Social Learning in Health Behaviour:

The Case of Mosquito Bed Nets in Tanzania

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Abstract

Malaria represents a heavy burden for developing countries. Mosquito bed nets have been proved to be an effective means of prevention and to reduce the rate of infection at the community level. However, in many African countries, bed net adoption is not as widespread as policy indications would suggest. This study uses a 13-year panel of individuals in Tanzania (KHDS) to assess the effect of social interactions in different social groups (households and neighbourhoods) on individual adoption decisions. To disentangle the effect of social interactions from that of characteristics common across group members we use a definition of social groups that exploits different timing in household membership, and is based on geographic distance for neighbourhood membership. Under the various specifications explored, we find that social learning at the household level, on average, increases the probability of adoption by up to 30% and this effect may be even higher for more educated and wealthier people. We also find that social interactions at neighbourhood level generate incentives to not adopt bed nets; the intensity of this effect is independent of geographic distance and is homogeneous across different categories of the population.

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1. Introduction

The burden of malaria has been widely documented, both from the short-time micro perspective and from the long-run macro one. Intimate linkages between this endemic disease, poverty and economic growth are undeniable[1]. In the last decade, international organizations as well as governments of the most affected countries have recognized the relevance of the problem. In 2000, by signing the United Nations Millennium Declaration, 189 countries have committed themselves to work together to attain the Millennium Development Goals, including reversing the incidence of malaria using effective prevention and treatment measures[2].

Moreover, in 2000, African leaders have made a further major commitment to prevention and treatment of malaria as part of the Roll Back Malaria (RBM) movement[3]. One of the specific goals concerns the protection of the population, especially children and pregnant women, with ITNs - insecticide treated mosquito bed nets (WHO 2000).

The use of ITNs has emerged as a cost-effective measure to prevent malaria. It has been estimated that ITNs can reduce the incidence of uncomplicated malarial episodes in areas of stable malaria by around 50% compared to no nets, and 40%

[1] Manley and Sachs (2002) provide a detailed analysis of the burden of malaria and more recently Conley et al. (2007) establishes the links between malaria, child mortality and fertility, and the effects on demographic transition in the long run.

[2] MDG number 6 is “Combat HIV/AIDS, Malaria and Other Diseases”. More specifically target number 8 is: “Have halted by 2015 and began to reverse the incidence of malaria and other major diseases”. Indicators number 21and 22 for monitoring progresses are respectively: prevalence and death rates associated with malaria, and proportion of population in malaria-risk areas using effective malaria prevention and treatment measures.

[3] Information on the roll back malaria partnership are available in the web site: http://rbm.who.int/

compared to traditional non treated nets (Lengeler, 2004). Moreover, malaria control positively affects general health conditions as well. For example in malaria-endemic African regions it can reduce incidence of anaemia and other mosquito-borne diseases (Korenromp 2004). In addition, there is relatively strong evidence of negative correlation between probability of transmission of the disease and coverage of mosquito bed nets at the community level (Curtis et Al. 2006). This is due to the effect of any type of nets in breaking the transmission cycle, as well as to the reduction of mosquito survival caused specifically by ITNs. As documented by Maxwell et al. (2002) and Curtis et al. (2003), this constitutes a reason to look at the private use of mosquito bed nets as a public good that produces positive externalities on the risk of infection for the whole community.

Regardless of campaigns and specific policy to increase the diffusion of mosquito bed nets adoption, the average population coverage is still far from the target, even though it has significantly increased in recent years. Furthermore it has been shown that, in spite of ownership, people sometimes do not use mosquito bed nets[4]. This suggests that the adoption decision may be determined by variables other than obvious socioeconomic factors directly influencing affordability. Social scientists have developed different theories to explain attitudes towards health, behaviours and behavioural change. One of them concerns models of diffusion of health innovations that emphasize communication and social learning[5].

This study focuses on the Kagera Region in the North-West of Tanzania, an area of high malaria incidence, and aims not only to generally shed some light on the

[4] Macintyre et al. (2006) in a case study from Eritrea testimony how possession does not imply effective use of bed nets.

[5] A brief overview of theories of health behaviour can be found in Scrimshaw (2001).

determinants of adoption of mosquito bed nets, but more in particular to analyse the role of social learning. The data available allows us to study social learning in different social groups of which individuals are part.

The body of empirical literature on social learning has been developed starting from the seminal papers of Besley and Case (1994) and Foster and Rosenzweig (1995), and aims to assess any evidence of learning in agricultural technology adoption at the community level. Munshi (2004) has contributed to the literature by exploring the same kind of effects in a heterogeneous population. Conley and Udry (2000) have introduced the social network dimension in this literature, while Bandiera and Rasul (2006) have compared correlations in adoption decisions within different networks: family, friends and religion-based networks. Social learning is conceived as a common process of experimentation, outcome observation and consequent adaptation, where the introduction of social networks is interpreted as a restriction of this common process within networks.
As far as we know, Kremer and Miguel (2003) and Leonard (2005)[6] were the first to consider the effect of social learning in health related behaviours, by looking respectively at the intake of de-worming drugs and at health care seeking.

The purpose of our study is to enrich the empirical literature on social learning in health related behaviours through the analysis of differences in the intensity of learning, across social groups.

[6] Leonard (2005) focuses mainly on individual learning but interpret residual correlation between errors as a potential signal of social learning.

This is done in the context of bed nets adoption, a health technology that, as explained above, can be considered a public good and therefore implies the coexistence of two types of social interaction effects that act in opposite directions. On the one hand, the more other people use bed nets, the more we may observe social learning that generates incentives to adoption. On the other hand, we may have positive externalities that reduce the individual risk of infection, and in turn generate incentives for free-riding behaviour, leading to non adoption. In this sense our work is very close in spirit to Kremer and Miguel (2004), however we conduct our analysis on non experimental data[7].

We use household panel data collected in the Kagera region of Tanzania (Kagera Health and Development Survey – KHDS) to identify social learning effects in three non-overlapping social groups of which every individual is part: household, close neighbourhood and far neighbourhood[8]. We try to assess the relationship, if any, between the intensity of different social ties linking individuals in different groups, and the intensity of social learning. To empirically identify social learning effects we look at how the presence of other people already using bed nets within a particular group affects individual decisions. We are able to solve problems related to the identification of social interaction effects, as illustrated by Manski (1993), through

[7] Experimental data generally presents the advantage of allowing the econometrician to analyze the effect of a randomised treatment and to infer conclusions not biased by self selction or other forms of endogeneity. On the other hand, experiments may present some artificiality that may raise doubts about the credibility of findings extrapolated from experimental settings. .In particular specific findings are related to a specific group in specific conditions. Kremer and Miguel (2006) themselves evidence how very different findings can be found under experimental and non experimental conditions. In our opinion this is not only due to non randomization issues.

[8] We define a household as the group of people living in the same dwelling. Close and far neighbourhood are defined as the group of people living in other households in the village which are respectively closer or further than the average distance between the household itself and all the other households in the village

the exploitation of the panel dimension of KHDS, of the specific structure of the KHDS-2004 sample (which includes all individuals previously interviewed and all new people who were living with them in 2004) and of GPS data on reciprocal distance between every pair of households in the same village.

We also analyse non-linear effects associated with social interactions in order to better understand our findings. When we find a positive correlation between individual decisions and group behaviour, the sign of non-linear terms enables us to test the the hypothesis of social learning as opposed to simple imitation; when we find a negative correlation, it enables us to test the hypothesis of free-riding behaviours as opposed to strategic delays in adoption.

Finally, we test the effect of interactions between social learning variables and indicators of education and income levels, which are recognized as important determinants of bed nets adoption.

In conclusion, our study contributes to the existing literature in several ways.

First of all, it represents a contribution to the identification of endogenous social interaction effects in non-experimental data, where Manski's reflection problem arises. In particular we exploit the panel dimension of the data to understand how the presence in the group of early bed net adopters affects adoption decisions of potential later adopters. We also use a definition of social groups that exploits different timing in household membership, and makes use of geographic distance for neighbourhood membership; this allows us to distinguish the effect of group behaviour from the effects of various observable and unobservable characteristics common across group members. Moreover the use of a first difference estimator on the sample of non-adopters allows us to rule out endogeneity related to simultaneity in adoption decisions. As far as we are aware, similar techniques have not been applied in the empirical literature on social learning.

Secondly, our definition of neighbourhood based on geographic distance between households can be considered a contribution to the literature on neighbourhood effects, where neighbourhoods are generally identified through administrative boundaries. In this sense our analysis represents also a test for proximity effects.

Thirdly, this study contributes to the empirical literature on social networks in two ways. Our analysis can be considered a test for the relevance of the distinction between social groups and proper social networks, in the sense that social interactions may produce very different incentives depending on the presence of specific social ties or not. In addition we estimate the effects generated from social interactions in non–overlapping social groups, whereas overlapping networks have generally been considered in the literature.

Finally, we believe that our findings may provide useful insights in terms of policy implications, as they may help in understanding the relevance of social interactions in people's decisions. Keeping this in mind may help in design more efficient policies.

Section 2 proposes a simplified theoretical framework for our empirical analysis. Section 3 describes the data and setting. Section 4 introduces the empirical strategy. Section 5 presents and discusses the results. Section 6 concludes and highlights policy implications and areas for further research.

2. Empirical Model

The following model aims to provide a framework to estimate social learning in adoption the of mosquito bed nets. We take into account the fact that the manifestation of social learning through a change in behaviour can be mitigated by disincentives to adoption. Disincentives come from the reduction of the probability of individual infection generated by spillover effects associated with the number of other people using bed nets. The model enables us to derive an empirical test for the intensity of learning effects across non-overlapping social groups[9] in the presence of free riding incentives, as described above.

Durlauf and Cohen-Cole (2005) identify two broad classes of questions related to social interactions, that are conceived as a complement to the traditional economic focus on individual interdependences mediated via prices. The first is "How do the characteristics and choices of others affect an individual's decision-making?" and the second is "How are these social influences reflected in equilibrium behaviours observed in a group as a whole?"

We limit our analysis to the first type of question and we aim to provide a theoretical explanation of why the behaviour of other people in the same group may have different final effects on individual adoption depending on who the other people are.

[9] We decide to use the term social group instead of social network because we do not have specific information on the network structure. We assume that people in the same social group are all related by the same type of relationship. We also assume that the same person is part of different, exogenously given and non-overlapping networks. Therefore, to avoid any misunderstanding we prefer to not abuse the term network.

We will focus on a short-term equilibrium, without any ambition to explain long-run diffusion processes[10].

This choice is driven by the empirical application of the model. Relatively widespread net adoption is recent in the data and the long term social equilibrium can not be modelled empirically and identified. Our data allow us to explore only the short-term individual determinants of adoption and the role played by social interactions.

The applications of this simple model are not restricted to the decision of mosquito bed net adoption, but can be extended to consumption decisions for a variety of goods that entail private costs and benefits, as well as positive externalities for the community.

2.1. The model

Suppose that there are N people, indexed by $i = (1,\ldots,N)$. Individual i has to decide whether to adopt a new technology, corresponding in this case to the health practice of sleeping under a mosquito bed net.

Let $M_{it} \in \{0,1\}$ be a binary variable that indicates the status of adoption; $M_{it} = 1$ if the agent is sleeping under a mosquito bed net in period t and $M_{it} = 0$ if she is not. $M_t = (M_{1t},\ldots,M_{Nt})'$ is an adoption profile. It is an N x 1 vector of adoption states for

[10] We are not aware of any theoretical model exploring long-term social equilibrium in technology diffusion in presence of a similar mixed incentive structure.

all N people. Letting Ω represents the space of all the possible states of M_t, every realization of $M_t \in \Omega$ can be thought as an equilibrium.

We assume individual *i* to be rational and therefore adopt behaviour $M_{it} = 1$ if this implies a positive added payoff.[11] We define the added payoff as the latent expected private benefit from adoption:

$$E_t\left[(U_{it}(M_{it}=1) - U_{it}(M_{it}=0)) - (C_{it}(M_{it}=1) - C_{it}(M_{it}=0))\right] \tag{1}$$

where U_{it} represents the utility derived from M_{it} and C_{it} represents the current cost of M_{it}, For simplicity we set $C_{it}(M_{it}=0)=0$.

We can define *i*'s strategy with respect to the choice of M_{it} as follows:

$$M_{it} = \begin{cases} 1 \ \ if \ E_t\left[U_{it}(M_{it}=1) - U_{it}(M_{it}=0) - C_{it}(M_{it}=1)\right] \geq 0 \\ 0 \ \ if \ E_t\left[U_{it}(M_{it}=1) - U_{it}(M_{it}=0) - C_{it}(M_{it}=1)\right] < 0 \end{cases} \tag{2}$$

We now introduce strategic interactions in the game by inserting other people`s behaviour as a determinant of the payoff from individual choice.

We assume that every other individual *j* in the community has a relationship with *i* through the membership of different non-overlapping social groups. Every individual *i* is part of *K* non overlapping social groups G_{ik} (e.g. household and neighbourhood) such that *i* is the only overlapping member of G_{ik} and G_{ik-1}, more formally $G_{ik} \cap G_{ik-1} = \{i\}, \forall k = 1,...,K$. For all $j \neq i$, $j \in G_{ik}$ for exactly on value of $k \in \{1,...,K\}$.

[11] This is a common assumption in social interaction models with binary dependent variables. A simple and similar setup is used for example by Jackson and Yariv (2006).

The utility payoff of individual i from decision $M_{it}=1$ depends not only on the individual specific attitude towards bed nets μ_{it}, but also on the number of adopters in every specific group to which i belongs to.

According to Manski (2000), economic agents interact through their chosen actions. This happens mainly through three channels: constraints, expectations and preferences. Our model considers two different forms of interactions in expectations that generate opposite effects on an individual's decision[12], so that the number of other people adopting mosquito bed nets in a specific reference group can affect *i*'s decision through two different channels. The first channel is a reduction of the individual probability of malaria infection, denoted by γ_{it}[13], and thus the larger the number of other people using mosquito bed nets, the larger the reduction in γ_{it}, the larger the private incentive to not adopt nets. The second channel is social learning. People can learn from each other about the existence of mosquito bed nets and about their positive effects on preventing malaria infection[14]. We do not model explicitly

[12] This characterizes interaction in the form of social learning, while imitation would be modelled through preferences interaction. In our model individual taste for mosquito bed net is not affected by other agents' actions.

[13] Mosquitoes are a vector of transmission but do not originate malaria themselves, and private use of mosquito bed nets entails positive externalities for the whole community by preventing mosquitoes from diffusing malaria. The probability of mosquitoes biting infected people and then healthy ones is reduced along whit a smaller probability of mosquitoes biting people in general. Moreover, in the case of ITNs, mosquitoes are repelled and killed by the insecticide and externalities are even stronger. Hawley et al. (2003), Magesa et al. (1991), Curtis el al. (2006) and Maxwell at al. (2002) among others document these effects.

[14] Social learning involves two aspects: diffusion of information and consequent revision of beliefs and then behaviours. In the context of use of mosquito bed nets we are not able to distinguish between learning and imitation, however we rule out the possibility of pure imitation. The reason is that people can not observe each other's behaviour in this context, but they need to be explicitly informed about it. Information will be diffused mainly by bed nets users, convinced of the benefits from adoption. It is reasonable to think that they also advertise good reasons for adoption and positive results related to adoption. Such a process of information transmission implies that when people receive information they modify their behaviour because they consciously aim at attaining better health outcomes. As Foster and Rosenzweig (1995) point out, this feature differentiates social learning from other

the learning process[15], as this would involve the introduction of dynamics that, given data constraints, we could not investigate empirically. We only aim to explore the presence of positive social learning effects on individual beliefs about the efficacy of bed nets ϕ_{it}. In particular we are interested in explaining how these effects can vary in intensity across social groups and can potentially overcome the effect of γ_{it}.

