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Publication Date
2008-12-01

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CCPR-2008-059

December 2008
Last Revised: December 2008

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10 October 2007

Abstract

Network-based strategies and competencies are probably even more important in poor societies with limited means of communication and less effective formal structures than in developed economies. And they often deal with life and death matters. This paper presents lessons from and insights about the nature of and the impacts of informal social networks in reducing fertility and coping with HIV/AIDS in Kenya and Malawi based on analyses of quantitative longitudinal data and qualitative data that the authors and their collaborators have been collecting and analyzing for over a decade. Specific lessons include the relevance of social networks and informal interactions for many different domains related to health – and thus life and death – in developing countries, the importance of accounting for the endogeneity of network partners in analyzing network effects, that networks are important even with control for endogeneity, that network effects may be nonlinear, that there may be multiple equilibria, that which networks may either reinforce the status quo or help diffuse new options and behaviors, that both the context (e.g., the degree of market development) and the density of networks matter (possibly interactively), and that multiple approaches, including both qualitative and quantitative analyses, can be informative in providing more in-depth understanding of what networks do and how they function.

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Section 1. Introduction

Theories of social interactions in demography rest on the interdisciplinary insight in the social sciences that individuals do not make decisions about demographic and other social behaviors in isolation, but rather with others. While the basic insight about the relevance of social interactions is old, dating back at least to the 19th century with the work of the sociologist Georg Simmel (1922), research in the last decades has achieved substantial progress in specifying, measuring, modeling and understanding the importance of network-based interactions on human behaviors on the micro-level, and on societal, economic and cultural dynamics on the macro-level. In particular, recent research has documented how social interactions offer opportunities for individuals to exchange information, to evaluate information, to learn about the rigidity or flexibility of social norms, and to influence the attitudes and behaviors of one another. The importance of social interactions, however, is not restricted to the micro-level where it affects how individuals behave in various contexts and how these behaviors are influenced by others.

A key insight of the recent work on social interactions has been a better understanding of micro-macro interactions, and in particular, how interrelated individual behaviors can chance the dynamics of social change. For example, social multiplier effects imply that the total societal change in response to an innovation or intervention is larger than it would have been in the absence of social interactions. Social interactions can also result in multiple social equilibria, that is, situations in which a society may be "stuck" in an inefficient societal state; multiple-equilibria, however, can also result in rapid and irreversible societal changes, such as a rapid transition from a high to low fertility regime. The interrelatedness of individual's decisions through social interactions can also imply that the dynamics of social change depend on the intricacies of the web of social relations, including for instance the structure, extent and heterogeneity of individuals' social networks. Hence, while mainstream demography – similar to contemporary sociology and mainstream economics – remains largely committed to a model of individuals acting in isolation from one another, recent empirical and theoretical research has brought about a sea of change towards recognizing the importance of social interactions for understanding individual behavior and social change. The availability of causal estimates of social interaction effects and new analytic or simulation-based modeling approaches also promise a quantum-leap towards establishing a model of individual behavior in the social sciences that is cognizant of the role of social interactions and informed by detailed empirical findings of how these interactions shape individual decision processes and aggregate societal dynamics.

Several reviews of the network literature have described the origins of network theories and analyses (e.g. Wellman 1988). For example, network studies were given an early applied focus by European anthropologists studying rapid social change associated with modernization in sub-Saharan Africa, who wrote of the network connections of urban migrants with each other and with the rural communities from which they came (Mitchell 1969) and by anthropologists studying class relationships in Britain (Bott 1971). An interest in social networks then developed among U.S. sociologists, who focused more on theories and methods of network analysis (Marsden 1990, Burt 1982, Valente 2005) than on substantive issues. Among the exceptions that later had a dominant influence on the field, for example, Fischer (1982) analyzed personal networks to investigate the social and psychological consequences of urban life, and Granovetter (1973) emphasized the importance of "weak ties" that transmit unique and nonredundant information across otherwise largely disconnected segments of social networks, thereby facilitating the diffusion of new information; "strong ties" and dense networks, on the other hand, are more likely to enforce norms and conventions that represent a "proper" way to behave. In a similar vein, Burt (1992) pointed to the strategic informational advantage that may be enjoyed by individuals who bridge "structural holes," that is, those with ties into multiple networks that are largely separated from one another, and the "new science of social networks" (Watts 1999) formalized the "small-world phenomenon"— the hypothesis that a short chain of social acquaintances connects most individuals— using a few random shortcuts in the midst of locally dense neighborhoods.

