Individual Equation (5) OLS (3)	Regional Equation (7) OLS (4)
<b>Panel A. Dependent variable: Sleeping under any type of bednet</b>				
Mother's secondary education	0.0265** (0.0131)	0.0676*** (0.0016)	0.0563*** (0.0042)	0.127** (0.0609)
Household wealth	0.0403*** (0.0117)	0.0328*** (0.0012)	0.0226*** (0.0021)	0.0446 (0.0334)
Age (/10)	-0.138*** (0.0070)	-0.153*** (0.0036)	-0.154*** (0.0055)	0.0828 (0.414)
Male	-0.0005 (0.0010)	-0.0015 (0.0009)	-0.0013 (0.0009)	-0.0274 (0.115)
Mother's age (/10)	-0.0066*** (0.0021)	0.0026*** (0.0007)	0.0036*** (0.0009)	-0.0034 (0.0565)
Household size	-0.0040*** (0.0011)	-0.0057*** (0.0001)	-0.0062*** (0.0003)	-0.0012 (0.0039)
Malaria ecology * Time trend		0.0642*** (0.0084)		0.0789* (0.0467)
Malaria ecology * Time trend <sup>2</sup>		-0.0037*** (0.0005)		-0.0053* (0.0030)
Precipitation (deviation) (/100)		-0.0048*** (0.0008)		0.0024 (0.0054)
Temperature (deviation)		-0.0068*** (0.0003)		-0.0061*** (0.0021)
Observations	662,105	662,105	662,105	1,436
R-squared	0.009	0.222	0.385	0.754
Number of (split) regions				472
<b>Panel B. Dependent variable: Sleeping under an ITN</b>				
Mother's secondary education	0.0189* (0.0101)	0.0533*** (0.0039)	0.0451*** (0.00356)	0.0810 (0.0572)
Household wealth	0.0391*** (0.0113)	0.0277*** (0.0023)	0.0179*** (0.0021)	0.0095 (0.0327)
Age (/10)	-0.106*** (0.0071)	-0.120*** (0.0053)	-0.122*** (0.0053)	0.144 (0.417)
Male	0.0006 (0.0010)	-0.0003 (0.0008)	-0.0003 (0.0008)	0.0345 (0.113)
Mother's age (/10)	-0.0021 (0.0020)	0.0026*** (0.0009)	0.0033*** (0.0009)	-0.0255 (0.0543)
Household size	-0.0041*** (0.0010)	-0.0044*** (0.0003)	-0.0047*** (0.0003)	-0.0048 (0.0041)
Malaria ecology * Time trend		0.0454 (0.0348)		0.0750* (0.0401)
Malaria ecology * Time trend <sup>2</sup>		-0.0019 (0.0025)		-0.0046 (0.0029)
Precipitation (deviation) (/100)		-0.0077** (0.0030)		-0.0124** (0.0054)
Temperature (deviation)		-0.0010 (0.0017)		-0.0030 (0.0024)
Observations	601,031	601,031	601,031	1,342
R-squared	0.007	0.260	0.396	0.815
Number of (split) regions				430
Average Xs		Yes		
Region FE		Yes		Yes
Time trend		Yes		Yes
Time trend <sup>2</sup>		Yes		Yes
Country FE × Time trend		Yes		Yes
Country FE × Time trend <sup>2</sup>		Yes		Yes
Survey type FE		Yes		Yes
Cluster FE			Yes	

Notes. The precipitation and temperature variables are the deviations from the monthly precipitation and temperature averages.

“Average Xs” include average child age, the proportion of male children, average mother's secondary education, mother's age, household size, and wealth in the region.

Robust standard errors, which are clustered by (split) region, are reported in parentheses.

\*\*\* denotes significance at 1% level. \*\* denotes significance at 5% level. \* denotes significance at 10% level.