We assume that the marginal effect on γ_{it}, generated by one extra person adopting a mosquito bed net, is independent of the group which the person belongs to[16]. In contrast, when considering social learning effects, we allow *i* to put different weights α_{ig} on the number of other people adopting mosquito nets, depending on the social group of which they are part. This implies that social learning effects are non-symmetric across groups. In other words, we keep the intensity of the positive externality effects symmetric across groups, while we allow the intensity of social learning effects to be group specific.

We can then express the private benefit from adoption as follows:[17]

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endogenous social effects, such as imitation or peer pressure, where there is no conscious attempt to improve outcomes. This is the reason why we exclude pure imitation effects in bed nets adoption.

[15] This is usually modelled as Bayesian learning. See for example Besley and Case (1994) and Bala and Goyal (1998). Our approach is similar in spirit to the equilibrium decision rule of Banerjee (1992). What we discussed in the previous note as Banerjee's "herd behaviour" is identified in our case as social learning.

[16] Our assumption is justified by two main reasons. First of all, the mechanism of transmission of malaria implies that if the probability of infection is reduced in one area of the village, due to a higher number of bed net adopters, then the effects are likely to spread around, unless other specific factors prevent this. Even though, especially in the very short run, it is plausible to think that the intensity of these spillovers may be affected by physical distance, this intensity is not related to social boundaries. Secondly our study focuses on social interactions and a potential reduction in the probability of infection can be observed by agent *i* independently of who the person using mosquito bed net is. The assumption that spillovers on the probability of infection are symmetric across social groups allows us to focus specifically on the effects of social ties.

[17] This specification is reminiscent of the specification used by Kremer and Miguel (2006), but differs from it in a few aspects. We explicitly introduce the group dimension, we do not distinguish pure

$$E_t\left[(U_{it}(M_{it}=1)-U_{it}(M_{it}=0))-C_{it}(M_{it}=1)\right]=$$
$$V_{it}[\gamma_{it}(x_{it},\sum_{k=1}^{K}\overline{M}_{ikt}),\sum_{k=1}^{K}\phi_{it}(x_{it},\alpha_{ik}\overline{M}_{ikt}),\mu_{it}(x_{it}),C_{it}(x_{it})] \quad (3)$$

Both γ_{it} and ϕ_{it} are functions of individual characteristics x_{it} and of the total number of adopters in every specific group $\overline{M}_{gt}$ .The costs of adoption C_{it} and the individual taste for mosquito bed nets μ_{it}, depend only on individual specific characteristics x_{it} [18].

We define $\overline{M}_{ikt}$ as the number of other people in group G_{ik} using mosquito bed net.

Let $\overline{M}_{ikt}=\sum_{j\neq i}G_{ik_{jt}}M_{jt}$ where $j\neq i\in\{G_{i1}\cup...\cup G_{iK}\}$ and $G_{ik_{jt}}=1$ if $j\in G_{ik}$ at time *t* for *k* = 1,…,G, and $G_{ik_{jt}}=0$ otherwise.[19]

This definition of $\overline{M}_{ikt}$ allows us to consider a static game structure where at time *t* person *i*'s decision is a best response[20] to other people's decisions. We can then think of any observed adoption profile M_t as a static equilibrium realisation.

The setting of the game contains the implicit assumption that agent *i* is perfectly informed about other people's behaviour. We believe that this assumption is plausible if we consider the two channels through which *j*'s decision influences *i*'s decision at time *t*.

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imitation effects and social learning effects, as explained above, and finally we limit our analysis to a static perspective.

[18] We can think of x_{it} as including household and community characteristics as well.

[19] Note that G_{ik} is an group of individuals defined with respect to *i*, while $G_{ik_{jt}}$ is an index telling us if individual *j* at time *t* is a member of group G_{ik} .

[20] A similar theoretical framework is used by Nakajima (2004) in analysing peer effects on youth smoking behaviour; however he focuses on a long-term dynamic structure.

γ_{it} is known to *i* and it can be thought as a signal of $\sum_{k=1}^{K} \overline{M}_{ikt}$. Due to the assumption of symmetry in the positive externalities on γ_{it}, we can think of γ_{it} as a signal for every $\overline{M}_{ikt}$. This does not involve a direct observation of other individuals' behaviour (which is probably not happening in reality) but, given the final observable effect, in our analysis we consider perfect information about the signal to be equivalent to perfect information about other people's behaviour. This is equivalent saying that any shock affecting the signal is observable to *i*[21].

With respect to social learning, we assume that the function generating beliefs about mosquito bed net efficacy ϕ_{it}, is the same for every $\alpha_{ik}\overline{M}_{ikt}$ observable to *i*. We are assuming symmetry in social learning and also underling perfect information about M_{jt}, but we are imposing a group specific parameter $\alpha_{ik} \geq 0$ to account for a different intensity of the relationship between *i* and *j*, depending on which group *j* belongs to. Keeping in mind the two components of social learning (information transmission and consequent behaviour modification) we can interpret $\alpha_{ik} \geq 0$ as a joint measure of both degree of information transmission and perceived reliability of the source of information. $\alpha_{ik} = 0$ can reflect either a lack of diffusion of information about bed nets, or a lack of trust between *i* and members *j* of group G_{ik}, so that *i* does not consider *j* a reliable source of information. In practice α_{ik} can be thought as a way to reshape the original assumptions of perfect information in the same group and of symmetry in social learning across different groups. In this way we are attributing

[21] This assumption is quite plausible in our context as shocks affecting the incidence of malaria in the village, such as longer rain season, would be common knowledge.

every potential limitation to the original assumptions to one factor only: the intensity of social ties in different groups.

Given this framework we can finally analyse the marginal effect of $\overline{M}_{ikt}$ on individual decisions:

$$\frac{\partial V_{it}}{\partial \overline{M}_{ikt}} = \frac{\partial V_{it}}{\partial \gamma_{it}} \frac{\partial \gamma_{it}}{\partial \overline{M}_{ikt}} + \frac{\partial V_{it}}{\partial \phi_{it}} \frac{\partial \phi_{it}}{\partial \alpha_{ik} \overline{M}_{ikt}} \alpha_{ik} \tag{4}$$

The effect of $\overline{M}_{ikt}$ on the private benefit from adoption (through the reduction of individual probability of infection), is always negative. $\frac{\partial V_{it}}{\partial \gamma_{it}} \frac{\partial \gamma_{it}}{\partial \overline{M}_{ikt}} < 0$, since $\frac{\partial V_{it}}{\partial \gamma_{it}} > 0$ and $\frac{\partial \gamma_{it}}{\partial \overline{M}_{ikt}} < 0$. This says that the benefit from protection increases along with the probability of infection, which in turn decreases in the total number of people using mosquito bed nets. This is due to the positive externality effects described above.

The effect of $\overline{M}_{ikt}$ on the private benefit from adoption through social learning is always positive, since the perceived benefit from protection is positively correlated with beliefs about bed nets efficacy, which in turns is increasing in the number of other people already using mosquito bed nets. More formally $\frac{\partial V_{it}}{\partial \phi_{it}} \frac{\partial \phi_{it}}{\partial \alpha_{ik} \overline{M}_{ikt}} \alpha_{ik} \geq 0$ always, since $\frac{\partial V_{it}}{\partial \phi_{it}} > 0$ and $\frac{\partial \phi_{it}}{\partial \alpha_{ik} \overline{M}_{ikt}} \alpha_{ik} \geq 0$.

The final effect of $\overline{M}_{ikt}$ on V_{it} captures social interaction's endogenous effects. It is ambiguous and depends on which one of the two specific effects prevails.

If $\alpha_{ik} > -\frac{\partial V_{it}}{\partial \gamma_{it}} \frac{\partial \gamma_{it}}{\partial \overline{M}_{ikt}} \Big/ \frac{\partial V_{it}}{\partial \phi_{it}} \frac{\partial \phi_{it}}{\partial \alpha_{ik} \overline{M}_{ikt}}$, group k social learning effects overcome positive externality effects and adoption decisions are strategic complements; if $\alpha_{ik} = -\frac{\partial V_{it}}{\partial \gamma_{it}} \frac{\partial \gamma_{it}}{\partial \overline{M}_{ikt}} \Big/ \frac{\partial V_{it}}{\partial \phi_{it}} \frac{\partial \phi_{it}}{\partial \alpha_{ik} \overline{M}_{ikt}}$ the two effects perfectly compensate each other; and finally, if $\alpha_{ik} < -\frac{\partial V_{it}}{\partial \gamma_{it}} \frac{\partial \gamma_{it}}{\partial \overline{M}_{ikt}} \Big/ \frac{\partial V_{it}}{\partial \phi_{it}} \frac{\partial \phi_{it}}{\partial \alpha_{ik} \overline{M}_{ikt}}$, positive externality effects overcome social learning effects in group *k*, and adoption decisions are strategic substitutes.

Every difference in $\frac{\partial V_{it}}{\partial \overline{M}_{ikt}}$ across groups is determined by the parameter α_{ik}. This means that if the relationship between *i* and *j* is strong enough, social learning may prevail over the effect of positive externalities and may generate social multipliers that trigger a prolific diffusion process.

2.2. Empirical test for differences in social learning across groups

We make three simplifying assumptions that allow us to derive an empirical test for differences in social learning across social groups in this context. We assume that V_{it} is linear in γ_{it} and in ϕ_{it}, that γ_{it} is separable in x_{it} and $\sum_{k=1}^{K} \overline{M}_{ikt}$, and finally that ϕ_{it} is separable in x_{it} and $\alpha_{ik} \overline{M}_{ikt}$. This is equivalent to saying *i* can disentangle the effect of $\overline{M}_{ikt}$ and x_{it} on γ_{it} and ϕ_{it} respectively.

Equation (3) becomes:

$$V_{it} = \gamma_{it}(x_{it}, \sum_{k=1}^{K} \overline{M}_{ikt}) + \sum_{k=1}^{K} \phi_{it}(x_{it}, \alpha_{ik} \overline{M}_{ikt}) + \mu_{it}(x_{it}) + C_{it}(x_{it}) \qquad (5)$$

and the marginal effect of $\overline{M}_{ikt}$ on V_{it} is reduced to the sum of the two separated marginal effects of $\overline{M}_{ikt}$ on γ_{it} and ϕ_{it} as follows:

$$\frac{\partial V_{it}}{\partial \overline{M}_{ikt}} = \frac{\partial \gamma_{it}}{\partial \overline{M}_{ikt}} + \frac{\partial \phi_{it}}{\partial \alpha_{ik} \overline{M}_{ikt}} \alpha_{ik} \tag{6}$$

We can think of V_{it} as a latent variable and derive the reduced form specification

$$M_{it} = \begin{cases} 1 \ \ if \ \sum_{k=1}^{K} \delta_k \overline{M}_{ikt} + \beta x_{it} + \varepsilon_{it} \geq 0 \\ 0 \ \ if \ \sum_{k=1}^{K} \delta_k \overline{M}_{ikt} + \beta x_{it} + \varepsilon_{it} < 0 \end{cases} \tag{7}$$

where x_{it} is a vector of individual, household and community characteristics, β is the vector of associated coefficients, $\overline{M}_{ikt}$ is defined as above and $\delta_k = \frac{\partial V_{it}}{\partial \overline{M}_{ikt}}$.

We can finally estimate

$$\Pr(M_{it} = 1) = F(\sum_{k=1}^{K} \delta_{ik} \overline{M}_{ikt} + \beta x_{it}) \tag{8}$$

where the specific form of the cumulative distribution function depends on the econometric model estimated.

From the sign of estimated coefficients δ_k, we can infer the sign of $\frac{\partial V_{it}}{\partial \overline{M}_{ikt}}$, otherwise unobserved to the econometrician. This gives us information about social learning in different groups. If $\delta_k > 0$, then $\frac{\partial V_{it}}{\partial \overline{M}_{ikt}} > 0$ and we can conclude that $\alpha_{ik} > -\frac{\partial \gamma_{it}}{\partial \overline{M}_{ikt}} \Big/ \frac{\partial \phi_{it}}{\partial \alpha_{ik} \overline{M}_{ikt}}$ and that social ties in group g are strong enough to generate social learning in group *k* intensively enough to overcome the effect of positive externalities. Analogous conclusions can be reached when $\delta_k = 0$ and $\delta_k < 0$. In the context of our model, $\delta_k > 0$ represents an evidence of social learning effects, while $\delta_k < 0$ represents an evidence of positive externalities on the reduction of probability of infection. Differences in δ_k across social groups reflect differences in social learning depending on the average intensity[22] of the social ties among members of the same group. For instance, if we have negative coefficients of different magnitudes in different groups, we can infer that the difference is determined by social learning that compensates for the incentive to free-ride, constant across groups.

Section 4 presents the specific empirical methodology adopted in this study to apply the test and to deal with endogeneity problems in the identification of social interaction effects.

[22] We talk about "average intensity" because every couple of individuals in the same group can be related trough different kinds of relationships. We are not taking into account specific relationships between individuals in the same group, but we are implicitly assuming that this relationship is the same for every $i, j \in G_k$. This also explains why, unlikely α_{ik}, δ_k is not indexed by *i*. α_{ik} can not be inferred from the data for every individual specifically, and we can only capture an average value across the population. This is somehow equivalent saying that $\delta_k = \frac{\sum_{i=1}^{N} \alpha_{ik}}{N}$.

3. Setting and Data

Our analysis is based on data from Kagera, a region in the North West of Tanzania bordering Burundi, Rwanda, Uganda and Lake Victoria. Kagera comprises six districts: Bukoba Rural, Bukoba Urban, Muleba, Karagwe, Biharamulo and Ngara[23]. According to the 2002 National Census, the population is 2,003,888 people with an annual growth rate of 3.1%. Over 90% of the population lives in rural areas and is primarily engaged in agricultural production (bananas and coffee in the North and maize, sorghum and tobacco in the South). Surpluses of food crops are traded mainly locally and exported to urban centres and neighbouring regions and countries.

3.1. Malaria incidence and policies in Tanzania and Kagera

According to the World Malaria Report 2005, Tanzania is classified as a malaria endemic country, subject to frequent and recurrent epidemics, mainly generated by anomalies of rainfall and/or temperature. 93% of the population is living in areas at risk of stable malaria[24]. Getting precise information about incidence and trends of malaria in Tanzania is not easy, mainly because malaria is not considered a notifiable disease in the country and because people, especially in rural areas, tend to cure diseases at home without seeking care to formal health providers. In 2003,

[23] Just recently Biharamulo has been split in Biharamulo and Chato and Bukoba Rural has been split in Bukoba Rural and Mishenyi.

[24] 'Stable malaria' refers to situations where infection is common and occurs with a frequency sufficient to develop some level of immunity. Stable malaria has to be distinguished from other situations where the risk of malaria is more seasonal and less predictable, for example because of either altitude or rainfall patterns.

10,712,526 clinically diagnosed cases of malaria were reported, out of a population of 36,977,000 inhabitants; this is equivalent saying that about 1 out of 3.5 people in the country experienced malaria. About 5% of the reported cases (512,019) were cases of severe malaria and 0.13% of them (14,156) led to death. 45% of reported cases (4,800,768) concerned children less than 5 years old. The number of reported cases seems to have decreased from 1990 to 1997 and then increased again to reach about the same initial level in 2003[25].