The effects of social interaction processes are likely to be particularly important when an individual is uncertain about the best response to an innovation or environmental change or to new social and economic circumstances. As a result, social interaction processes and their effect on social dynamics have been investigated extensively in the context of the diffusion of innovations (e.g., Rogers 2003), social change and collective action (Kim and Bearman 1997; Klandermans 1992), and search or matching processes in the labor market or similar markets (Granovetter 1973, 2005). In demography, an important stimulus to incorporating social networks in analyses was a by-product of interest in explaining fertility declines in historical Western Europe and the developing world. Although it was expected that fertility declines could be understood as individual responses to structural changes associated with modernization (e.g. urbanization, the transformation of the labor force from agricultural to industrial, declines in infant and child mortality), the associations between measures of these changes and fertility declines were typically modest (Coale and Watkins 1986; Cleland and Wilson 1987). This led to postulating the importance of interpersonal diffusion (Knodel and van de Walle 1979) and emphasis on social networks to structure analyses of diffusion (Watkins 1991, Casterline 2001; Kohler 2001; Montgomery and Casterline 1996; Munshi and Myaux 2007). Applications in demography have also included the perception of mortality change (Montgomery 2000), the onset of sexual behavior among teenagers (e.g., Rodgers and Rowe 1993), and international migration (Massey et al. 1994, Munshi 2003),

The discipline of economics began to contribute to analyses of social networks, and more broadly social interaction, with studies of rapid changes in behavior that suggested underlying changes in preferences (cascades etc). Economists also insisted on attention to the causal impacts of networks rather than just the associations that prevailed in much of the literature (perhaps due to reverse causality or homophilous selectivity of network partners), a concern regarding empirical interpretation that had previously been mostly absent.

Despite evidence collected by demographers interested in understanding incipient fertility declines in the developing world, and family planning advocates interesting in promoting the adoption of modern contraception -- evidence that showed that developing country villagers talked to each other about family planning and family size -- demographers paid little attention to the role of social networks prior to the 1990s. In part this was due to the absence of data on networks; that absence, however, was due to a dominant model of social behavior that privileged individual and family characteristics over social interactions. Only in the 1990s were new data collected in developing countries that permitted detailed descriptions of social networks and rigorous analyses of social network effects, for example in Ghana (Casterline et al, 2000), in Kenya (www.kenya.pop.upenn.edu) and in Malawi (www.malawi.pop.upenn.edu).

In summary, social network studies in demography have a pedigree in anthropology, sociology and economics, and there is related contemporary work in these three disciplines. However, there is little cross-citation and limited cross-fertilization, and the research-emphases in the different disciplines remain distinct. Within demography, where an important focus has been the empirical measurement and identification of social interaction effects on fertility and health outcomes, a few researchers -- including the authors of this paper – have collected longitudinal data that permit careful description and rigorous analyses of the causal impacts of networks. Our work for well over a decade in investigating the roles of social interaction for important demographic behaviors has been based on data collected in Kenya and Malawi. Below we summaries the key substantive findings of these studies of social interaction pertaining to life (fertility) and death (HIV/AIDS). We also highlight some specific lessons for the study of social networks in other contexts, which include the importance of accounting for the endogeneity of network partners in analyzing network effects, that networks are important even with control for endogeneity, that network effects may be nonlinear, that there may be multiple equilibria, that which networks may either reinforce the status quo or help diffuse new options and behaviors, that both the context (e.g., the degree of market development) and the density of networks matter (possibly interactively), and that multiple approaches, including both qualitative and quantitative analyses, can be informative in providing more in-depth understanding of what networks do and how they function. We begin in Section 2 with a description of our data, we then turn in Section 3 to our studies of the role of social networks in determining fertility-related behaviors, then turn in Section 4 to the role of social networks in perceived HIV/AIDS risks, and conclude in Section 5 with lesions learned for the broader analysis of networks.