Table IV. Regressions for preventive behaviors for women, for child deliveries in the last two years (OLS)

	Individual Equation (5) OLS (1)	Individual Equation (5) OLS (2)	Individual Equation (5) OLS (3)	Regional Equation (7) OLS (4)
<b>Panel A. Dependent variable: One dose of Fansidar or more</b>				
Secondary education	-0.0156 (0.0263)	0.0599*** (0.0066)	0.0507*** (0.0067)	0.469** (0.215)
Household wealth	0.0727*** (0.0182)	0.0306*** (0.0043)	0.0143*** (0.0047)	0.124* (0.0678)
Age (/10)	-0.0168*** (0.00524)	0.0022 (0.0017)	0.0021 (0.0019)	-0.106 (0.103)
Household size	0.0097*** (0.0020)	0.0003 (0.0005)	0.0001 (0.0003)	0.0086 (0.0101)
Malaria ecology * Time trend		-0.0213 (0.0696)		0.0756 (0.0784)
Malaria ecology * Time trend <sup>2</sup>		0.0021 (0.0045)		-0.0042 (0.0051)
Observations	95,555	95,555	95,555	388
R-squared	0.017	0.454	0.580	0.901
Number of (split) regions				146
<b>Panel B. Dependent variable: Two doses of Fansidar or more</b>				
Secondary education	-0.0024 (0.0163)	0.0379*** (0.0053)	0.0334*** (0.0057)	0.206 (0.206)
Household wealth	0.0441*** (0.0121)	0.0192*** (0.0041)	0.0081* (0.0048)	0.0851 (0.0547)
Age (/10)	-0.0127*** (0.0033)	0.0005 (0.0015)	0.0006 (0.0016)	-0.128* (0.0757)
Household size	0.0084*** (0.0013)	-3.18e-05 (0.0003)	-0.0001 (0.0002)	0.0032 (0.0076)
Malaria ecology * Time trend		0.0653 (0.0605)		0.123** (0.0566)
Malaria ecology * Time trend <sup>2</sup>		-0.0033 (0.0040)		-0.0070* (0.0037)
Observations	88,316	88,316	88,316	356
R-squared	0.016	0.276	0.412	0.878
Number of (split) regions				136
Average Xs		Yes		
Region FE		Yes		Yes
Time trend		Yes		Yes
Time trend <sup>2</sup>		Yes		Yes
Country FE × Time trend		Yes		Yes
Country FE × Time trend <sup>2</sup>		Yes		Yes
Survey type FE		Yes		Yes
Cluster FE			Yes	

Notes. “Average Xs” include average age, secondary education, household size, and wealth in the region. Robust standard errors, which are clustered by (split) region, are reported in parentheses.

\*\*\* denotes significance at 1% level. \*\* denotes significance at 5% level. \* denotes significance at 10% level.



Table V. Social multipliers

	Sleeping under any type of bednet	Sleeping under an ITN	One dose of Fansidar or more	Two doses of Fansidar or more
Mother's or woman's secondary education	2.364 (0.449) [1.742, 3.353]	1.715 (0.549) [0.703, 2.793]	9.243 (2.229) [7.302, 14.435]	6.161 (2.826) [2.609, 16.369]
Household wealth	2.159 (0.444) [1.273, 3.009]	0.861 (0.493) [-0.309, 1.710]	8.701 (3.614) [4.296, 18.791]	10.413 (29.360) [3.186, 49.365]

Notes. The multipliers are computed using the individual-level models that control for cluster fixed effects and the regional-level models. We bootstrap the standard errors and confidence intervals of the social multipliers, applying a panel bootstrap using 1,000 replications. The standard errors of the social multipliers are reported in parentheses. The 95% bias-corrected confidence intervals of the social multipliers are reported in brackets.

Table VI. Regional-level regressions for preventive behaviors for children (OLS and split-sample IV)