Malaria represents a heavy burden for the country. According to the Tanzanian ministry of Health, in 2002 malaria was still a leading cause of health service attendance and also of death (it was responsible for over 25% of total deaths), both among children and adults.

Information about the incidence of malaria in Kagera is not easily available, but the region is classified as being at high risk of malaria and easily subject to serious outbreaks. On one hand, the only information about Kagera reported in the World Malaria Report provides encouraging data for Muleba district, documenting a reduction from 164,642 to 30,907 reported cases between 2000 and 2002[26]. On the other hand Kagera region has recently been in the news head lines because of a serious malaria outbreak and the same district, Muleba, was one of the most affected

[25] According to World Malaria Report 2005, malaria is not a notifiable disease in the country, so that information on reported malaria is expected to be incomplete. Nevertheless, comprehensive reported malaria data was collected in 109 districts out of 114, representing about 96% coverage of all health facilities. The report is warns that “Malaria reporting from national surveillance systems varies in quality and reporting completeness and may have limited value in understanding the actual malaria burden”, nevertheless these are the only statistics available and we think that they can be useful to give a general overview of the incidence and trend of the disease in the country.

[26] According to Census 2002, Muleba has a population of about 386 thousand inhabitants. This allows us to infer that in the same year there was around one case of reported malaria for every 12 inhabitants.

districts[27]. Other very serious malaria crises in Kagera were reported in 1994 and 1998-99. Malaria epidemics in the region have historically been caused by heavier or longer rainfall and by inflows of refugees from neighbouring countries.

The NMCP (National Malaria Control Program), introduced by the Tanzanian Government after the Abujia Summit in 2000, focuses on four main guidelines: prompt and effective treatment, vector control, prevention of malaria in pregnancy and prevention and control of epidemics. The National Malaria Medium-term Strategic Plan finalised in 2002 places a major emphasis on the widespread use of ITNs as an effective strategy both for vector control and for prevention. Since 1983 much work has been done on ITNs in Tanzania. Initially it only consisted of efficacy and effectiveness studies and policy developments, while effective policy implementation began in 2000 only[28]. A comprehensive programme to promote the scaling up of ITNs is in place and is targeting both the supply and the demand side of the market, respectively through social marketing and vouchers distribution[29].

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[27] An IFRC Bulletin in July 2006 says: "According to a report received from the Tanzania Red Cross National Society (TRCNS) on 10 July 2006, there has been a rise in the number of malaria cases resulting in increased mortality, especially among children aged under five years. The two most affected districts are Karagwe and Muleba in Kagera region, which have reported about 300 deaths of children aged under five since January 2006, excluding unreported cases that might have occurred at home. The number of deaths per month among children increased from 2,295 in February to 3,542 in May in Muleba District and from 3,014 to 3,944 in Karagwe District. It was not until June that the emergency situation became apparent, when the number of admitted patients with severe anemia increased from 89 to 170, raising the demand for blood transfusion in the Rubya and Nyakahanga hospitals in Karagwe and Muleba respectively.".

[28] See Magesa et al. (2005) for a complete narrative of policies for ITNs promotion in Tanzania.

[29] The final aim of the Strategic Social Marketing for Expanding the Commercial Market for ITNs in Tanzania (SMARTNET) is to promote the expansion of Tanzanian manufacturers' wholesale and retail networks. A critical point of the implementation of the programme is the availability of bed nets in local shops. The Tanzania National Vouchers Scheme (TNVS) aims at giving every pregnant woman who attends an antenatal clinic a printed voucher which can be used to purchase an ITN at a discounted price from any commercial retailer involved in the initiative. Moreover, techniques for long-lasting insecticide treatment of nets have been developed and although long-lasting insecticidal nets (LLINs) are more expensive than conventional ones, they have a lower cost of maintaining coverage. Two brands of LLINs are now recommended by WHO, and one of them is a Tanzanian producer who began the activity in 2004. Technology transfer to high-malaria settings is seen as the

These policies have been implemented only in some area of the country and have not reached a national coverage yet[30]. As far as we are aware, Kagera has not been targeted by any of these governmental policies. This does not exclude the implementation of specific projects in certain villages by NGOs or international agencies.

The most recent statistics on the coverage of mosquito bed nets at national and regional level are available from the Demographic Health Survey (DHS) 2004[31].
The average number of nets per household has been calculated to be 0.9 in Tanzania. 46% of all Tanzanian households own[32] at least one mosquito bed net, but only half of these own an ITN. The same figures rise to 74% and 47% when considering urban areas and drop to 36% and 14% when looking at rural areas. An even higher difference is found when disaggregating by income. 56% of the households in the highest wealth quintile own at least one ITN, while only 6% of households in the lowest wealth quintile own one. The average percentage of children under 5 years who sleep under a mosquito bed net is about 30% (only 16% if we consider ITNs in particular). Very similar figures apply to women and pregnant women and great disparities are reported when disaggregating per area, income and education.

In Kagera the percentages of households owning at least one mosquito bed net or an ITN are slightly smaller compared to the national average. This is likely to reflect the

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way to bring prices down while stimulating industrial activities. The combination of these three policies qualifies this inclusive programme as an exceptional example.

[30] See Ebenezeri et al. (2005) for a detailed description and evaluation of ITNs policies in Tanzania

[31] See NBS Tanzania and OCR Macro (2005). DHS (Demographic and Health Survey) has been conducted in Tanzania almost yearly since the beginning of the 90s, but questions on use of mosquito bed nets were not introduced until the most recent rounds, whose related reports are available for 2004 only.

[32] In this section we assume that ownership implies utilization, and we use the two terms equivalently.

predominant rural nature of the area. More in detail, the average number of nets per household is 0.5, while the percentages of households owning at least one bed net and one ITN are respectively 31.3% and 13.9%. 24.6% of children less than 5 years old sleep under a mosquito bed net, while only 13.1% sleep under an ITN. The same percentages decrease to 22.2% and 11.2% for women and 24.4% and 12.6% for pregnant women.

This data clearly shows that ITNs are not as diffused as non-impregnated bed nets. There are good reasons to think that these differences may be related to ITN availability, ITN affordability (ITNs can be more than twice as expensive as common nets) and to people's awareness of the nets characteristics and their efficacy.

We do not have information on net coverage through time and we cannot have a precise idea of net and ITN diffusion before 2004. However if we look at the sample covered by Ebenezeri et al. (2005), which does not include Kagera, the number of people using ITNs has significantly increased since 2000 as a result of implemented governmental policies. However this is not informative about the diffusion of nets in general in Kagera during the '90s.

3.2. Kagera Health and Development Survey (KHDS)

The Kagera Health and Development Survey (KHDS)[33] is a 13-year individual panel survey of people in Tanzania. It is a World Bank Living Standards Measurement

[33] Information, documentation and the full data set of the KHDS (1991-1994 and 2004) are available on the Living Standards Measurement Study website: http://www.worldbank.org/lsms/. Ainsworth *et al*. (1992), Beegle at al. (2006a) and (2006b) and World Bank (1993) and (2004) provide a complete description of the survey and its characteristics.

Study and it contains a great variety of indicators of well-being (consumption, expenditure, asset holdings, morbidity, health, nutrition, and education). The sample was not specifically designed to be self-weighting, but following a comparison with the 1991 Household Budget Survey, it turned out to be representative of the Kagera region for the period considered.

The Survey was originally launched in 1991 as a longitudinal household survey by the World Bank and Muhimbili University College of Health Sciences (MUCHS). It was part of a research project on "The Economic Impact of Fatal Adult illness from AIDS and Other Causes in Sub Saharan Africa". The baseline consists of a sample of 915 households interviewed up to four times between 1991 and 1994 (at 6-7 month intervals). In addition to the household survey, the KHDS included surveys of communities, prices and facilities. The KHDS 2004 aimed at collecting data and providing information on the same individuals 10 years later, to understand economic mobility and changes in living standards. As a result, 93% of the baseline households (defined as at least one previous household member) were re-interviewed in 2004. All tracked individuals[34], together with all their new household members, are part of KHDS 2004 sample, which consists of 2,774 households re-contacted from the 832 baseline households. The rate of attrition is much lower compared to the average experienced for surveys in developing countries, which generally cover a shorter period of time[35].

Individual information on health and health practices is included in section 6 of the survey. Questionnaires have been modified along waves and questions concerning

[34]Many individuals were tracked even though they moved out of Kagera region or out of Tanzania. 2% were tracked in Uganda.

[35] Alderman et al. (2001) discuss the issue of attrition in these kinds of surveys.

use of mosquito bed nets were introduced in KHDS 2004 only. People were asked the following questions: "Do you sleep under a mosquito net to protect yourself against mosquitoes?". In the case of a positive answer, they were also asked "For how long have you been using a mosquito net?" and "Has the net you sleep under ever been impregnated?". Although people interviewed in the baseline were not directly asked about use of a mosquito bed net, we can use recalled information to infer their behaviour[36].

Reporting information on bed net adoption back from KHDS 2004 to baseline KHDS requires two implicit assumptions. First, we assume that once people start using a mosquito bed net they continue, so that from negative answers in 2004 we can infer that the same people were not using any bed net at the baseline time. In other words we rule out the possibility of technological regress[37]. Our assumption is legitimised by the analogy with the whole body of literature on technology adoption and economic growth, where technologic regress is not even contemplated. Moreover, our assumption is strongly supported by the already discussed evidence of an increasing trend in mosquito bed net adoption. Finally we could argue that we are interested in learning processes and therefore in peple's permanently changed behaviour. The second assumption we need is about the reliability of answers given by people on how long they have been using a mosquito bed net. Looking at the answers, we notice that people answered "10 years" are more than twice those who said "9 years", and more than eight times those who answered "11 years". On one

[36] This implies that the information can be reported back from KHDS 2004 to baseline KHDS only for those people interviewed both in the baseline and in KHDS 2004.
[37] If the assumption was not true, we would be excluding from our analysis all people who were using bed nets at the time of the baseline survey, but then stopped.

hand this may be interpreted as a sign of roughly recalled information, but on the other hand in April-August 1994 Kagera experienced an exceptionally heavy malaria season which lasted for 5 months[38]. We also notice that the number of people who report to have been using mosquito bed nets since 2000 is twice as high as the number of people who report to have been using it since 1998. Again this may be interpreted as a delayed reaction to another exceptionally heavy malaria season recorded in Kagera between October 1997 and June 1998. Finally we notice that the number of people who started to use mosquito bed nets after 2000 increases shrply year by year. This may reflect the additional attention paid by governmental and non governmental agencies to malaria related issues after the Abuja summit in 2000. We conclude that, while some measurement error is likely, there are no strange patterns in the answers and therefore the effect of noise in recalled information seems to be relatively small and probably random.

Given the aim of our analysis, we exploit the KHDS survey as a two-wave survey which includes data from KHDS 1994 and KHDS 2004 and reports information on use of mosquito bed nets back from 2004 to 1994, as explained above. This choice brings more coherence to our analysis, as we consider only a regular time interval, and it also reduces the relevance of possible noise in recall data.

The sample of KHDS 1994 consists of all members of those households interviewed for the fourth time in 1994[39], for a total of 4,336 individual observations and 2,774 households. The sample of KHDS 2004 consists of all people living in households

[38] Wort et al. (2006).

[39] The alternative would have been to consider all households and people interviewed in 1991. This would have increased the number of observations in the baseline, but reduced the variability in net adoption, as the number of people using mosquito bed nets seems to have doubled between 1991 and 1994.

tracked from the baseline, that account for 12,854 individuals and 759 households. Our empirical analysis is carried out at the individual level and focuses on 3,225 people interviewed in both waves and about whom we have specific information on their use of mosquito bed nets.

KHDS 2004 also contains very precise information, derived from GPS data, on distances between each pair of households in the same village. Baseline KHDS was carried out in 51 villages, but only 49% of re-interviewed households stayed in the same village. Information on distances is available only for those households who were still living in the same cluster in 2004. As we base our definition of neighbourhood on distances between households, our sample for the analysis is subject to an ulterior cut and reduces to the 2,540 people who have been tracked and who were still living in the same cluster in 2004. As such, the analysis will offer insights on the presence of social learning and externalities among a population living in a particular locality, and not among a random sample in 1994.

3.3. Some descriptive statistics

KHDS data does not allow a very specific identification of the rate of malaria in the region. We only know whether people experienced malaria during the 4 weeks prior to the interview. Although answers can not be considered representative of the average situation, mainly because they are based on self diagnosis[40] and are subject

[40] The questionnaire asked people whether they experienced any illness during the four weeks prior to the interview. If the answer was positive, they were asked about self diagnosis and whether they consulted a health practitioner and in this case what his diagnosis was. Because only less than half of the sample consulted a health practitioner, we decided to use self diagnosis. This is also coherent with

to seasonality issues, we found that 20% of people experienced malaria, while 49% of households in the sample report to have at least one person who experienced malaria. Very similar figures were found for 1994.

19.5% of individuals in the 2004 sample were sleeping under a mosquito bed net, and in 30% of the households there was at least one person sleeping under a mosquito bed net. These percentages drop to 9% and 13% if we focus on the use of ever-treated mosquito bed nets. From this point of view KHDS seems to be representative of the population in Kagera as these percentages are almost exactly the same as those reported in the DHS 2004 report. Moreover, data confirms the increasing trend in adoption witnessed in other regions of Tanzania, even though there is no evidence of governmental and regional policies conducted in these areas. 69% of those people sleeping under a mosquito bed net in 2004 started doing it in 2000 or later, while only 7% had already adopted bed nets in 1994. Looking at our final KHDS sample for 1994 and using recalled information, only 3% of people were sleeping under a mosquito bed net and they were distributed across 9% of households.

If we disaggregate data for 2004 by gender, we do not find relevant differences. 19% of men and 20% of women reported to be using bed nets. With respect to categories targeted by policies, we find that 26% of pregnant women, 19% of women practicing

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the hypothesis of our model: people decide on mosquito bed net adoption based on their own perception of disease diffusion.

breast feeding and 18% of children less than 5 years old were sleeping under a mosquito bed net.[41]

Information on implemented policies is not available, but it is reasonable to expect different conditions in terms of net coverage in different villages, due to specific policy implementation (for example policies targeting refugees in bordering areas), the availability of bed nets (for example in rural versus urban areas) or different environmental and climatic conditions (for example lake versus mountain regions). Combinations of these characteristics may generate very different effects, and we believe that there may be good reasons to think that they may affect learning outcomes.

In fact bed nets adoption shows substantial variability across villages and districts. In 1994, percentages varied across districts as following: Biharamulo 4.5%, Bukoba Urban 6.5%, Bukoba Rural 2.2%, Karagwe 0.8%, Muleba 1.9%, Ngara 2.5%. In 22 out of 51 clusters, nobody was using mosquito bed nets, and the maximum number of people using them in the same village was 8. The presence of at least one person in the village using mosquito bed nets is negatively correlated (-0.21) with the percentage of people having experienced malaria in the last 4 weeks. This may imply different interpretations, not necessarily related to the efficacy of mosquito bed nets. For example the presence of someone using a mosquito bed net in the village may be a signal of a more careful attitude toward health practices in the village.

[41] Figures for women and pregnant women are very close to those reported by the DHS 2004 report, while for children KHDS reports a percentage which is 5 points smaller.

In 2004[42] only two villages still had nobody using a mosquito bed net, and the average percentage of people using bed nets in the village was 16%, with a peak at 53% in one case. Again the percentage of people who use bed nets at village level exhibits a negative and significant (at 12% level) correlation with the number of people who experienced malaria in the month prior to the interview.