Section 2. General Overview of Survey Data and Contexts

Our analyses are based on data from the Kenyan Diffusion and Ideational Change Project (KDICP) and the Malawi Diffusion and Ideational Change Project (MDICP). In both cases, the data consist of longitudinal household survey and qualitative data that we collected in rural areas during 1994–2000 for Kenya and 1997–2006 for Malawi. In both cases the initial primary motive for collecting these data was to analyze the role of social networks in the diffusion of innovations to increase the use of "modern" family planning methods and to reduce fertility, provoked substantially by the limited explanatory power of individualistic formulations to explain the European fertility decline (see the introduction). Subsequently the focus of the projects – and therefore of the data collection -- shifted increasingly towards HIV/AIDS because of the rapid spread of the epidemic in the populations being studied. The sampling frame for the surveys was ever-married women of childbearing age (15-49) and their husbands (if currently married); a new sample of adolescents was added to the Malawi study in 2004.

Our quantitative data are, to our knowledge, unique because they also include detailed accounts about women's and men's interactions about family planning (for the studies that are summarized in Section 3) or the HIV/AIDS epidemic (for Section 4) with social network partners (besides their spouses) that allow us to investigate the role and importance of these interactions.[1] In particular, the data include information on egocentric networks, that is, networks that contain the respondent and network partners with whom the respondent had chatted about family planning or HIV/AIDS, with detailed information on up to four network partners. The term "chat" was used in survey questions to indicate informal conversations rather than lectures at clinics. The network data were collected by first asking the respondents how many people they had chatted with about these respective topics.[2] They were then asked a series of questions about these network partners (covering a maximum of four network partners if more than four were identified). The questions asked of the respondent about her/his network partners included relationship (e.g., co-wife, sister-in-law, sister); the degree of closeness (confidant, friend, acquaintance); the network partner's age, sex, and wealth; and the perception of the respondents about the views and behaviors of the network partner on family planning or about the risk of becoming infected with HIV/AIDS.

In Kenya, the first wave of the longitudinal household survey (KDICP 1) was conducted in December 1994 and January 1995 in South Nyanza District. The second wave (KDICP 2) reinterviewed these women and men two years later, and a third wave was conducted in January and February 2000 (KDICP 3). Only the second and third waves of the survey addressed AIDS. In total, 545 ever-married women (408 husbands) participated in both of these last two rounds of the data collection.

In Malawi in 1998, the project interviewed 1,541 women and 1,065 men topics related to AIDS and family planning (MDICP 1) in the Rumphi (North), Mchinji (Center), and Balaka (South) regions.

[1] Other data sets on AIDS have information on respondents' sexual partners (information that we do not have for our overall samples, though we do have for some subsamples) but not on their social networks in which they discuss HIV/AIDS risks and ways of coping with such risks.

[2] The question about the number of conversations did not have an explicit time reference. A related question in the Kenyan survey about the time of the last conversation shows that many conversations were relatively recent: the last conversation with the network partner occurred within one year prior to the survey in more than 80% of all cases. We expect that this pattern is similar in Malawi.

Follow-up surveys were conducted in 2001 (MDICP 2), 2004 (MDICP 3) and 2006 (MDICP 4), with further follow-ups scheduled for 2008 (MDICP 5) and 2011 (MDICP 6). Details of data collection and analyses of attrition and data quality are available at http://www.malawi.pop.upenn.edu and in a special issue of *Demographic Research* (Watkins et al. 2003).

There are similarities and differences between our sites in Kenya and Malawi. In both Kenya and Malawi, the areas covered by the surveys are primarily characterized by subsistence agriculture. In Kenya and, to a lesser extent, in Malawi, education is valued as a route out of poverty. Although most men and women have attended school, few in our samples had studied beyond the primary grades. Those with more schooling seek work in the cities. Cash necessary for such expenses as school fees and clothing is obtained from remittances, wage labor, or, especially for women, small-scale retailing (e.g., buying bananas in a larger market and reselling them locally). Despite broad similarities in the overall socioeconomic contexts, there is marked variation across survey sites in the level of market activity and proximity to major transport routes. Moreover, variation in marriage patterns between our sites in Kenya and Malawi suggests the possibility of different network dynamics. In the Kenyan site and in one of the three sites in Malawi, residence is ideally patrilocal. Thus, men who are de jure residents of their natal villages are related to each other through a common ancestor. Women, however, must modify their networks after marriage to include their husband's relatives, although they do retain links with their natal families in other parts of the region. The other two sites in Malawi, however, are predominantly matrilocal: it is the men rather than the women who must modify their networks after marriage.