	Regional OLS (1)	Regional SSIV (2)
<b>Panel A. Dependent variable: Sleeping under any type of bednet</b>		
Mother's secondary education	0.127** (0.0609)	0.1551** (0.0638)
Household wealth	0.0446 (0.0334)	0.0403 (0.0329)
Observations	1,436	1,436
R-squared	0.754	0.882
Number of (split) regions	472	472
First stage F-stat for education [P-value]		650.31 [0.0000]
First stage F-stat for wealth [P-value]		4920.48 [0.0000]
Kleibergen-Paap Wald F-stat		199.61
<b>Panel B. Dependent variable: Sleeping under an ITN</b>		
Mother's secondary education	0.0810 (0.0572)	0.0748 (0.0602)
Household wealth	0.0095 (0.0327)	0.0173 (0.0337)
Observations	1,342	1,342
R-squared	0.815	0.874
Number of (split) regions	430	430
First stage F-stat for education [P-value]		673.78 [0.0000]
First stage F-stat for wealth [P-value]		3838.72 [0.0000]
Kleibergen-Paap Wald F-stat		237.13
<b>Panel C. Dependent variable: One dose of Fansidar or more</b>		
Secondary education	0.469** (0.215)	0.5012** (0.2363)
Household wealth	0.124* (0.0678)	0.1758* (0.0650)
Observations	388	388
R-squared	0.901	0.959
Number of (split) regions	146	146
First stage F-stat for education [P-value]		68.32 [0.0000]
First stage F-stat for wealth [P-value]		403.25 [0.0000]
Kleibergen-Paap Wald F-stat		66.41
<b>Panel D. Dependent variable: Two doses of Fansidar or more</b>		
Secondary education	0.206 (0.206)	0.2017 (0.1691)
Household wealth	0.0851 (0.0547)	0.1014* (0.0546)
Observations	356	356
R-squared	0.878	0.945
Number of (split) regions	136	136
First stage F-stat for education [P-value]		33.38 [0.0000]
First stage F-stat for wealth [P-value]		558.47 [0.0000]
Kleibergen-Paap Wald F-stat		33.63
Region FE	Yes	Yes
Time trend	Yes	Yes
Time trend <sup>2</sup>	Yes	Yes
Country FE × Time trend	Yes	Yes
Country FE × Time trend <sup>2</sup>	Yes	Yes
Survey type FE	Yes	Yes

Notes. Split-sample estimates to correct for sampling error in education and wealth in regional models. Robust standard errors, which are clustered by (split) region, are reported in parentheses.

\*\*\* denotes significance at 1% level. \*\* denotes significance at 5% level. \* denotes significance at 10% level.

## Online Appendix A

Table A.I. Variables used

Label	DHS, MIS, AIS	MICS Wave 2	MICS Wave 3	MICS Wave 4
Sleeping under any type of bednet	hv228, v460, hml12	ml8	ml10	tn11
Sleeping under an ITN	hml12, hml19, ml0	ml9	ml12, ml13, ml14	tn5
Taking Fansidar	m49a	Not available	mn6*	mn14a
No. of doses of Fansidar	ml1	Not available	mn6d	mn16
Child is male	hv104, b4	hl3	hl4	hl4
Child age	hv105, b8	hl4	hl5	hl6
Mother/Woman's age	hv105, v012	wi3b, memage, hl4, age	wm9, hl5	wb2, hl6
Mother/Woman's education	hc61, v106	melevel	melevel	melevel
Water	hv201	ws1	ws1	ws1
Sanitation	hv205	ws3	ws7	ws8
Urban residence	hv025	hi6	hh6	hh6
Cluster	hv001, v001	wiclno, chclno, hi1	hh1	hh1
Region	hv024, v024	hi7	hh7	hh7
Year	hv007, v007	hi3y	hh5y	hh5y

Notes. This table contains the “general” variables that we use in the analysis. Note that for some countries, we additionally use country-specific variables. For many countries, the region variable is country-specific.

## Online Appendix B

Table B.I. Regression to predict the malaria ecology index

		PfPR	
		Coeff.	S.e.
Minimum precipitation		-0.0140***	(0.0050)
-	square	0.0007*	(0.0004)
-	cube	-1.44e-05	(1.14e-05)
-	quartic	8.77e-08	(9.21e-08)
Average precipitation		0.0139**	(0.0058)
-	square	-9.83e-05	(7.04e-05)
-	cube	4.66e-07	(3.67e-07)
-	quartic	-8.20e-10	(6.86e-10)
Maximum precipitation		-0.0052**	(0.0021)
-	square	3.02e-05***	(9.79e-06)
-	cube	-7.15e-08***	(1.94e-08)
-	quartic	5.24e-11***	(0)
Minimum temperature		-0.123	(0.772)
-	square	0.0243	(0.0629)
-	cube	-0.0013	(0.0022)
-	quartic	2.18e-05	(2.91e-05)
Average temperature		-21.63***	(4.707)
-	square	1.353***	(0.302)
-	cube	-0.0373***	(0.0085)
-	quartic	0.0003***	(8.95e-05)
Maximum temperature		12.25***	(2.884)
-	square	-0.661***	(0.159)
-	cube	0.0158***	(0.0038)
-	quartic	-0.0001***	(3.48e-05)
Constant		43.50**	(19.46)
Observations		399	
R-squared		0.636	

Notes. In this table, the observation is the (unsplit) region. The table presents the results of the regression of PfPR in the region on a number of precipitation and temperature variables in the same region, in a very nonlinear setting. Our malaria ecology index is the linear prediction from this regression.