This negative correlation seems to support the idea of the presence of positive externalities on the infection rate associated with the percentage of people using mosquito bed nets. More interestingly, there is a negative correlation of -0.25 significant at the 5% level between percentage of people using mosquito bed net in 1994 in village and percentage of people who experienced malaria in 2004[43].

[42] Due to the nature of KHDS 2004 sample, information disaggregated by cluster has been calculated including only people living in households who are still living in the same cluster where they were living during the baseline survey. This sample includes 6,548 individuals.

[43] The measure of malaria is based on self diagnosis; therefore the reduction on the rate of incidence could also be related to a better awareness of disease symptoms. However the result is a reduction in the perceived incidence of malaria, which in conclusion is what can affect individual bed net adoption.

4. Empirical Methodology

The aim of our empirical analysis is to test and compare social learning effects, if any, across three specific social groups. With respect to the model in section 2 we specify K=3. This implies that the same individual i is a member of the three following non-overlapping groups: the household network G_1, the group of close neighbours G_2 and the group of far neighbourhood G_3.

Note that when dealing with social groups, one important issue which often arises is the overlap between groups due to the contemporaneous individual membership of different groups. For example, if one individual $j \neq i$ was a member of both groups 1 and 2, we would not be able to univocally attribute the estimated social interaction effects to the social tie characterizing group 1 or 2. The groups that we take into consideration exclude this possibility; one individual can not be at the same time member of the household itself and member of close or far neighbourhoods. Therefore, unlikely other papers, we can in principle insert variables for behaviour in different social groups into the same regression. As far as we are aware, this has not been done previously; our work represents a contribution to the literature as it allows the identification of learning effects due to the contemporaneous membership of different non-overlapping social groups[44].

[44] Non-overlapping is defined as contemporaneous non-overlapping. For instance, someone who joined the household today might have been a neighbour yesterday, and vice versa some neighbours today might have been a member of the household yesterday: however this is likely to be a very limited case in our data. Moreover, as it will be clear, we estimate the effect of learning on *i*'s

We can now specify the empirical test presented in equation (8) in section 2 as follows:

$$\Pr(M_{ihvt}=1)$$
$$= F(\varphi_1 \overline{M}_{1hvt} + \varphi_2 \overline{M}_{2hvt} + \varphi_3 \overline{M}_{3hvt} + \delta T_t + \beta_1 x_{ihvt} + \beta_2 z_{ihv} + \beta_3 s_{hvt} + \beta_4 r_{hv} + \gamma V_v) \tag{9}$$

where M_{ihvt} is a dummy taking value 1 if individual *i* in household *h* in village *v* uses a mosquito bed net[45] at time *t*. $\overline{M}_{1hvt}$, $\overline{M}_{2hvt}$ and $\overline{M}_{3hvt}$, as defined in section 2.1 , refer to the number of people using a mosquito bed net in each specific group at time *t*. T_t is a dummy for time period, x_{ihvt} and z_{ihv} are sets of individual time variant and time invariant characteristics, and r_{hv} are sets of household time variant and time invariant characteristics and V_v is a vector of village dummies.[46]

We develop our empirical analysis on a two-wave panel dataset consisting of the last wave of baseline KHDS (completed in 1994) and KHDS 2004.[47] Our sample is therefore restricted to those individuals interviewed both in baseline KHDS and in KHDS-2004. The exigency of the identification of neighbours for every individual

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behaviour at a specific time, so that we can identify learning effect by the type of relationship connecting *i* and *j* at that specific time.

[45] In our empirical analysis, due to the lack of detailed information concerning ITNs, we consider the use of mosquito bed nets in general, without distinguishing ITNs in particular.

[46] F(x) here is a general cumulative density function, whose specific form depends on the assumption required by different binary response model; when we estimate a logit model we use the logistic distribution $\Lambda(x)$, while when we estimate a probit model we use the normal distribution $\Phi(x)$.

[47] KHDS baseline distinguishes between wave and passages. In our sample for 1994 we include observations from the 4th wave and 4th passage only. This is a convenient choice mainly for two reasons. First we consider a constant time lag, 10 years, between waves. Second we reduce the potential estimation bias from measurement errors. We can trust individuals answers that discriminate between use of bed nets for more or less than ten years, and we can make statements about states of adoption in 1994, but it becomes harder to trust answers that discriminate exactly between 11 and 12 or 13 years.

entails a further restriction of the sample to those individuals who have always been living in the same village[48]. This means that our findings will refer to a specific sample and not to a random sample of the population[49].

The specification presented in equation (9) raises a series of issues that are common to the identification of social interaction[50] effects in general. We analyse the problems in the empirical identification of social interaction effects in our context and we address them through a careful definition of the variables that we use to test for social learning and through the choice of econometric model to be estimated.

4.1. Problems and solutions in the identification of social interaction effects

Our specification allows us to infer the presence of social learning from the observation of a tendency to similar behaviour among individuals in the same group. This is a common practice in the estimation of social interaction effects; however, as conceptualized by Manski (1995), there are three hypotheses which could potentially explain this observed tendency: exogenous (or contextual) effects, correlated effects and finally endogenous effects. Exogenous effects refer to the effects of exogenous characteristics common to group members; correlated effects are caused by similar

[48] Those people who moved out of KHDS clusters after 1994 have been traced, but there is not information about other individuals living in the same village.
[49] This is an important point to bear in mind as social learning could have very different effects for other categories of people. For example people who have migrated could be more open to innovations, or people who have been living without using bed nets for a certain number of years, may get smaller incentives to adoption and even if they learn, they may still prefer not to adopt. From this point of view younger people may be more likely to adopt. Another example is that ITNs are much more effective than normal bed nets and learning effects may be much stronger if we considered ITNs adoption only. People may be more easily convincible to adopt when net effectiveness is higher.
[50] Endogenous social interaction effects can be considered a comprehensive concept whose different forms have been analysed in the literature: peer influences, neighbourhood effects, social learning, and imitation, just to mention some of them.

individual characteristics and common institutional and socio-economic environment, while endogenous[51] effects refer to the propensity to adopt a given behaviour according to the group one. The lack of very detailed information usually makes it very difficult to differentiate among these three hypotheses.

While endogenous and contextual effects represent two different channels of influence from the social environment, correlation effects are related to non social aspects. This implies that endogenous and contextual effects can be identified with respect to correlated effects by controlling for observable and unobservable characteristics that are common across group members. The separation of endogenous from contextual effects is trickier and represents the core of what is known in the literature as Manski's "reflection problem"[52].

In the context of our analysis, the reflection problem implies that coefficients φ_k could fail to distinguish endogenous effects from correlation and contextual effects. In the specific context of the adoption of mosquito bed nets, correlation effects could derive from common characteristics across individuals of the same group, such as scarce availability of mosquito bed nets or implementation of health programmes in the area, or else level of education, income or health awareness. Contextual effects

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[51] Endogenous effects and social interaction effects are equivalent in Manski's terminology. In our context, related to the use of mosquito bed nets, they can take the form both of social learning and positive externalities on the reduction of probability of malaria infection at the village level. The sign of the coefficient associated with group behaviour will help us too understand which specific form of social interaction effects identified is prevalent.

[52] Manski (2000) clearly made the point: "This identification problem arises because mean behaviour in the group is itself determined by the behaviour of group members. Hence data on outcome do not reveal whether group behaviour actually affects individual behaviour, or group behaviour is simply the aggregation of individual behaviour. This reflection problem is similar to the problem of interpreting the (almost) simultaneous movements of a person and his reflection in a mirror. Does the mirror image cause the person's movements or reflect them?".

could derive from the same various socio-economic factors that affect net adoption and that characterise the group of reference. In our context this could be related to the fact that all the most wealthy and educated people seem to live in the same neighbourhood of the village, or that they seem to belong to the same households, which are then more likely to adopt bed nets. This illustrates how the empirical difficulty in isolating contextual from endogenous effects stems from individuals' self selection in groups.

Brock and Durlauf (2004) show how the reflection problem in the identification of social interaction does not arise in binary choice models provided we have random assignment of individuals to groups and appropriate controls for unobservable group characteristics. They show how these two conditions can break the linear dependence between variables which capture individual expectation about group behaviour and other regressors included in the specification. This linear dependence is at the origin of Manski's findings of non-identification in the linear case.[53]

We define proxy variables for social learning that allow us to identify endogenous effects. They rely on a definition of groups which is based on exogenous characteristics, in the case of neighbourhood, or which exploits the different timing in group membership, in the case of households. In this way we can control for common characteristics and also avoid the endogeneity generated from self selection issues. Furthermore our social learning variables refer to the behaviour at time *t-1* of

[53] They also provide condition for identification in presence of group level unobservables and non random assignment to groups.

members of the group at time *t*; this rules out those issues related to simultaneity bias and reverse causality.

In spite of the definition of our variables to test for social learning, the problems in the identification of endogenous effects are still present for those individuals in our sample who do not change their behaviour over time.

There are three conceptually different categories of individuals in our sample: individuals who were already using a bed net in 1994 (for whom $MN_{ihv94} = 1$ and $MN_{ihv04} = 1$), individuals who never used bed nets (for whom $MN_{ihv94} = 0$ and $MN_{ihv04} = 0$) and finally individuals who adopted mosquito bed nets between 1994 and 2004 (for whom $MN_{ihv94} = 0$ and $MN_{ihv04} = 1$). The habits of individuals who belong to the first and second categories lead to simultaneity in adoption or non adoption decisions and the estimation of coefficients related to variables for social learning would be biased if we did not take this into account. Moreover, while controls for common characteristics are still effective for groups whose definition is based on exogenous characteristics, they are not effective anymore when the different timing in group membership is exploited. We address this issue applying a first difference estimator to the reduced sample of individuals not using bed nets in 1994.

4.2. Variables for social learning

Following KHDS, we define a household as a group of people living in the same dwelling. The structure of the KHDS 2004 sample allows us to identify people who joined the household between 1994 and 2004. We do not have information about these people prior to 2004, and therefore we exclude them from the sample used for estimations. However, due to the recalled nature of this precise information, we know if and when they adopted bed nets.

We can define $\overline{M}_{1hvt-1} = \sum_{j \neq i} (G_{1jhvt} - G_{1jhvt-1}) M_{jhvt-1}$[54], where $G_{1jhvt} = 1$ if individual j is a member of household h=1,..., H in village v=1,..., V at time t.

With respect to every household, we define close and far neighbourhoods exploiting information on reciprocal distance between every pair of households in the same village. For every household we first calculate the average distance from all the other households in the village, and then we define close neighbours to be those people living in all other households which are closer than the average distance and far neighbours to be those people living in all households further than the average distance.

We define $\overline{M}_{2hvt-1} = \sum_{l \neq h} \sum_{j=1}^{N} G_{2lvt} M_{jlvt-1}$, where $G_{2lvt} = 1$ if household l is a member of close neighbourhood of household h in village v and $G_{2lvt} = 0$ otherwise.

Analogously we define $\overline{M}_{3hvt-1} = \sum_{l \neq h} \sum_{j=1}^{N} G_{3lvt} M_{jlvt-1}$, where $G_{3lvt} = 1$ if household l is a member of far neighbourhood of household h in village v and $G_{3lvt} = 0$ otherwise.

[54] We use the time index t-1to underline the fact that we look at the behaviour at time t-1 of individuals who are members of the reference group at time t.

Note that, due to data limitations, $\overline{M}_{1hvt-1}$, $\overline{M}_{2hvt-2}$ and $\overline{M}_{3hvt-3}$ can be defined for 2004 only. For the waves in baseline KHDS we can not identify new household members (and even if we could, there would not be as many relevant changes in the household structure in three years as in ten years). Also information on reciprocal distance from every pair of households in the same village is available for 2004 only.

When we define our proxy for social learning in the household, we treat the entrance in the household of new people already using bed nets as an exogenous shock. The use of information on past behaviour of new household members only, allows us to include in our specification various controls for observable household characteristics and to identify social learning from correlated and contextual effects. We cannot control explicitly for household unobservable characteristics and it could be argued that as a consequence of household matching processes, household members self select and new entrants have characteristics similar to previous members. This would imply that similar behaviours could be explained by similar characteristics; however in our case this does not prevent the identification of social learning effects, as we capture the effect of the behaviour of new household members, before joining the household, on previous household members. The temporal sequence in adoption excludes the possibility of common behaviour determined by common unobservable characteristics. This is a peculiarity of our analysis, which is allowed by the structure of KHDS-2004 sample and by the use of recalled information about use of mosquito bed nets.

Our definition of neighbourhoods, based on exogenous characteristics (the distance between households in the same village) allows us to control for correlation effects in two ways. First of all, neighbourhoods are heterogeneous across households in the same village and therefore not characterized by common qualities other than those common at village level. Secondly the heterogeneity allows us to control for village observables and unobservables, which may be the source of correlation, and for contextual effects. In fact, the most relevant conditions affecting the decision about the use of mosquito bed nets, such as net availability, incidence of malaria or availability of drugs and health care services, affect the whole village equally. Moreover, the exploitation of information on different timing of adoption excludes the bias generated by reverse causality issues in the case of simultaneous action. Our definition of neighbourhood represents an enhancement of the literature, where neighbourhoods have typically been defined through common geographic, administrative or socioeconomic characteristics. Such a definition generates difficulties in controlling for observable and unobservable characteristics common across members of the same groups.

4.3. Estimation strategy

4.3.1. Econometric model

We showed how our definition of variables to test for social learning allows us to control for common unobservables, for selection bias and for reverse causality related to simultaneity: however we still have to address the reflection problem that arises from the presence in our sample of people who never change their behaviour over time.

To solve this problem we estimate a first difference model with ($\Delta M_{ihvt} = M_{ihv04} - M_{ihv94}$) as the dependent variable and with individual, household and village controls for 1994.

ΔM_{ihvt} =1 identifies individuals who started using mosquito bed nets after 1994. ΔM_{ihvt} =0 identifies both those individuals who were already using mosquito bed nets in 1994 and those who have never used mosquito bed nets. Social interactions do not affect the adoption decision of those individuals who already adopted bet nets in 1994 and in this case a positive correlation may in fact stem from contextual effects related to simultaneity in adoption decisions.[55] As we are interested in understanding the adoption process of non-users in 1994, we restrict our sample to individuals not using mosquito bed nets in 1994. This enables us to identify the effect of group behaviour, but it also implies that our results are valid, not on a random sample of the population, but on the sample of non-adopters in 1994 only[56].

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[55] As a simple data description we estimate a multinomial logit to check if there is some evidence of different effects of group behaviour on people who adopted bed nets between 1994 and 2004, with respect to people who have always been using bed nets and to people who have never used them. We define a multinomial dependent variable A_{ihv} =1 if individuals adopted bed nets in 1994, A_{ihv} =2 if individuals adopted bed nets in 2004 and A_{ihv} =3 if individuals have never been using mosquito bed nets. We select A_{ihv} =2 as base outcome. We find positive and significant coefficients associated with household and close neighbourhood social learning variables for A_{ihv} =1, while the same coefficients for A_{ihv} =3 become respectively negative and significant for household behaviour and negative and insignificant for close neighbourhood behaviour. Very different results for the two categories suggest that people adopting bed nets between 1994 and 2004 behave quite differently both from early adopters and from people who never adopted bed nets.

[56] The sample reduction implies that our dependent variable identifies individuals who adopted bed nets between 1994 and 2004, by talking value 1, and individuals who never used mosquito bed nets, by taking value 0. Due to the restriction of the sample to non-users in 1994, the probability of changing behaviour is the same as the probability of using a bed net in 2004 conditional on not using one in 1994, so the difference and the level are effectively the same for this selected sub-sample.