Section 3. *Social Networks* and *Life* -- the Diffusion of Family Planning

This section summarizes three papers on different dimensions of social networks as related to the adoption of "modern" methods of family planning in the high-fertility poor developing context of rural Kenya. These papers are motivated by the increasing attention that has been given by demographic analysts and family planning program supporters to the possible roles of social interactions in the diffusion of knowledge, attitudes and behaviors related to family planning. The few previous empirical studies of this topic suggest that if social interactions are important, their omission from empirical models is likely to result in distorted estimates of the direct effects of family planning programs. However a number of empirical issues regarding the functioning of these networks had not been investigated prior to our studies that we now summarize.

Section 3.1 Empirical Assessments of Social Networks, Fertility and Family Planning Programs: Nonlinearities and their Implications from Kohler, Behrman and Watkins (2000)

This analysis adds to the previous literature by showing that there are some important implications of using nonlinear models for measuring program effects and for evaluating the roles of social interaction that have not been explicitly considered in the previous empirical literature. We demonstrate some of these properties formally, and investigate them empirically using data that includes measures of social interactions. We find that for Nyanza, Kenya, the nonlinear versus the linear specifications indeed lead to different substantive results with different implications for demographic analysts and program supporters.

To provide intuition for some dimensions of our analysis in this section as well as below, we first present a simple model to illustrate some of the advantages that our data have for such analysis. The availability of unusual longitudinal data, including that on social networks, and the use of statistical methods that control for unobserved factors provide a unique opportunity to extend the individualistic rational-actor models to incorporate social interaction and to estimate the causal effects of social networks on attitudes and behaviors under certain assumptions about the nature of the unobserved effects. In particular we use an empirical specification of the relation determining contraceptive behaviors in which there is explicit recognition that, in addition to observed right-side variables (including social networks prior to time *t*), there are unobserved fixed factors that might affect both contraceptive use directly and through social networks. For example, preferences for family orientation or for traditional types of social relations might affect both. A first-order linear approximation to the model for the determinants of contraceptive behavior is

$Y_{it} = a \cdot N_{it-} + b \cdot \mathbf{X}_{it-} + f_i + e_{it}$, (1)

where Y_{it} is the observed contraceptive behavior of individual i at time t; N_{it-} is the social network for individual i prior to time t (we use the subscript "t–" to emphasize that the variable N refers to the time prior to t; we use this notation also for other predetermined variables); $\mathbf{X}_{it-}$ is a vector of other state variables for individual i determined prior to time t (e.g., age, marital status, completed schooling of adults, wealth indicators); f_i represents unobserved fixed factors that are assumed to affect directly contraceptive behaviors by individual i (e.g., the persistent part of preferences, unobserved current community characteristics, expectations regarding future prices, and interfamilial and community resources on which the individual can draw) and also affect social networks; and e_{it} is an i.i.d. disturbance term that affects the contraceptive behavior of individual i at time t due to, for example, new information on the probability of conceiving children from using traditional contraceptive methods or about the advantages and disadvantages of children in a high HIV/AIDS prevalence context, or price shocks that are deviations from the long-run secular price trends.[3]

The formulation in equation (1) is consistent with Montgomery and Casterline's (1996) "social multiplier" model of diffusion in which, if b is the direct impact of some change on an individual's risk perceptions and Y_{it} and N_{it-} are measured in the same terms (e.g., N_{it-} is the average contraceptive behavior by social network partners), the social multiplier that captures the long-run effect through the network is $1 / (1 - a)$. Therefore, to estimate this social multiplier, as well as the direct determinants of contraceptive behaviors of an individual, it is important to obtain unbiased estimates of the coefficients a and b.

If OLS estimates are made of equation (1), however, inconsistent (biased) estimates are likely to result because the unobserved fixed effects are correlated with the characteristics of social network partners if they indeed affect the choice of network partners, so the OLS estimated value of a is biased because the social network variable is representing in part the unobserved fixed effects in addition to the effects of social network per se. By virtue of having longitudinal data, however, we are able to control for the individual fixed effects to compare the fixed effects estimates with the OLS estimates to learn how much difference control for unobserved fixed effects makes in inferences about the magnitudes of network effects.[4]

While we investigate the potential roles of unobserved heterogeneity on estimates of equation (1) in subsequent sections, we focus here on aspects of the specification of the probability model in relation (1). In particular, we formally identify the *direct* program impact versus *total* effect (i.e., the direct effect modulated by social interactions, see below) of increases in family planning program efforts in both linear and nonlinear models. We then compare the implications of linear and nonlinear models in situations in which program efforts are increased and in situations in which social interactions are intensified.