Here the sample contains 399 (unsplit) regions. Note that this number of regions (399) is larger than the number of (unsplit) regions used in the rest of the paper (340 - See Table I). Indeed, here we use all the available countries from Sub-Saharan Africa, with information on PfPR, precipitation and temperature, to run the regression above and get a very general malaria ecology index. Some of the countries we use here (Comoros, Equatorial Guinea, Guinea Bissau, Somalia, South Africa, and Sudan) do not have usable DHS/MIS/AIS/MICS data, and consequently cannot be used in the rest of the paper.

Standard errors are reported in parentheses.

\*\*\* denotes significance at 1% level. \*\* denotes significance at 5% level. \* denotes significance at 10% level.

## Online Appendix C

We here relax the assumption that survey fixed effects, region fixed effects, country-specific time trends, malaria ecology interacted with time trends, and precipitation and temperature deviations completely address the endogeneity of  $\overline{X}_{gt}$  in equation (7).

Assume that after controlling for all these variables, there is still a  $v_{gt}^*$  that is correlated with  $\overline{X}_{gt}$ . Our strategy to address endogeneity takes the first difference of equation (7) and applies a GMM/IV estimator. Because different countries have surveys in different years, our first differences will not be with respect to the previous calendar year, but with respect to the previous survey year which will be different by country. Specifically, our transformation is given by

$$\begin{aligned} \overline{P}_{gt_{l,c}} - \overline{P}_{gt_{l-1,c}} &= [\overline{X}_{gt_{l,c}} - \overline{X}_{gt_{l-1,c}}] \left( \frac{\beta + \delta}{1 - \gamma} \right) \\ &+ \frac{\theta_1 (Z_{1ct_{l,c}} - Z_{1ct_{l-1,c}})}{1 - \gamma} + \frac{\theta_2 (Z_{2gt_{l,c}} - Z_{2gt_{l-1,c}})}{1 - \gamma} \\ &+ \frac{v_{gt_{l,c}}^* - v_{gt_{l-1,c}}^*}{1 - \gamma} + (\overline{\varepsilon}'_{gt_{l,c}} - \overline{\varepsilon}'_{gt_{l-1,c}}) \end{aligned}$$

This transformation eliminates the time-invariant component  $v_g$ , but  $v_{gt_{l,c}}^* - v_{gt_{l-1,c}}^*$  will still be correlated with  $[\overline{X}_{gt_{l,c}} - \overline{X}_{gt_{l-1,c}}]$  by definition. To obtain consistent estimates of  $\frac{\beta + \delta}{1 - \gamma}$ , we apply instrumental variables to this equation, using the lags  $\overline{X}_{gt_{l-2,c}}$  as instruments for  $[\overline{X}_{gt_{l,c}} - \overline{X}_{gt_{l-1,c}}]$ . The main limitations of this approach is that it can only be implemented for countries for which we have at least three waves of data and that the lags  $\overline{X}_{gt_{l-2,c}}$  are likely to be a weak instrument for  $[\overline{X}_{gt_{l,c}} - \overline{X}_{gt_{l-1,c}}]$ .

Table C.I presents the results of the GMM/IV approach for children's preventive behaviors (in column (2)). The estimates are unreliable because of weak instruments (see the low value of the first-stage F-statistics).

We do not provide the results of the GMM/IV method for women's preventive behaviors because the regional-level sample with three waves of data is too small.

Table C.I. Regional-level regressions (OLS and GMM/IV)

	Regional OLS (1)	Regional GMM/IV (2)
<b>Panel A. Dependent variable: Sleeping under any type of bednet</b>		
Mother's secondary education	0.127** (0.0609)	-3.9056 (22.8540)
Household wealth	0.0446 (0.0334)	0.8832 (3.6296)
Observations	1,436	492
R-squared	0.754	-6.016
Number of (split) regions	472	302
First stage F-stat for education [P-value]		3.58 [0.0144]
First stage F-stat for wealth [P-value]		1.21 [0.3057]
Kleibergen-Paap Wald F-stat		0.0100
<b>Panel B. Dependent variable: Sleeping under an ITN</b>		
Mother's secondary education	0.0810 (0.0572)	-0.9385 (3.9133)
Household wealth	0.0095 (0.0327)	1.2718 (0.9006)
Observations	1,342	482
R-squared	0.815	-0.188
Number of (split) regions	430	293
First stage F-stat for education [P-value]		4.02 [0.0080]
First stage F-stat for wealth [P-value]		1.17 [0.3216]
Kleibergen-Paap Wald F-stat		0.04
Region FE	Yes	Yes
Time trend	Yes	Yes
Time trend <sup>2</sup>	Yes	Yes
Country FE × Time trend	Yes	Yes
Country FE × Time trend <sup>2</sup>	Yes	Yes
Survey type FE	Yes	Yes

Notes. GMM/IV estimates to address the endogeneity of education and wealth in regional models.