We estimate the following probit model on the sample of non-users in 1994:

$$\Pr(\Delta M_{ihvt}=1)$$
$$=\Phi(\varphi_1\overline{M}_{1hvt-1}+\varphi_2\overline{M}_{2hvt-1}+\varphi_3\overline{M}_{3hvt-1}+\beta_1 x_{ihvt-1}+\beta_2 z_{ihv}+\beta_3 s_{hvt-1}+\beta_4 r_{hv}+\gamma V_v) \quad (10)$$

Data reported in section 3 suggests high variability in the use of mosquito bed nets across villages. This in turn suggests that, unless we have a full set of controls for unobservables, we cannot have convincing evidence of social interaction effects, as the group behaviour term may be picking up unobservable village level effects. We include village dummies in our specifications to control for various observable and unobservable characteristics common across the whole village, such as incidence of malaria, availability of mosquito bed nets and health infrastructures.

If there are only a small number of observations per village, then the maximization of a joint likelihood function with village fixed effects can generate an incidental parameter problem, leading to inconsistent estimators. As pointed out by Chamberlin (1980), unlike a joint likelihood approach, a conditional likelihood approach applied to the fixed effects logit probability model, is corrected for degrees of freedom and therefore ensures a consistent estimation of the coefficients. This is due to the coincidence of the joint and the conditional maximum likelihood estimators, which is a special feature of the logistic functional form.

As an alternative, we estimate the following conditional logit model with village fixed effects on the sample of non-users in 1994:

$$\Pr(\Delta M_{ihvt}=1)$$
$$=\Lambda(\varphi_1\overline{M}_{1hvt-1}+\varphi_2\overline{M}_{2hvt-1}+\varphi_3\overline{M}_{3hvt-1}+\beta_1 x_{ihvt-1}+\beta_2 z_{ihv}+\beta_3 s_{hvt-1}+\beta_4 r_{hv}) \quad (11)$$

While the probit with village fixed effects estimator allows the estimation of partial effects on the response probability, but it may be subject to the incidental parameter problem, the conditional logit with village fixed effects is not subject to the incidental parameter problem, but does not allow the estimation of partial effects on the response probabilities. For this reason we consider models (10) and (11) as complementary.[57]

4.3.2. Why not other alternatives?

The use of KHDS as a proper two-wave panel of individuals interviewed both in 1994 and 2004 would enable us to control for individual unobservables in our estimations. The difficulty in exploiting KHDS as a two-wave panel is related to the fact that both new household members and neighbours cannot be identified for individuals in the baseline KHDS data. This implies the impossibility of defining $\overline{M}_{1hvt-1}$, $\overline{M}_{2hvt-1}$ and $\overline{M}_{3hvt-1}$ for individual *i* in household *h* in 1994. Nevertheless we could overcome this difficulty if we assumed that adoption among group members at *t-1* is set equal to 0, when considering person *i*'s behaviour in 1994[58].

[57] In principle another sensible alternative would be the estimation of a conditional logit model with initial household fixed effects. We would consider a conditional logit model more appropriate than a probit with household fixed effect which in this case would definitely produce estimations suffering from incidental parameter problem. Social learning effects at the household level would then be identified from contextual and correlation effects not only through the exploitation of the different timing of adoption, but also through a control for initial household unobservable characteristics.
In practice, because of the small number of individuals in the same household in 1994, we can not consider this model a valid alternative. Due to this small variability and to collinearity among other variables, more than two thirds of the observations in our sample are dropped and they include almost all the adopters of bed nets in 2004. The effect of the presence of new household members already using bed nets on the probability of adoption is positive but far from significant; however due to the problems just illustrated, those results are not credible and the introduction of a model with fixed effects for household in 1994 would not provide any useful insights.
[58] This assumption could be supported but would still be arbitrary. Only 1.5% of the over 1,800 people interviewed in KHDS 2004, and who were using a bed net in 2004, had already adopted this

The most sensible estimation strategy which we could apply to panel data with binary dependent variables would be a conditional logit model with individual fixed effects. This model would allow us to account for individual unobservables correlated with other regressors. We could then identify endogenous effects; however in our context, this model cannot be applied. The main assumption of the logit fixed effects model would require M_{ihvt-1} and M_{ihvt} to be independent, conditional on regressors and individual unobservables. This is not the case due to the assumption of no technological regress, which implies that once bed nets are adopted, M_{ihvt} is always predetermined by M_{ihvt-1}.[59]

The other alternative model for panel data with binary dependent variables would be a random effects model, but it requires the assumption of no correlation between

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behaviour in 1984. There is a trade-off between a potential measurement error bias and the possibility to account for individuals unobservable through a individual fixed effects estimation.

[59] Non technological regress implies that our dependent variable can only switch from 0 to 1 over time, but never from 1 to 0. This generates a non concave maximum likelihood function which prevents the identification of the coefficients associated with different regressors.

The conditional likelihood in our model with t=0,1 is calculated as $L = \prod_{i=1}^{N} \text{Prob}(Y_{i0} = y_{i0}, Y_{i1} = y_{i1} \mid \sum_{t=0}^{1} Y_{it})$. In theory there are four combinations (Y_{i0}, Y_{i1}) =(0,0), (1,1), (0,1), (1,0), where $\text{Prob}(Y_{i0} = 0, Y_{i1} = 0 \mid \sum_{t=0}^{1} Y_{it} = 0)$ =1 and $\text{Prob}(Y_{i0} = 1, Y_{i1} = 1 \mid \sum_{t=0}^{1} Y_{it} = 2)$ =1. These observations are not taken into account in the estimation of the fixed effect model as they do not tell anything about the process driving the dependent variable from 0 to 1.

In our case, due to the assumption of non technological regress, $\text{Prob}(Y_{i0} = 0, Y_{i1} = 1 \mid \sum_{t=0}^{1} Y_{it} = 1)$ =1 and $\text{Prob}(Y_{i0} = 1, Y_{i1} = 0 \mid \sum_{t=0}^{1} Y_{it} = 1)$ =0. This is the reason why a maximum for the likelihood function in our case cannot be calculated and the fixed effects model cannot be estimated.

If the assumption of independence of individual outcomes through time was satisfied, we would have $\text{Prob}(Y_{i0} = 0, Y_{i1} = 1 \mid \sum_{t=0}^{1} Y_{it} = 1) = \frac{\text{Prob}(0,1)}{\text{Prob}(0,1) + \text{Prob}(1,0)}$ and $\text{Prob}(Y_{i0} = 1, Y_{i1} = 0 \mid \sum_{t=0}^{1} Y_{it} = 1) = \frac{\text{Prob}(1,0)}{\text{Prob}(0,1) + \text{Prob}(1,0)}$.

unobservables and independent variables. This assumption is not credible in our context, and even if it were, random effects coefficients would still be subject to simultaneity bias, generated by the presence of individuals who never change their behaviour over time[60].

In conclusion it seems that the use of KHDS as a proper two-wave panel would not bring any advantage in the identification of social interaction effects and it would introduce a risk of measurement error bias in the estimation, as explained above.

4.3.3. Control Variables

We include in our specifications a set of variables to control for heterogeneity in individual and household characteristics in 1994. We also include a full set of village dummies in the probit specification.

At the individual level we control for age, gender, and education[61]. We control for the type of working activity through the inclusion of dummies for employment in a

[60]An alternative could be a random effects model estimated on the sample of non users in 1984, which by assumption is the whole sample. The effect of group behaviour on individual decision would be identified only through variables for group behaviour in 2004, as by definition the choice of people who adopted in 1994 would be influenced by their own characteristics only. To identify the effect of social interaction we could set the variables for group behaviour equal to 0 in 2004 for those individuals already adopting in 1994. This strategy would not imply any advantages in the identification of social interaction effects with respect to models (10) and (11); it would only improve the estimation of the effect of control variables that would require ad hoc strategies anyway to produce strong estimation results. Furthermore, if we really wanted to improve the estimation of the effect of individual characteristics on adoption, we would have to set the values of variables in 2004 to be equal to the value in 1994 for those individuals who adopted in 1994. This would lead again to a non-concave likelihood function and would prevent anyway the identification of the effect related to different regressors.

[61] We insert not only a control for the number of years spent in school, but also a dummy taking value 1 for individuals who are still in school. This is meant to account for the possibility of continued

farm activity, self-employment in a farm activity and employed in a non farm activity. The idea is that people involved in more highly remunerated jobs face a higher opportunity cost of getting malaria and therefore are more likely to protect themselves. It is also possible that people involved in different types of work activities are exposed differently to innovations. We also include dummies for the individual role or status in the household (i.e. head of the household, spouse, son, daughter and so on) to account for different opportunity costs of getting malaria (related to the degree of contribution to household activities and income) and different bargaining power in the household.

We insert controls for household characteristics such as household size and household size squared, per capita log consumption[62], gender, age and level of education of the head of the household, and finally dummies for religion and ethnicity. To account for the level of awareness in health practices and for the access to health infrastructures, we introduce a dummy taking value 1 if all children in the household have a vaccination card. We also introduce dummies that indicate to which type of health practitioner and heath infrastructure household members seek care in case of illness[63].

improvement of the level of education and for a different exposure to factors that potentially affect bed net adoption.

[62] As a proxi for income we use household per capita consumption. We find it more appropriate than assets in this context. Nobody would ever sell a cow to buy a bed net, while people would buy it if their general level of consumption allows them to afford it.

[63] The variable is a dummy taking value 1 if in the household there is at least one person who experienced illness in the 4 weeks prior to the interview and who went to seek care in the specific health facility.

Table A1 in appendix reports descriptive statistics for 1994 and 2004 for individual and household control variables included in the specification.[64]

According to the theoretical model presented in section 2, we interpret the coefficients estimated for $\overline{M}_{1hvt-1}$, $\overline{M}_{2hvt-1}$ and $\overline{M}_{3hvt-1}$, when they are positive, as an evidence of social learning, and when they are negative, as an evidence of positive externality incentivising to free-ride. However, alternative hypothesis could explain our findings. To support our interpretation and provide a deeper analysis of the effects generated through social interaction,, we implement some robustness checks, which are illustrated in the following sub-section.

4.4. Robustness checks

While all the different models estimated are meant to check the robustness of results with respect to different sources of endogeneity, we also control for robustness of our results with respect to the introduction of non-linear effects and to different definitions of the variables for group behaviour. This can also provide some useful insights for the interpretation.

[64] It would have been interesting to check the effect of other variables, but due to variables availability and consistency over time, there are many constraints on the selection. For example it would have been very interesting to control for the effect of distance from health infrastructure.
We also tried to estimate our regressions with a set of other controls, such as the number of children in the household, or the incidence of malaria in neighbourhood areas, or finally various housing conditions. None of them ever had a significant effect or changed the output result for other variables. Moreover they are all highly correlated with other control variables, respectively household size, village controls and consumption as proxy of income. We decided not to introduce them. In particular, with respect to malaria incidence, we consider the available variable to be non representative, as it is derived from self diagnosis of illness and refers to the month prior to the interview only. We consider village fixed effects to be inclusive of control for malaria incidence in the area.

Social learning and positive externalities, as described in our model, may have non linear effects on the probability of adoption. For instance it is possible that effects are stronger in the earlier stage of adoptions than later or vice-versa. We can test this hypothesis by introducing squared values of variables for group behaviour in our specifications. We re-estimate models (10) and (11) explicitly allowing for nonlinear effects.[65]

We also explore alternative definitions of group behaviour. First define variables for group behaviour as the ratio of people who adopted bed nets in 1994 among all new household members and all close and far neighbours. We define $R_{khvt-1} = \overline{M}_{khvt-1} / N_{khvt}$ for k=1,2,3, where N_{1hvt}, N_{2hvt} and N_{3hvt} are respectively the total number of new household members and of close and far neighbours in 2004. The definition of variables to test for social learning as ratios implies also a test for social learning as determined by the relative diffusion of adoption among the population instead of the absolute level of diffusion[66].

We also try to understand if the simple fact of having at least one person in the reference group already using a mosquito bed net affects individual decisions. We define D_{ghvt-1}=1 if $\overline{M}_{ghvt-1}$>0 and D_{ghvt-1}=0 otherwise. We re-estimate regressions (10) and (11) using those two different variables, ratios and dummies, as proxies of groups behaviour, instead of the previously defined ones.

[65] We also re-estimate the regressions for robustness checks allowing for non-linear effects, as we think this could provide useful insights for result interpretation.

[66] In the context of learning the two definitions are not really different, but in a context of imitation they could imply that people care about the relative diffusion of some behaviour and not simply about the number of people adopting. This in turn could affect the shape of the curve of behaviour diffusion along time. As already explained imitation is unlikely in the case of bed net adoption.

One concern when estimating all the previous models is related to the potential correlation between $\overline{M}_{1hvt-1}$, $\overline{M}_{2hvt-1}$ and $\overline{M}_{3hvt-1}$ and N_{1hvt}, N_{2hvt} and N_{3hvt} as defined above[67]. The definition of variables as ratios should already control for this potential correlation, but we re-estimate models (10) and (11) explicitly inserting controls for group size.

Another factor potentially affecting our results is seasonality in the use of mosquito bed nets. For example it can be strongly associated with rain seasons. People who report having been using mosquito bed nets for less than 1 year, may be both people who only adopted nets very recently and people who are using it temporarily. As a test for the robustness of our results to seasonality, we re-estimate all the discussed regressions excluding from the sample all people who have been using mosquito net for less than one year. We do not expect relevant changes as this restriction implies a reduction in the sample of 51 observations only.

[67] The total number of people entering the household between 1994 and 2004, and already using mosquito bed nets in 1994, may be correlated with the total number of people entering the household. Analogously the total number of people living in the close or far neighbourhood in 2004, and already using mosquito bed nets in 1994, may be correlated with the density of population in the neighbourhood. This can happen through two channels that produce contrasting effects: on one hand the higher population density in the group, the higher the probability of getting malaria, on the other hand the higher population density, the higher the probability of having in the group someone already using a mosquito bed net to learn from.

We also control directly for the correlation between $\overline{M}_{1hv1}$, $\overline{M}_{2hv1}$, $\overline{M}_{3hv1}$ and respective group densities. Both the correlations between $\overline{M}_{1hv1}$ and respectively N_{1hv1} and the total household size are very small. Vice-versa the correlation between the total number of new household members and the household size is higher. This suggests that household size should already be controlling for the total number of new household members. With respect to the potential correlation between $\overline{M}_{2hv1}$ and $\overline{M}_{3hv1}$ and respectively N_{2hvt} and N_{3hvt}, we argue that village controls together with the relative definition of close and far neighbourhoods should prevent the discussed correlation. Indeed the correlation is significant but very small.

4.5. Interactions between Social Learning and Income and Education

Reports on the impact of the TVNS programme implemented in pilot areas in Tanzania (Ebenezeri at al.2005 among others) suggest that ITNs adoption is strongly correlated with income and education. Coefficients estimated for the number of years of schooling and for the average level of consumption (inserted as controls in all the regressions) are indicators of the impact of those variables on adoption. However there are good reasons to think that education and income may affect social learning effects as well. To explore this possibility we allow for interactions between learning variables and indices for education and income. We believe that these estimations, in spite of the slightly vaguedefinition of education and wealth categories, can provide useful policy insights.