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[3] The assumption that the disturbance term *eit* is i.i.d. also excludes autocorrelation; the model therefore assumes that persistent heterogeneity in contraceptive behaviors among individuals with similar observed characteristics is primarily due to heterogeneity in fixed characteristics (captured by the fixed effect, f_i) rather than to lasting effects of past "shocks" (captured by lagged values of the disturbance term e_{it}).

[4] Fixed effects estimates control for unobserved fixed factors, but not for unobserved time-varying factors (see Section 4.2 below).

Linear probability model: We begin with the linear model because it is simpler and more transparent despite its well-known limitations. Let the probability that a woman adopts modern family planning ($y = 1$) be:

$P(y=1 \mid z, y_c) = a^*(-.5 + y_c) + b^* z + d$ (2)

The term $a^*(-.5 + y_c)$ represents the influence of social interaction on a woman's probability to use family planning and is chosen to match our subsequent specification of the nonlinear model. The parameter *a* reflects the 'strength' or relevance of social interaction and determines the extent to which the adoption probability is affected by the contraceptive behavior in the village or reference group (y_c). If the contraceptive prevalence in the reference group (y_c) is above 0.5, then social interaction increases the probability of using family planning as compared to the situation when no social interaction is present, and otherwise it decreases the probability. The coefficient *b* is the direct effect of program efforts (*z*), and larger program efforts increase the probability of using contraception when $b > 0$. For simplicity, in our discussion of this theoretical model in this section (but not in our estimates discussed below) we consider only women who are identical with respect to individual characteristics, which permits us to combine the effect of these characteristics into the constant term d. The solid line in Figure 1a plots the curve implied by equation (2): the vertical axis gives an individual's probability of using contraception as related to the average contraceptive use for the individual's reference group (y_c, on the horizontal axis) given the program effort *z* (e.g., proportion of other villagers who "heard a family planning message on the radio"). The slope of the solid line indicates how the probability of individual use changes when there is a discrepancy between the probability of an individual's use and the average contraceptive use of other women in her village. The linear model in Figure 1a exhibits only one equilibrium, the point at which each individual's behavior mirrors the village average -- where the solid line intersects the 45^o ray from the origin in Figure 1a.[3] This equilibrium therefore satisfies $P(y=1 \mid z, y_e) = y_e$, where y_e is the equilibrium level of contraceptive use. To the left of it the individual probability of use is above the village average use; therefore the average village use increases because the individual is in the reference group for others in the village, which causes movement to the right towards the equilibrium (and *vice versa* to the right of the equilibrium).

[Figure 1 about here.]

What happens when there is an increase in program effort, for example a new media campaign? We depict this changed relation between the program and social interaction as a shift from the solid to the dashed line in Figure 1a. The *direct* effect on the probability of the individual's use of changing program efforts is the vertical distance indicated as the "direct program effect" in Figure 1a (the result of changing program effort by one unit while holding constant village average use). This direct program effect is not modulated by social interactions. If, however, the individual adjusts to her reference group, we get a *social multiplier* (Montgomery and Casterline 1993). The social multiplier leads to a new and higher equilibrium level of contraceptive use, i.e., where the dashed line intersects the 45^o ray. The *total* increase in the probability of contraceptive use is thus the total program effect, consisting of a direct program effect plus its multiplication by social interaction.

A nonlinear model: In the nonlinear form of the model, we use a logistic specification that is frequently used in theoretical models of social interactions (Brock and Durlauf 1995, Kohler 2000a,b, Manski 1993) and for empirical estimates (Arends-Kuenning 1997, Entwisle and Godley 1998, Kohler, Behrman, and Watkins 2001, Montgomery and Chung 1998, Munshi and Myaux 1997). In this model we assume that the disutility from deviating from the average behavior of woman's reference group is related linearly to the difference between an individual's decision to use or not to use and the average reference group behavior y_c. More specifically, we assume that the social utility term takes the form of $a^*(-.5 + y_c)$, where .5 is the critical level above which the prevalence of contraceptive use in a woman's village or reference group has a positive influence on the adoption of family planning, and *a* is the 'strength' or relevance of this social interaction effect. The standard derivation leads to the probability that a woman uses a modern method of family planning given by