Robust standard errors, which are clustered by (split) region, are reported in parentheses.

\*\*\* denotes significance at 1% level. \*\* denotes significance at 5% level. \* denotes significance at 10% level.

## Online Appendix D

Table D.I. Models controlling for wealth inequality

	Individual OLS (1)	Regional OLS (2)
<b>Panel A. Dependent variable: Sleeping under any type of bednet</b>		
Mother's secondary education	0.0563*** (0.0042)	0.118* (0.0605)
Household wealth	0.0226*** (0.0021)	0.0365 (0.0377)
S.d. of household wealth		-0.0311 (0.0561)
Observations	662,105	1,436
R-squared	0.385	0.754
Number of (split) regions		472
<b>Panel B. Dependent variable: Sleeping under an ITN</b>		
Mother's secondary education	0.0451*** (0.0035)	0.0781 (0.0571)
Household wealth	0.0179*** (0.0021)	0.0091 (0.0360)
S.d. of household wealth		-0.0124 (0.0565)
Observations	601,031	1,342
R-squared	0.396	0.814
Number of (split) regions		430
<b>Panel C. Dependent variable: One dose of Fansidar or more</b>		
Mother's secondary education	0.0507*** (0.0067)	0.445** (0.208)
Household wealth	0.0143*** (0.0047)	0.0930 (0.0681)
S.d. of household wealth		-0.187* (0.103)
Observations	95,555	388
R-squared	0.580	0.903
Number of (split) regions		146
<b>Panel D. Dependent variable: Two doses of Fansidar or more</b>		
Mother's secondary education	0.0334*** (0.0057)	0.198 (0.204)
Household wealth	0.0081* (0.0048)	0.0736 (0.0558)
S.d. of household wealth		-0.0781 (0.0852)
Observations	88,316	356
R-squared	0.412	0.878
Number of (split) regions		136
Cluster FE	Yes	
Region FE		Yes
Time trend		Yes
Time trend <sup>2</sup>		Yes
Country FE × Time trend		Yes
Country FE × Time trend <sup>2</sup>		Yes
Survey type FE		Yes

Notes. The same controls as in Table III and IV are included.  
Robust standard errors, which are clustered by (split) region, are reported in parentheses.

\*\*\* denotes significance at 1% level. \*\* denotes significance at 5% level. \* denotes significance at 10% level.

## Online Appendix E

Our analysis in Section 6 has investigated social interactions for Sub-Saharan Africa as a whole. However, one may expect differences in the level of social interactions between East and West Africa, since West Africans are much more tribalists than East Africans, historically at least (we thank Michael Darden for this suggestion). To examine that point, we break down our sample into Eastern and Western countries, and re-estimate the individual- and regional-level models separately for the two samples. In our list of countries, the countries in West Africa are the following: Mali, Burkina Faso, Niger, Benin, Côte d'Ivoire, Gambia, Ghana, Liberia, Senegal, Sierra Leone, Togo, and Nigeria, whereas the countries in East Africa are the following: Tanzania, Kenya, Uganda, Rwanda, Burundi, Ethiopia, Mozambique, Madagascar, Malawi, Zambia, and Zimbabwe. These list follow the United Nations scheme of geographic regions. Note that Angola, Cameroon, Central African Republic, Chad, and the Democratic Republic of the Congo, which are in Middle Africa according to the UN, are not separately analyzed because the number of observations is too small. Namibia and Swaziland, which are part of Southern Africa, are not analyzed either, because they also represent too few observations in our sample.

The results of the analysis are presented in Table E.I. Panels A and B report the results for children's preventive behaviors. The coefficients imply that for sleeping under any type of bednet, the social multiplier associated with the mother's education is larger than one in East Africa, whereas the social multiplier associated with household wealth is larger than one in West Africa. For sleeping under a treated net, the multiplier on household wealth is also larger than one in West Africa.