First we explore the interactions between social learning and education levels. We define individuals as educated if they have completed primary school and as not educated if they have not[68]. We define $E_{ihvt}=1$ if individual *i* has completed primary school at time *t* and $E_{ihvt}=0$ otherwise. Symmetrically we define $NE_{ihvt}=1$ if individual *i* has not completed primary school and $NE_{ihvt}=0$ if individual *i* has completed primary school. We then interact the two dummies for education status with variables for social learning with respect to different groups and we re-estimate regressions (10) and (11) with these six new interacted variables.

$$\begin{aligned}&\Pr(\Delta M_{ihvt}=1)\\&=\Phi(NE_{ihvt}*(\varphi_1\overline{M}_{1hvt-1}+\varphi_2\overline{M}_{2hvt-1}+\varphi_3\overline{M}_{3hvt-1})+E_{ihvt}*(\varphi_1\overline{M}_{1hvt-1}+\varphi_2\overline{M}_{2hvt-1}+\varphi_3\overline{M}_{3hvt-1})\\&+\beta_1x_{ihvt-1}+\beta_2z_{ihv}+\beta_3s_{hvt-1}+\beta_4r_{hv}+\gamma V_v)\end{aligned} \qquad (12)$$

[68] Data provides information on the total number of years in school as well as information about whether people completed primary school or not.

$$\Pr(\Delta M_{ihvt}=1)$$
$$=\Lambda(NE_{ihvt}*(\varphi_1\overline{M}_{1hvt-1}+\varphi_2\overline{M}_{2hvt-1}+\varphi_3\overline{M}_{3hvt-1})+E_{ihvt}*(\varphi_1\overline{M}_{1hvt-1}+\varphi_2\overline{M}_{2hvt-1}+\varphi_3\overline{M}_{3hvt-1}) \qquad (13)$$
$$+\beta_1 x_{ihvt-1}+\beta_2 z_{ihv}+\beta_3 s_{hvt-1}+\beta_4 r_{hv})$$

We then explore the interactions between social learning and income levels. We define individuals as rich (or poor) if in their household per capita consumption is greater (or smaller) than the average level of household per capita consumption in the village.

We define $R_{ihvt}=1$ if individual *i* is rich and $R_{ihvt}=0$ if not, and $P_{ihvt}=1$ if individual *i* is poor and $P_{ihvt}=0$ otherwise.

We then define six interactions of dummies for wealth status with variables for social learning, and we re-estimate regressions (10) and (11) allowing coefficients for social leaning to vary for different levels of income.

$$\Pr(\Delta M_{ihvt}=1)$$
$$=\Phi(R_{ihvt}*(\varphi_1\overline{M}_{1hvt-1}+\varphi_2\overline{M}_{2hvt-1}+\varphi_3\overline{M}_{3hvt-1})+P_{ihvt}*(\varphi_1\overline{M}_{1hvt-1}+\varphi_2\overline{M}_{2hvt-1}+\varphi_3\overline{M}_{3hvt-1}) \qquad (14)$$
$$+\beta_1 x_{ihvt-1}+\beta_2 z_{ihv}+\beta_3 s_{hvt-1}+\beta_4 r_{hv}+\gamma V_v)$$

$$\Pr(\Delta M_{ihvt}=1)$$
$$=\Lambda(R_{ihvt}*(\varphi_1\overline{M}_{1hvt-1}+\varphi_2\overline{M}_{2hvt-1}+\varphi_3\overline{M}_{3hvt-1})+P_{ihvt}*(\varphi_1\overline{M}_{1hvt-1}+\varphi_2\overline{M}_{2hvt-1}+\varphi_3\overline{M}_{3hvt-1}) \qquad (15)$$
$$+\beta_1 x_{ihvt-1}+\beta_2 z_{ihv}+\beta_3 s_{hvt-1}+\beta_4 r_{hv})$$

5. Estimation Results

Table A1 in the appendix presents descriptive statistics of control variables inserted in the various empirical specifications[69]. We notice an increase in the percentage of people using bed nets from 2% to about 16% between 1994 and 2004. We also notice an average increase in the household level of consumption per capita, as well as in the education of the head of the household and in the individual level of education. On average, the lowest levels of consumption per capita and education are reported for non-adopters. Among adopters, early adopters present higher values of the same variables compared to later adopters.

Looking at the number of early adopters among neighbours and new household members, we notice that these numbers are smaller for people who never adopted nets compared to those who did. In particular the highest numbers of adopters in the reference groups are reported for individuals who adopted bed nets before 1994.

Descriptive statistics suggest the presence of strong contextual and correlation effects related to individuals' self selection in groups. Across the three categories of adopters, the difference in the number of early adopters among new household members is more relevant than the difference in the number of early adopters among neighbours. This can be seen as the result of a voluntary matching process leading to household formation, as opposed to the random assignment to neighbourhoods following our definition. Comparing the percentages of earlier and later adopters

[69] Descriptive statistics have been calculated on the sample of individuals interviewed both in baseline KHDS and in KHDS 2004 and who didn't move out of KHDS clusters between 1994 and 2004. This corresponds to the sample considered when applying our empirical methodology.

who have at least one close and one far neighbour who had already adopted a mosquito bed net in 1994, we note that earliest adopters have the highest percentage of people with at least one close neighbour already using bed nets, while non-adopters have the highest percentage of people with at least one far neighbour already using bed net. This suggests that people with different characteristics tend to live in different areas of the same village.

Table 1 presents results from the estimation of regressions (10) and (11).

Table 1: Effects of Social Interactions on Bed Net Adoption

	Probit	**Conditional Logit**
Dependent variable: Use of bed net after 1994		
Year	0.001	0.010
	(1.10)	(0.93)
Age	0.037**	0.305*
	(2.11)	(1.72)
Female	0.012**	0.117**
	(3.87)	(3.70)
Years in school	0.077**	0.707**
	(3.14)	(3.08)
In school	0.007	0.081
	(0.30)	(0.34)
Non Farm Work	0.043*	0.395
	(1.650	(1.25)
Farm Self Employed	0.018	0.189
	(0.87)	(0.92)
Farm Non Self Employed	0.031*	0.276
	(1.70)	(1.46)
Log consumption	-0.052	-0.522
	(-1.31)	(-1.11)
Head of household	-0.051	-0.470
	(-1.32)	(-1.01)
Spouse	-0.018	-0.143
	(-0.52)	(-0.38)
Son / Daughter	0.079	0.629
	(1.34)	(1.28)
Grand Children	-0.091*	-1.418
	(-1.76)	(-1.40)
Grand Father / Mother	-0.063	-0.762
	(-1.58)	(-1.49)
Siblings	-0.043	-0.465
	(-0.92)	(-0.79)
Niece / Nephew	-	-14.212
	(-)	(-0.01)
Son / Daughter in law	0.025	0.302
	(0.28)	(0.34)
Sibling in law	-	-15.053
	(-)	(0.00)

Head of household Male	-0.057**	-0.475**
	(-2.07)	(-1.97)
Head of household Age	-0.001	-0.013**
	(-1.56)	(-1.44)
Head of household Education	0.018**	0.175**
	(4.83)	(4.48)
Hosehold size	0.036**	0.342**
	(5.13)	(4.41)
Household Size ^2	-0.001**	-0.013**
	(-4.62)	(-3.81)
Muslim	0.039	0.274
	(0.57)	(0.42)
Catholic	0.000	-0.024
	(0.00)	(-0.04)
Protestant	-0.021	-0.183
	(-0.38)	(-0.29)
Other Christian	-0.017	-0.197
	(-0.27)	(-0.28)
Mhaya	-0.065	-0.609
	(-1.35)	(-1.30)
Mnyambo	-0.046	-0.466
	(-0.85)	(-0.79)
Mangaza	-0.095**	-1.257
	(-1.89)	(-1.46)
Msubi	-0.053	-0.560
	(-1.01)	(-0.79)
Kishubi	-	-14.348
	(-)	(-0.02)
Mzinza	-0.056	-0.735
	(-0.72)	(-0.70)
All children have vaccination card	0.014	0.124
	(0.60)	(0.48)
Seek Care in Hospital	0.045	0.350
	(1.42)	(1.25)
Seek Care in Health Centre	0.003	-0.004
	(0.08)	(-0.01)
Seek Care in Dispensary	-0.040	-0.350
	(-1.47)	(-1.25)
Seek Care at Practitioner 's Home	0.043	0.432
	(1.21)	(1.25)
Seek Care in Public Place	0.004	0.046
	(0.13)	(0.16)
Seek Care in Mission	-0.045	-0.529
	(-1.35)	(-1.34)
Number of Early Net Adopters in close neighbourhood	-0.108**	-0.958*
	(-2.17)	(-1.79)
Number of Early Net Adopters in far neighbourhood	-0.107**	-0.972*
	(-2.12)	(-1.78)
Number of Early Net Adopters among new household members	-0.034	-0.325
	(-0.40)	(-0.41)
Village Dummies	Yes	
Village Fixed Effects		Yes
Number of Observations	1649	1664
PseudoR^2	0.185	0.132

Notes:
Sample: Non bed nets adopters in 1994
* denotes significance at 10% level; ** denotes significance at 5% level.
Z statistic are reported in brackets and calculated on robust standard errors.
Marginal effects are reported for probit; Coefficients are reported for logit.
Z statistic are reported in brackets and calculated on robust standard errors.

It is interesting to note that positive and significant coefficients are associated with proxies for the levels of education and income. We also find positive and significant coefficients associated with household size and education of the head of the household. Looking at gender variables, women seem to be more likely to adopt bed nets and the probability of bed net adoption seem to be smaller if the head of household is a man. Other individual characteristics, such as age, relative status or role in the household and type of occupation, do not seem to have any influence on the bed net adoption decision. Similar results apply to household control variables such as religion, ethnicity and level of awareness in health practices or health infrastructure accessibility. Cluster dummies are not reported in the table, but there is evidence of great variability in the probability of adoption across villages. This seems to confirm the presence of different village environments, which can promote bed net adoption at different degrees.

The sign and significance of coefficients associated with control variables are unchanged in any further exploration and robustness tests, so we will not return to these variables, but instead focus largely on our variables of interest in a discussion on social learning.

Before looking at results for variables capturing group behaviour, note that our definition of a neighbourhood as a social group includes people who potentially belong to a variety of social networks[70]. Some neighbours may be related to *i* through a very strong relationship (for example networks of relatives or friends), while others may be totally unrelated to individual *i*. In this sense we could say that we are estimating social interaction effects when individuals are related by an "average neighbourhood relationship".

[70] We use the term networks to refer to specific social ties among neighbours that we can not observe.

A difference between coefficients associated with household and close neighbourhood group behaviour can be interpreted as a consequence of a different intensity in social ties. A difference between coefficients associated with close and far neighbourhood group behaviour can be interpreted more as a proximity effect than as the effect of a different intensity of specific social ties linking different individuals in the group, which we do not take into account anyway.

With respect to social learning effects, results from the first set of regressions suggest that the number of people already using bed nets and joining the household does not have any significant effect on the probability of adoption. Though far from significant, the coefficient is in fact negative. This seems to provide evidence against any type of social interaction effects at the household level.

The negative and significant coefficients associated with the number of early bed net adopters living in close and far neighbourhoods, suggest the presence of incentives to free-riding behaviour when other people already use a bed net. Moreover the coefficients are not different in magnitude. This implies that there is no evidence supporting the presence of proximity effects. However, if we interpret this evidence in the framework of our model in section 2, two different situations could explain the result. The first one is that positive externalities on the reduction of the rate of malaria infection are symmetric across all the groups and there are no relevant social learning effects at neighbourhood level. The second one would rely on a different assumption stating asymmetry both in social learning and positive externalities effects across different groups. Both of these effects could be stronger across close neighbours so that they compensate and the final result of social interaction effects is the same at close and far neighbourhood levels. If that was the case, there would not be any evidence supporting the assumptions in our model.

The first set of results seems to suggest that social interactions at the household level do not affect the probability of bed net adoption, while at the neighbourhood level they may generate incentives for free-riding behaviour, whose intensity is not affected by geographic proximity.

Tables 2 and 3 present the results obtained from the estimation of the same models but respectively allowing for non-linear effects in the group behaviour terms and using different definitions of the variables capturing group behaviour (ratios of adopters among the population of the reference group and dummies taking value one if there is at least one person already using a bed net in the reference group).[71]

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[71] We present results from the inclusion of non-linear terms separately for the two sets of group behaviour variables (household and neighbourhood ones). This choice is motivated by some sign of collinearity between the number of new household members already using bed nets and variables for group behaviour in neighbourhoods. This is likely to be a consequence of the small variability in the number of new household members already using bed nets and of common characteristics among net adopters, who also seem to be more concentrated in certain areas of the village. This implies that all the people having some early bed net adopters entering the household are probably also those people having the highest number of neighbours who adopted early. If we estimated effects of the two sets of variables inserting them in the same regression, then the effects could confuse and we would not have significance of the household term.
Later we present results from the estimation of household and neighbourhood variables together. When we do it, it is because there is no relevant difference in the coefficients and the significance with respect to the case where we estimate the effects of household and neighbourhood group behaviour separately.
One of the differences of this paper with respect to the previous empirical literature is that we estimate social interaction effects in non-overlapping groups. In principle this allows us to introduce variables for social learning with respect to different groups in the same regression, however even when we cannot do it, the point is still valid as social interaction effects, if any, are produced through the interaction among people related by a univocally identified social tie.

Table 2: Non linear Effects of Social Interactions on Bed Net Adoption Decision

	Probit	Conditional Logit	Probit	Conditional Logit
Dependent variable: Use of bed net after 1994				
Number of Early adopters in close n.	-0.081**	-0.731**		
	(-2.02)	(-2.07)		
Number of Early adopters in close n. ^2	-0.001	-0.010		
	(-0.69)	(-0.51)		
Number of Early adopters in far n.	-0.087**	-0.791**		
	(-2.06)	(-2.13)		
Number of Early adopters in far n. ^2	-0.001	-0.006		
	(-0.26)	(-0.22)		
Number of Early Net Adopters in far n.			0.465**	3.094**
			(2.30)	(2.03)
Number of Early Net Adopters in far n. ^2			-0.173**	-1.145*
			(-2.15)	(-1.68)
Individual Controls	Yes	Yes	Yes	
Household Controls	Yes	Yes	Yes	
Village dummies	Yes		Yes	
Village Fixed Effects		Yes		Yes
Number of Observations	1649	1664	2179	2190
PseudoR^2	0.185	0.132	0.140	0.097

Notes:
Sample: Non bed nets adopters in 1994
* denotes significance at 10% level; ** denotes significance at 5% level.
Z statistic are reported in brackets and calculated on robust standard errors.
Marginal effects are reported for probit; Coefficients are reported for logit.
Z statistic are reported in brackets and calculated on robust standard errors.

Table 3: Effects of Social Interactions on Bed Net Adoption - Robustness Checks

	Probit	Conditional Logit	Probit	Conditional Logit
Dependent variable: Use of bed net after 1994				
Ratio of Early adopters in close n.	-2.269	-26.561		
	(-1.15)	(-1.60)		
Ratio of Early adopters in far n.	-1.092	-14.019		
	(-1.01)	(-1.54)		
Ratio of Early adopters new household members	0.243	1.971		
	(1.57)	(1.31)		
Dummy for Early adopters in close n.			-0.029	-0.322
			(-0.62)	(-0.71)
Dummy for Early adopters in far n.			-0.023	-0.261
			(-0.67)	(-0.72)
Dummy for Early adopters new hhold members			0.280**	1.491*
			(1.92)	(1.79)
Individual Controls	Yes	Yes	Yes	Yes
Household Controls	Yes	Yes	Yes	Yes
Village dummies	Yes		Yes	
Village Fixed Effects		Yes		Yes
Number of Observations	1649	1664	1649	1664
PseudoR^2	0.185	0.133	0.184	0.131

Notes:
Sample: Non bed nets adopters in 1994
* denotes significance at 10% level; ** denotes significance at 5% level.
Z statistic are reported in brackets and calculated on robust standard errors.
Marginal effects are reported for probit; Coefficients are reported for logit.
Z statistic are reported in brackets and calculated on robust standard errors.