$$P(y=1|\, z, y_c) = F(a^*(-.5 + y_c) + b^* z + d) \quad (3),$$

where d is a constant including the effect of the individual characteristics and F is the cumulative logistic distribution. The total effect of family planning programs in the presence of social interactions can be characterized in the above nonlinear model, as in the linear case, by equilibria in which an individual's choice probability mirrors the cluster or village average (Figure 1b). That is, an equilibrium is a level of contraceptive use that satisfies $P(y=1|\, z, y_e) = y_e$, or equivalently, an equilibrium is a fixed point at which $y_e = F(a^*(-.5 + y_e) + b^* z + d)$. These equilibria are thus at intersections of the "s-shaped" curve F(.) with the diagonal. The solid line in Figure 1b displays a case in which only one such equilibrium exists. The solid line in Figure 1c, on the contrary, shows a case with three intersections. The equilibria at low and high levels of contraceptive use are stable for reasons parallel to those discussed with regard to Figure 1. The same reasoning, however, indicates that the center equilibrium always is unstable. A population converges to one of the two stable equilibria depending on whether it is to the left or right of the unstable equilibrium.

The comparison of the linear and nonlinear specification in Kohler et al (2000), including both the theoretical implications of a linear versus nonlinear specification as well as the differences of these models in their empirical estimation using KDICP data, yield the following major results:

First, as noted, we distinguish between the direct effects of a family planning program on an individual's probability of using family planning and the indirect effects due to social interaction. Our empirical estimates show that the nonlinear model of the relations among program effects, social interaction and of modern family planning leads to some fairly large differences in the estimates of program effects from those obtained with the linear model – e.g., with estimated direct program effects on the ever use of family planning from 20% lower to 27% higher for the linear than the nonlinear model. We then show empirically that in our data as much as 43% of total program effects are due to social interaction.[5] This *social multiplier effect* is due to a feedback loop that occurs because social interaction renders the family decisions of community members interdependent. Because of this social multiplier effect, attributing all of the total change in contraceptive behavior to a direct impact of changes in program effort would be a substantial overestimate of the direct program effect. In addition, the linear specification that is presented above for simplicity and that has been used in the prior literature assumes that the total program effect and the social multiplier are identical across subpopulations with different levels of contraceptive use. This need not be the case in the nonlinear model, and our results show important differences in these effects between the women with low and high schooling: social interaction leads to substantially larger multiplier effects in the high-schooling subpopulation with a higher overall propensity of using family planning.

Second, we show formally that if the model is nonlinear (Figure 1b-c), there may be both a low-level Malthusian equilibrium in which contraceptive use remains relatively low despite ongoing program efforts as well as an equilibrium in which contraceptive use is high.[6] If a population is at a low-contraceptive-use and high-fertility equilibrium – a situation that may characterize much of sub-Saharan Africa, including places with family planning programs – small program changes have relatively small effects. However, large increases in program efforts – even if transitory – may cause a shift to a high-contraceptive-use and low-fertility equilibrium. In a linear model, in contrast, large program efforts can lead to high contraceptive use, but the program efforts must be maintained at high levels to sustain high contraceptive use. Our empirical analysis does not indicate the presence of multiple equilibria in our data.

[5] That is, if the social multiplier is 175%, the proportion of the total effect due to social interaction is 75/175.

[6] Related models of multiple equilibria and path dependency in the context of fertility decline are found in, for example, Becker, Murphy and Tamura (1990), Galor and Weil (1996) and Kohler (1997, 2000b).

Thus, these estimates suggest that there is little likelihood that a sharp transitory increase in program activities in Nyanza would lead to a rapid shift to much higher sustained levels of contraceptive use. But such possibilities may exist in other contexts.

Third, we show formally that intensified social interactions may either increase or decrease the total effect and social multiplier effect resulting from family planning program efforts, and ‘more’ social interaction can thus reinforce or retard the diffusion of an innovation. When a nonlinear (logistic) model is used, increasing the impact of social interactions is *status quo* reinforcing close to a stable equilibria (whether at low or high contraceptive use) in a multiple-equilibria situation. Therefore, if a new program effort were to intensify social interactions near the stable equilibria, the total—or long-term—change in contraceptive use resulting from the program effort is reduced and these more intensive social interactions would retard the diffusion of family planning after the program interventions. Our nonlinear empirical estimates for Nyanza District imply that when social interactions are intensified, they reduce the total effect associated with program interventions, but slightly increase the social multiplier effect. These findings are in contrast to the linear estimates that imply that more intense social interaction leads to a larger social multiplier effect and an increased total effect after the program interventions.