Panels C and D contain the estimates for women's preventive behaviors. For taking one dose of Fansidar or more, the social multiplier associated with education is greater than one in West Africa.



Table E.I. Main model for East and West Africa

	Individual OLS (1)	Regional OLS (2)	Individual OLS (3)	Regional OLS (4)
	East Africa		West Africa	
<b>Panel A. Dependent variable: Sleeping under any type of bednet</b>				
Mother's secondary education	0.0932*** (0.0073)	0.227** (0.0966)	0.0305*** (0.0040)	-0.117 (0.105)
Household wealth	0.0232*** (0.0032)	0.0012 (0.0599)	0.0214*** (0.0033)	0.0838* (0.0474)
Observations	254,078	545	297,542	627
R-squared	0.407	0.832	0.346	0.698
Number of (split) regions		168		202
<b>Panel B. Dependent variable: Sleeping under an ITN</b>				
Mother's secondary education	0.0760*** (0.0062)	0.116 (0.0911)	0.0265*** (0.0035)	-0.0402 (0.110)
Household wealth	0.0196*** (0.0031)	-0.0552 (0.0570)	0.0169*** (0.0038)	0.0888* (0.0456)
Observations	250,351	536	250,571	572
R-squared	0.410	0.868	0.361	0.805
Number of (split) regions		168		175
<b>Panel C. Dependent variable: One dose of Fansidar or more</b>				
Secondary education	0.0585*** (0.0084)	0.131 (0.226)	0.0300*** (0.0084)	0.972** (0.442)
Household wealth	0.0105* (0.0053)	0.106 (0.112)	0.0212** (0.0084)	0.0952 (0.0753)
Observations	54,021	244	38,043	126
R-squared	0.554	0.895	0.614	0.952
Number of (split) regions		86		51
<b>Panel D. Dependent variable: Two doses of Fansidar or more</b>				
Secondary education	0.0354*** (0.0067)	0.0220 (0.216)	0.0248** (0.0119)	0.503 (0.538)
Household wealth	0.0059 (0.0051)	0.117 (0.0794)	0.0120 (0.0087)	0.0214 (0.0755)
Observations	47,286	212	37,558	126
R-squared	0.394	0.892	0.421	0.891
Number of (split) regions		76		51
Cluster FE	Yes		Yes	
Region FE		Yes		Yes
Time trend		Yes		Yes
Time trend <sup>2</sup>		Yes		Yes
Country FE × Time trend		Yes		Yes
Country FE × Time trend <sup>2</sup>		Yes		Yes
Survey type FE		Yes		Yes

Notes. The same controls as in Table III and IV are included.

Robust standard errors, which are clustered by (split) region, are reported in parentheses.

\*\*\* denotes significance at 1% level. \*\* denotes significance at 5% level. \* denotes significance at 10% level.

## Online Appendix F

Table F.I. Excess variance across groups and social interactions

Group		Standard deviation			
		Sleeping under any type of bednet	Sleeping under an ITN	One dose of Fansidar or more	Two doses of Fansidar or more
<b>Panel A. Unadjusted standard deviations of malaria preventive behaviors</b>					
Individual		0.4582	0.4126	0.3862	0.4731
Cluster	Actual	0.2886	0.2595	0.2404	0.3535
	Counterfactual	0.1230	0.1109	0.1454	0.1740
	Ratio	2.3463	2.3399	1.6534	2.0316
Region	Actual	0.2322	0.2194	0.2108	0.3238
	Counterfactual	0.0270	0.0254	0.0254	0.0332
	Ratio	8.6000	8.6378	8.2992	9.7530
<b>Panel B. Standard deviations of malaria preventive behaviors adjusted for observed characteristics</b>					
Individual		0.4469	0.3876	0.3716	0.4516
Cluster	Actual	0.2729	0.2233	0.2197	0.3298
	Counterfactual	0.1206	0.1038	0.1394	0.1643
	Ratio	2.2629	2.1513	1.5760	2.0073
Region	Actual	0.1121	0.1118	0.2108	0.1717
	Counterfactual	0.0236	0.0214	0.0230	0.0238
	Ratio	4.7500	5.2243	9.1652	7.2143
Avg. cluster size		20.44	20.32	10.66	10.83
Avg. region size		464.27	451.58	290.61	291.48