Results from the introduction of non-linear terms suggest the presence of social learning at the household level. In particular, the negative and significant coefficient associated with the non linear term implies an increasing and concave relationship between the probability of bed net adoption and the entrance in the household of earlier adopters. The concave shape of the learning curve seems to confirm the hypothesis of learning versus imitation or peer-pressure effects. Pure imitation and peer pressure would imply a convex relationship as the more peers adopt a certain behaviour, the more the individual would tend to conform. Our interpretation is supported also by the non-significance of the ratio of early bed net adopters among new household members, compared to the higher significance of the dummy term.

This underlines the fact that what seems to matter is the acquisition of information and the example from people related to the individual by a strong social tie. In case of peer pressure or imitation what increases incentives to conform is the relative number or the proportion of people adopting certain behaviour. Our interpretation is supported also by Young (2006), who explains how diffusion of behaviour through social learning is characterized by an increasing and concave adoption curve in the initial stage.[72] Although in a different context and at a more aggregate level, he also interprets negative and significant coefficients associated with non-linear terms as a definitive proof of social learning against imitation.

With respect to the close and far neighbourhoods, results from tables 2 and 3 confirm the presence of a negative and linear relationship between the probability of adoption and the number of early adopters both in the close and in the far neighbourhood.

The non-significance of the squared terms seems to support the hypothesis of free-riding behaviour at neighbourhood level, incentivised by positive externalities. The alternative interpretation, which is adopted in the empirical social learning literature[73] to explain negative coefficients associated to group behaviour, is represented by strategic delay considerations in adoption. This hypothesis is typically supported by the evidence of a U-shaped relationship, which we do not find in our data.

The presence of positive externalities of bed nets on the reduction of the rate of infection is also directly supported by empirical evidence. First of all, we find a negative and significant correlation at the village level between malaria diffusion in

[72] Young (2006) also illustrates how the diffusion curve is S-shaped in a heterogeneous population. This could in principle be the case in our context, but our data do not allow this test.
[73] See for example Bandiera and Rasul (2006).

2004 and the presence of people already using mosquito bed nets in 1994[74]. More evidence supporting our hypothesis is provided through the estimation, as a descriptive statistic, of the individual probability of experiencing malaria. Controlling for individual use of mosquito bed net and other individual, household and village characteristics, we find a negative and significant coefficient associated with the presence of people in the village using bed nets in 1994[75]. Even though a more careful analysis would be required to make causality statements, this suggests that in villages where there was an earlier adoption of mosquito bed nets, the probability of malaria infection is now lower.

Results from this second set of estimations provide quite strong evidence of social learning at the household level: in particular the hypothesis of social learning against imitation is supported by the negative and significant coefficient associated with the non-linear term. Results also confirm the presence of incentives to free-ride generated by social interactions at neighbourhood level. Moreover the alternative interpretation of the negative coefficient as a signal of strategic delay in adoption is not supported, due to the non significance of the non-linear term, which instead supports the hypothesis of positive externalities at village level.

[74] Using data at the village level we find a correlation of -0.25 between the ratio of people using bed nets in 1994 and the ratio of people who experienced malaria in 2004. This has to be considered as a descriptive test only, as our information is not very precise. First of all, we do not have information about the use of mosquito bed nets among all people in the village in 1994. Secondly the information on malaria is based on self diagnosis and refers only to those people who experienced an illness during the month prior to the interview.

[75] The dependent variable is a dummy taking value 1 if the individual experienced malaria in the four weeks before the interview in 2004. Independent variables are village, household and individual controls for 2004, including own use of bed nets, and a dummy taking value 1 if there is at least one person in the village already using bed net in 1994.

Results in table 4, presented below, show that our findings are robust to controls for the size of the reference group. In particular we notice a significant, positive and concave relationship between probability of adoption and group density[76]. The consistency of this result across different groups suggests that individuals tend to rationally protect themselves more when they are living in environments with a higher population density. A higher population density increases the probability of malaria transmission and infection. In some sense this can also be considered as proof of positive externalities on the probability of malaria transmission, generated from the use of bed nets. Positive externalities are realised through a break in the chain of transmission. Ideally, from this point of view, having one more person using a bed net[77] is equivalent to having one less person in the reference group.

Regarding dynamics at the household level, we notice a much higher significance of the term that we use to test for social learning when controlling for group size. This confirms our results and allows us to reject the alternative hypothesis that our variable is simply capturing an increase in availability of bed nets in the household when some early adopter joins.[78] If that were the case, we would have a negative, or at least non-significant, coefficient associated with the number of new entrants. Moreover we would also have a significantly positive coefficient associated with the ratio of new household members previously using bed nets, and a much less

[76] Table 1 shows similar findings for household size.
[77] This refers explicitly to the use of general bed nets as ITNs generates even higher externalities.
[78] Imagine a household where nobody is using mosquito bed nets and where the importance of this practice is known, but the cost of acquiring a bed net is too high. If someone already using a bed net becomes a household member and brings his net into the household, then the marginal cost of one more person using the net is zero. In fact in African villages is common to have more than one person sleeping on the same bed.

significant coefficient associated with the dummy indicating the presence of at least one new member already using a bed net.

Table 4: Effects of Social Interactions and Groups Size on Bed Net Adoption

	Probit	**Conditional Logit**	**Probit**	**Conditional Logit**	**Probit**	**Conditional Logit**
Dependent variable: Use of bed net after 1994						
Number of Early adopters in close n.	-0.119** (-2.37)	-1.091** (-1.91)			-0.088** (-2.14)	-0.810** (-2.21)
Number of Early adopters in close n. ^2					-0.002 (-1.01)	-0.015 (-0.73)
Number of Early adopters in far n.	-0.121** (-2.38)	-1.133** (-1.95)			-0.103** (-2.37)	-0.941** (-2.45)
Number of Early adopters in far n. ^2					-0.001 (-0.34)	-0.008 (-0.28)
Close n. Population Density	-0.056 (-0.65)	-0.567 (-0.69)			0.003 (0.85)	0.021 (0.64)
Close n. Population Density ^2					0.000** (2.02)	0.000** (1.95)
Far n. Population Density	0.009* (2.80)	0.076** (2.39)			0.004 (1.54)	0.040 (1.31)
Far n. Population Density ^2					0.000 (1.32)	0.000 (1.10)
Number of Early adopters new h. m.	0.008** (3.01)	0.080** (2.55)	0.433** (2.05)	3.019** (2.00)		
Number of Early adopters new h. m. ^2			-0.162** (-1.92)	-1.121* (-1.72)		
Number of New hhold members	0.017** (2.50)	0.166** (2.38)	0.063** (4.79)	0.456** (4.31)		
Number of New hhold members ^2			-0.009** (-3.88)	-0.063** (-3.39)		
Individual Controls	Yes	Yes	Yes	Yes	Yes	Yes
Household Controls	Yes	Yes	Yes	Yes	Yes	Yes
Village dummies	Yes		Yes		Yes	
Village Fixed Effects		Yes		Yes		Yes
Number of Observations	1649	1664	2179	2190	1649	1664
PseudoR^2	0.193	0.141	0.150	0.109	0.193	0.140

Notes:
Sample: Non bed nets adopters in 1994
* denotes significance at 10% level; ** denotes significance at 5% level.
Z statistic are reported in brackets and calculated on robust standard errors.
Marginal effects are reported for probit; Coefficients are reported for logit.
Z statistic are reported in brackets and calculated on robust standard errors.

Even when controlling for the size of the reference groups, results confirm the evidence of opposite effects generated by social interactions in different groups: social learning at the household level and incentives to not adopt due to positive externalities on the reduction of the rate of infection at the neighbourhood level. Moreover we find evidence of a significant, positive and concave relationship between group size and probability of adoption.

We now explore results further by looking at the effects of social interactions among people with different levels of income and education. Descriptive statistics suggest that adopters are concentrated among more educated and wealthier individuals. Results from the estimation of the effect of group behaviour variables, interacted with education and income indices, can help in understanding if and how these determinants of adoption affect learning. Table 5 presents results from the estimation of regressions (12), (13), (14) and (15).

Table 5: Effects of Social Interactions combined with Education and Income Indicators

	Education					
	Probit	**Conditional Logit**	**Probit**	**Conditional Logit**	**Probit**	**Conditional Logit**
Dependent variable: Use of bed net after 1994						
E* Number of Early ad. in cl. n.	-0.119** (-2.29)	-1.051* (-1.81)			-0.082** (-2.04)	-0.741** (-2.07)
E* Number of Early ad. in cl. n. ^2					-0.001 (-0.51)	-0.008 (-0.39)
E* Number of Early ad. in far n.	-0.118** (-2.24)	-1.064* (-1.81)			-0.083** (-1.94)	-0.758** (-2.01)
E* Number of Early ad. in far n. ^2					-0.001 (-0.31)	-0.008 (-0.28)
E* Number of Early ad. new hhold members	-0.043 (-0.49)	-0.382 (-0.47)	0.567** (2.14)	3.907** (2.02)		
E*Number of Early ad. new hhold members ^2			-0.211** (-2.06)	-1.455* (-1.73)		
NE*Number of Early ad. in close n.	-0.127** (-2.43)	-1.128** (-1.94)			-0.077* (-1.9)	-0.715** (-1.95)
NE*Number of Early ad. in close n. ^2					-0.003 (-1.31)	-0.021 (-0.8)
NE*Number of Early ad. in far n.	-0.129** (-2.43)	-1.143** (-1.92)			-0.111** (-2.41)	-1.010** (-2.36)
NE* Number of Early ad. in far n. ^2					0.002 (0.45)	0.017 (0.42)

NE*Number of Early ad.	-	-14.864	-	-12.766		
new hhold members	(-)	(-0.01)	-	(-0.01)		
NE*Number of Early ad.			-	-		
new hhold members ^2			(-)	(-)		
Individual Controls	Yes	Yes	Yes	Yes	Yes	Yes
Household Controls	Yes	Yes	Yes	Yes	Yes	Yes
Village dummies	Yes		Yes		Yes	
Village Fixed Effects		Yes		Yes		Yes
Number of Observations	1644	1660	2173	2185	1645	1660
PseudoR^2	0.188	0.136	0.141	0.098	0.189	0.136

Income

	Probit	**Conditional Logit**	**Probit**	**Conditional Logit**	**Probit**	**Conditional Logit**
Dependent variable: Use of bed net after 1994						
R* Number of Early ad.	-0.088*	-0.791			-0.071*	-0.636*
in cl. n.	(-1.79)	(-1.47)			(-1.74)	(-1.75)
R* Number of Early ad.					-0.002	-0.014
in cl. n. ^2					(-0.77)	(-0.64)
R* Number of Early ad.	-0.098**	-0.905*			-0.049	-0.455
in far n.	(-1.96)	(-1.66)			(-1.03)	(-1.08)
R* Number of Early ad.					-0.007	-0.065
in far n. ^2					(-1.56)	(-1.46)
R* Number of Early ad.	-	15.355	-	15.851		
new hhold members	(-)	(0.01)	(-)	(0.01)		
R* Number of Early ad.			-	-		
new hhold members ^2			(-)	(-)		
P*Number of Early ad.	-0.099**	-0.889*			-0.077**	-0.687**
in cl. n.	(-2.02)	(-1.67)			(-1.93)	(-1.93)
P*Number of Early ad.					-0.002	-0.019
in cl. n. ^2					(-0.95)	(-0.82)
P*Number of Early ad.	-0.094*	-0.857			-0.090**	-0.811**
in far n.	(-1.87)	(-1.57)			(-2.13)	(-2.15)
P* Number of Early ad.					-0.001	-0.005
in far n. ^2					(-0.18)	(-0.16)
P*Number of Early ad.	-0.048	-0.462	0.316	2.104		
new hhold members	(-0.600)	(-0.61)	(1.36)	(1.24)		
P*Number of Early ad.			-0.117	-0.771		
new hhold ^2			(-1.28)	(-1.07)		
Individual Controls	Yes	Yes	Yes	Yes	Yes	Yes
Household Controls	Yes	Yes	Yes	Yes	Yes	Yes
Village dummies	Yes		Yes		Yes	
Village Fixed Effects		Yes		Yes		Yes
Number of Observations	1646	1664	2176	2190	1649	1664
PseudoR^2	0.184	0.138	0.137	0.099	0.191	0.138

Notes:
Sample: Non bed nets adopters in 1994
* denotes significance at 10% level; ** denotes significance at 5% level.
Z statistic are reported in brackets and calculated on robust standard errors.
Marginal effects are reported for probit; Coefficients are reported for logit.
Z statistic are reported in brackets and calculated on robust standard errors.

Results from interaction with education clearly show how people who adopt bed nets are concentrated among the most educated in each village. In fact, the interacted term at household level is dropped for less educated people, due to small variability. This prevents us from directly comparing coefficients, however the marginal effect of social learning on the probability of bed net adoption, is higher for the sub-sample of more educated people than for the whole sample.[79] With respect to the coefficients associated with group behaviour at the close and far neighbourhood level, we do not find relevant differences when we disaggregate the effects for educated and non-educated individuals.

Results from interaction with income do not provide any direct evidence supporting the idea that social learning at the household level may be happening in a different way among richer and poorer individuals. The term for household behaviour has been dropped when combined with a dummy for higher level of income, due to small variability. This suggests that households with new members who were previous bed net adopters are concentrated among those with a lower level of consumption.[80] Terms for social learning are not significant when they are interacted whit a dummy for lower level of consumption. One possible interpretation could be related to the hypotheses of lack of manifestation of learning, due to non affordability of bed nets for these people. This does not necessarily mean that they do not learn, but only that, even if they do, they do not modify their behaviour; however this is still a conjecture.

[79] Probit marginal coefficients are respectively 0.57 and 0.46.
[80] Results may be different considering assets instead of consumption as a proxy for income.

Even when we disaggregate for more and less wealthy individuals, we do not find relevant differences in the coefficients associated with group behaviour at close and far neighbourhood level.

Our analysis provides strong evidence supporting the presence of social learning effects in the adoption of mosquito bed nets at the household level. We also find evidence of incentives for free riding behaviours generated by social interactions at the neighbourhood level through positive externalities on the reduction of the rate of malaria infection associated with the number of people already using bed nets in the reference group. Furthermore the effects related to positive externalities at neighbourhood level do not vary depending on geographic proximity. This seems to confirm the assumption of the model presented in section 2 regarding symmetry of positive externalities across groups.

Strong social ties seem to represent a precondition to the realisation of social learning. This suggests that social interactions may produce social learning and therefore multiplicative effects on behaviour diffusion only if individuals in a certain group are related by strong enough social ties. In contexts where individuals cannot learn from others by freely observing their behaviour and the consequences, a strong enough social relationship represents the precondition, on one hand for the transmission of information, and on the other hand for a level of trust in the source of information sufficient to cause a change in behaviour and complete the learning process.

Furthermore our findings suggest that low income levels may prevent the modification of individual behaviour following social learning, probably through the imposition of constraints, while higher levels of education may promote it. On the other hand, neither income or education levels seem to interfere significantly with social interaction effects at the neighbourhood level.

6. Conclusions

We have provided a theoretical framework to analyse the effects of social learning in different groups (households and neighbourhoods) on mosquito bed net adoption, and through the exploitation of KHDS data we have been able to empirically distinguish social interaction effects from contextual and correlated effects.

Our analysis provides evidence of social learning at the household level; social learning among household members may, on average, increase the probability of adoption by up to 30%. Household members surely share similar characteristics, which in the context of bed net adoption seems to be not only a typical factor leading to adoption, but also a necessary condition for social learning to happen. This relates to the nature of learning in this context, which requires both transmission of information and a high enough level of trust in the source of information to lead to a change of behaviour. Specific social ties seem to be a precondition for both of these components of learning. We provided evidence that in groups where social ties are weaker, learning may not happen. For example proximity has been proved to not imply an intense enough level of relationship. Moreover, in case of behaviour that generates positive externalities, incentives to free-ride may be generated instead of learning.

Our analysis also provides evidence that social groups and proper social networks need to be treated in different ways. Social groups do not necessarily imply a relationship between individuals, while social networks do. This fundamental difference can generate very different social interaction effects. For instance, in the case of mosquito bed net adoption, social interactions at the neighbourhood level, which should be considered a social group, generate effects that are opposite to those generated at the household level, which instead is a proper social network.

We have found evidence of heterogeneity in social learning effects depending on individual characteristics, such as education and income levels. In particular, higher education seems to promote learning (social learning at household level may increase the probability of nets adoption by up to 50% among more educated people), while higher income levels seem to be a necessary condition for the manifestation of learning through behaviour modification. Neither education nor income level seems to affect incentives to free-ride, generated by social interactions at the neighbourhood level.

Our analysis also provides also a few key insights that may be relevant from the policy perspective. First, in the context of bed net adoption, there is evidence of endogenous interaction effects among individuals in the same social group, which need to be taken into account in policy development. In particular, those effects can generate both incentives and disincentives to adopt bed nets, depending on the intensity of social ties that characterise particular social groups. When we consider proper social networks and when social ties are strong enough, social learning from other group members may take place and give rise to multiplicative effects in adoption. This suggests that the positive incentives to adoption generated by policies that promote the use of bed nets, may be amplified if specific individuals in social networks are targeted, while opposite effects may result if policies target individuals without taking into account their social networks. Finally the heterogeneity in learning across individuals, for example based on income or education characteristics, need to be taken into account in policy design.

The results of our analysis apply to a specific sample, which is not random and not representative of the Kagera population. In addition, as we look at how individuals modify their own habits as a consequence of learning, we focus on a particular manifestation of learning. Nevertheless, we have good reasons to believe that in the specific case of use of bed nets, learning can be manifested in other, maybe less straightforward ways. For example if individuals learn about the relevance of the use of bed nets, they may prefer that other more vulnerable people in the household use them, such as women and children. These considerations could motivate future research into other manifestations of learning and in particular into the effects on finally adopted behaviour caused by interactions between learning and different intra-household decisional mechanisms.

Areas for further research include also learning dynamics within a particular network. For example, people with different roles in the same network, on one hand may have a different level of influence on other individuals' decisions, and on the other hand may receive a different exposure both to learning and to constraints on the actual modification of their behaviour. Moreover, the role of specific social ties linking individuals in the same network may be an important determinant of learning.

For example, even if we did not find any evidence of proximity effects among people who belong to the same social group, very different findings could apply if we considered proximity among individuals of the same specific social network.

From the theoretical point of view, in the literature there is no model exploring the effects of social interactions on the adoption of behaviour that implies private costs and generates both individual and social benefits. In particular it would be interesting to explore these effects from the perspective of the long term social equilibrium.

We consider social interactions to be a very fruitful area of research, whose relevance is determined by strong potential policy implications. For example, as we have shown, they may deeply affect the diffusion of certain behaviours and in this way they could potentially cause a significant increase or decrease in the efficacy of specific policies.

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Appendix

Table A1: Descriptive Statistics

Variable	Year	All Sample Mean	All Sample S.D.	Net Users 1994 Mean	Net Users 1994 S.D.	Net Users 2004 Mean	Net Users 2004 S.D.	Never Used Net Mean	Never Used Net S.D.
Use bed net*	1994	0.02	(0.003)	1.00	(0.000)	0.00	(0.000)	0.00	(0.000)
	2004	0.16	(0.007)	1.00	(0.000)	1.00	(0.000)	0.00	(0.000)
Age	1994	26.95	(0.415)	34.68	(2.715)	23.61	(0.935)	27.30	(0.462)
	2004	32.17	(0.382)	37.12	(2.529)	30.50	(0.867)	32.29	(0.426)
Female	1994	0.52	(0.012)	0.66	(0.075)	0.52	(0.031)	0.51	(0.013)
	2004	0.51	(0.010)	0.61	(0.065)	0.55	(0.028)	0.50	(0.011)
Years in school	1994	3.10	(0.070)	5.41	(0.471)	3.74	(0.191)	2.93	(0.076)
	2004	4.69	(0.061)	6.42	(0.418)	6.03	(0.149)	4.43	(0.066)
In school*	1994	0.30	(0.011)	0.10	(0.047)	0.41	(0.031)	0.28	(0.011)
	2004	0.22	(0.008)	0.26	(0.059)	0.20	(0.022)	0.22	(0.009)
Wage Work*	1994	0.14	(0.008)	0.24	(0.068)	0.15	(0.023)	0.14	(0.009)
	2004	0.23	(0.009)	0.19	(0.053)	0.22	(0.023)	0.24	(0.009)
Farm Self Employed	1994	0.91	(0.007)	0.90	(0.047)	0.92	(0.017)	0.91	(0.007)
	2004	0.87	(0.007)	0.74	(0.059)	0.84	(0.020)	0.88	(0.007)
Non Farm Self Employed*	1994	0.20	(0.009)	0.44	(0.078)	0.24	(0.027)	0.19	(0.010)
	2004	0.20	(0.008)	0.26	(0.059)	0.30	(0.025)	0.18	(0.008)
Log consumption	1994	11.83	(0.013)	12.39	(0.075)	11.93	(0.034)	11.80	(0.015)
	2004	11.95	(0.013)	12.56	(0.097)	12.23	(0.033)	11.89	(0.014)
Head of hhold*	1994	0.22	(0.010)	0.37	(0.076)	0.17	(0.024)	0.22	(0.011)
	2004	0.35	(0.010)	0.37	(0.064)	0.38	(0.027)	0.34	(0.010)
Spouse*	1994	0.17	(0.009)	0.15	(0.056)	0.14	(0.022)	0.17	(0.010)
	2004	0.20	(0.008)	0.26	(0.059)	0.27	(0.025)	0.18	(0.008)
Son/Daughter*	1994	0.42	(0.012)	0.32	(0.074)	0.42	(0.031)	0.42	(0.013)
	2004	0.31	(0.009)	0.16	(0.049)	0.26	(0.024)	0.32	(0.010)
Grand Children*	1994	0.06	(0.006)	0.02	(0.024)	0.08	(0.017)	0.06	(0.006)
	2004	0.06	(0.005)	0.09	(0.038)	0.03	(0.009)	0.07	(0.005)
Grand father /mother*	1994	0.01	(0.003)	0.05	(0.034)	0.01	(0.006)	0.01	(0.003)
	2004	0.01	(0.002)	0.02	(0.018)	0.01	(0.004)	0.01	(0.002)
Siblings*	1994	0.04	(0.005)	0.02	(0.024)	0.06	(0.014)	0.04	(0.005)
	2004	0.03	(0.004)	0.05	(0.030)	0.02	(0.008)	0.04	(0.004)
Niece/nephew*	1994	0.03	(0.004)	0.02	(0.024)	0.03	(0.010)	0.03	(0.004)
	2004	0.01	(0.002)	0.00	(0.000)	0.01	(0.006)	0.01	(0.002)
S/D in law*	1994	0.00	(0.002)	0.02	(0.024)	0.00	(0.000)	0.00	(0.002)
	2004	0.01	(0.002)	0.02	(0.018)	0.01	(0.005)	0.01	(0.002)
Sibling in law*	1994	0.01	(0.002)	0.00	(0.000)	0.01	(0.007)	0.00	(0.002)
	2004	0.01	(0.001)	0.00	(0.000)	0.01	(0.005)	0.00	(0.002)
Non relative*	1994	0.00	(0.001)	0.00	(0.000)	0.00	(0.000)	0.00	(0.001)
	2004	0.00	(0.001)	0.00	(0.000)	0.00	(0.000)	0.00	(0.001)
Head of Hh male*	1994	0.79	(0.010)	0.78	(0.065)	0.78	(0.026)	0.79	(0.010)
	2004	0.73	(0.009)	0.74	(0.059)	0.78	(0.023)	0.72	(0.010)
Head of Hh age	1994	49.29	(0.341)	47.58	(2.098)	46.51	(0.882)	49.79	(0.374)
	2004	49.32	(0.350)	51.51	(1.795)	43.88	(0.844)	50.11	(0.387)
Head of Hh education	1994	4.40	(0.070)	6.24	(0.455)	5.58	(0.212)	4.16	(0.074)
	2004	4.78	(0.065)	6.65	(0.491)	6.36	(0.158)	4.48	(0.070)
Hhold size	1994	7.31	(0.081)	6.71	(0.385)	8.03	(0.216)	7.21	(0.089)
	2004	5.89	(0.063)	5.91	(0.350)	5.75	(0.152)	5.91	(0.070)

Hhold size2	1994	65.61	(1.727)	50.90	(6.035)	76.29	(4.631)	64.24	(1.901)
	2004	44.32	(1.080)	41.81	(5.674)	40.52	(2.293)	44.98	(1.217)
Muslim*	1994	0.10	(0.007)	0.12	(0.052)	0.11	(0.020)	0.09	(0.007)
	2004	0.12	(0.007)	0.11	(0.041)	0.11	(0.017)	0.12	(0.007)
Catholic*	1994	0.61	(0.011)	0.59	(0.078)	0.57	(0.031)	0.62	(0.012)
	2004	0.60	(0.010)	0.65	(0.064)	0.53	(0.028)	0.61	(0.011)
Protestant*	1994	0.21	(0.009)	0.24	(0.068)	0.23	(0.027)	0.20	(0.010)
	2004	0.18	(0.008)	0.16	(0.049)	0.25	(0.024)	0.17	(0.008)
Other Christian*	1994	0.05	(0.005)	0.05	(0.034)	0.07	(0.016)	0.05	(0.006)
	2004	0.09	(0.006)	0.09	(0.038)	0.10	(0.017)	0.09	(0.006)
Mhaya*	1994	0.59	(0.012)	0.68	(0.074)	0.57	(0.031)	0.59	(0.013)
	2004	0.59	(0.010)	0.56	(0.066)	0.59	(0.027)	0.59	(0.011)
Mnyambo*	1994	0.15	(0.008)	0.05	(0.034)	0.16	(0.023)	0.15	(0.009)
	2004	0.16	(0.007)	0.11	(0.041)	0.17	(0.021)	0.16	(0.008)
Mangaza*	1994	0.13	(0.008)	0.10	(0.047)	0.13	(0.021)	0.13	(0.009)
	2004	0.14	(0.007)	0.18	(0.051)	0.13	(0.018)	0.14	(0.008)
Msubi*	1994	0.04	(0.004)	0.00	(0.000)	0.03	(0.010)	0.04	(0.005)
	2004	0.03	(0.004)	0.00	(0.000)	0.02	(0.007)	0.04	(0.004)
Kishubi*	1994	0.00	(0.002)	0.00	(0.000)	0.00	(0.000)	0.01	(0.002)
	2004	0.00	(0.001)	0.02	(0.018)	0.00	(0.003)	0.00	(0.001)
Mzinza*	1994	0.01	(0.002)	0.02	(0.024)	0.01	(0.006)	0.01	(0.002)
	2004	0.00	(0.001)	0.00	(0.000)	0.00	(0.003)	0.01	(0.002)
All chil hae vac card*	1994	0.87	(0.008)	0.88	(0.052)	0.87	(0.021)	0.87	(0.008)
	2004	0.94	(0.005)	0.91	(0.038)	0.96	(0.011)	0.94	(0.005)
Seek care hospital*	1994	0.14	(0.008)	0.02	(0.024)	0.21	(0.026)	0.13	(0.009)
	2004	0.18	(0.008)	0.33	(0.063)	0.19	(0.022)	0.17	(0.008)
Seek care health centre*	1994	0.06	(0.005)	0.15	(0.056)	0.06	(0.015)	0.06	(0.006)
	2004	0.03	(0.004)	0.07	(0.034)	0.06	(0.013)	0.03	(0.004)
Seek care dispensary*	1994	0.29	(0.011)	0.29	(0.072)	0.30	(0.029)	0.29	(0.012)
	2004	0.25	(0.009)	0.37	(0.064)	0.26	(0.024)	0.24	(0.009)
Seek care pratict home*	1994	0.06	(0.006)	0.02	(0.024)	0.07	(0.016)	0.06	(0.006)
	2004	0.00	(0.000)	0.00	(0.000)	0.00	(0.000)	0.00	(0.000)
Seek care public place*	1994	0.31	(0.011)	0.39	(0.077)	0.33	(0.030)	0.31	(0.012)
	2004	0.32	(0.009)	0.54	(0.067)	0.35	(0.026)	0.31	(0.010)
Seek care mission*	1994	0.07	(0.006)	0.02	(0.024)	0.05	(0.014)	0.08	(0.007)
	2004	0.00	(0.000)	0.00	(0.000)	0.00	(0.000)	0.00	(0.000)
Seek care private place*	1994	0.00	(0.000)	0.00	(0.000)	0.00	(0.000)	0.00	(0.000)
	2004	0.17	(0.008)	0.23	(0.056)	0.19	(0.022)	0.16	(0.008)
Seek care designated place*	1994	0.00	(0.000)	0.00	(0.000)	0.00	(0.000)	0.00	(0.000)
	2004	0.04	(0.004)	0.21	(0.054)	0.06	(0.014)	0.03	(0.004)
Seek care trad healer*	1994	0.00	(0.000)	0.00	(0.000)	0.00	(0.000)	0.00	(0.000)
	2004	0.02	(0.003)	0.00	(0.000)	0.02	(0.007)	0.02	(0.003)
Num Early Ad Close n.	2004	1.95	(0.057)	4.16	(0.613)	2.49	(0.189)	1.80	(0.058)
Num Early Ad Far n.	2004	0.69	(0.033)	0.68	(0.210)	1.10	(0.114)	0.63	(0.034)
Num E Ad New hhold m	2004	0.02	(0.003)	0.32	(0.094)	0.03	(0.011)	0.01	(0.002)
Ratio Early Ad Close n.	2004	0.02	(0.001)	0.05	(0.007)	0.02	(0.002)	0.02	(0.001)
Ratio Early Ad Far n.	2004	0.01	(0.001)	0.02	(0.007)	0.02	(0.002)	0.01	(0.001)
Ratio E Ad New hhold m	2004	0.01	(0.002)	0.17	(0.047)	0.02	(0.006)	0.00	(0.001)
Early Ad in close n.*	2004	0.53	(0.010)	0.68	(0.062)	0.61	(0.027)	0.52	(0.011)
Early Ad in far n.*	2004	0.26	((0.009)	0.30	(0.061)	0.40	(0.027)	0.23	(0.009)
Early Ad New hhold m *	2004	0.01	((0.002)	0.21	(0.054)	0.02	(0.009)	0.00	(0.001)
Number of observations		4284		98		577		3609	

Note:
*Denotes dummy variables. Percentages are reported for dummy variables