Thus, we show formally that there are some important implications of nonlinear models of social interactions that have not been emphasized in the previous literature and how they contrast with the implications of linear models, and we show empirically that in the Nyanza case there are some substantial differences in estimating program effects required for a sustainable fertility transition between the nonlinear and the linear specifications. The value of having the right model may be considerable and the implications of nonlinear models in this context need to be understood to interpret fully their results.

Section 3.2 The Density of Social Networks and Fertility Decisions: Evidence from South Nyanza District, Kenya from Kohler, Behrman and Watkins (2001)

Previous studies emphasized the content of social interactions, usually measured by the proportion of contraceptive users in a respondent’s network, on family planning choices. These studies typically found that the probability of a woman’s using contraceptives is related strongly to content, and that the relationship is positive: the more users in a network, the more likely that the woman herself uses family planning. In this paper we expand this approach by proposing that network structure modifies the impact of the content of the interaction. We include measures of network density, distinguishing between dense networks, in which all the network partners know each other, and sparse networks, in which the network partners are connected only through their ties to the respondent. We exploit the implications of variations in network structure to address an important theoretical question: what are the mechanisms by which social interaction influences behavior?

We focus on two mechanisms emphasized in the literature: *social learning* and *social influence*. The former stresses that decisions about contraceptive adoption are subject to substantial uncertainty: for example, about the medical side effects and/or the costs and benefits of modern methods of family planning. Learning about other women’s experiences through networks may reduce this uncertainty, thus increasing the probability that a risk-averse woman will adopt modern contraception herself. The second aspect, social influence, emphasizes normative influences on behavior rather than processes of learning about unknown characteristics. Social influence therefore implies that the fertility-related opinions and behavior of an individual’s network partners influence and alter her preferences regarding modern contraception and/or number of children.

We argue that when social learning dominates, network density should not matter. In situations of uncertainty, information is important. Because all members of a dense network are likely to possess the same information, we expect weak, possibly negative effects of density on the adoption decision when the content of the interaction is controlled. If social influence dominates, however, density is expected to be important. In particular, when the normative acceptability of contraceptive use is the issue, dense networks with a low proportion of contraceptive users should reduce the probability of using family planning; dense networks with a high proportion of users should increase that probability; and sparse networks should be relatively neutral.

[Table 1 about here]

We estimate the probability of using modern contraception on the basis of data gathered in South Nyanza District, Kenya, as part of the KDIC Project. Summary statistics for all women in the data, as well as for the subset of women with a social network of at least three members, which are used in for the estimation of these models, are reported in Table 1. The results of our analyses are reported in Table 2. In addition to some standard socioeconomic characteristics, the estimated models in Table 2 include the proportion of contraceptive users in the social network, the density of the network, and an interaction between these measures of content and structure in what basically is an extension of equation (1) to include these interactions. We find that both our measure of network content and our measure of network structure are related to the probability that a woman uses family planning. The patterns of the interactions between content and structure in our empirical modeling, however, suggest that context determines whether social learning or social influence dominates. In Obisa, one of the regions of our study, the probability of a woman's contraceptive use is affected primarily by the measure of the content of the interaction; network structure has little relevance. In Obisa, social learning apparently is the mechanism through which social interaction affects contraceptive decisions. In Owich, Kwadhgone and Wakula South (OKW), the other region, social influence appears to be the primary mechanism through which networks influence individual behavior. In OKW, the interaction between content and structure is critical: dense networks discourage an individual from using contraception if the network includes few contraceptive users, but dense networks encourage use when contraceptive use in the network is relatively high. Thus, when social learning is the mechanism by which networks affect contraceptive decisions, a comparison across contexts confirms the simple account: the higher the proportion of contraceptive users in a woman's network, the more likely she is to use family planning. Where social influence dominates, however, the influence of networks is ambivalent: they may either facilitate or constrain the adoption of family planning.

[Table 2 about here]

These differential implications of social learning and social influence on the probability to use family planning are also depicted in Figure 3. Given the same social network, the ever-use of contraception is higher in Obisa than in the region of Owich, Kawadhgone and Wakula South. If we compare the lines for dense networks and sparse networks in Obisa, we see that a woman is more likely to have ever-used modern contraception if she has a sparse network than if she has a dense network, given the same prevalence of family planning in a respondent's social network. Moreover, as the proportion of network partners using family planning increases, the lines diverge. Therefore, when the prevalence of users within the network is low, women with sparse networks are about as likely to use family planning as women with dense networks. When the prevalence of family planning in the network is high, however, women in sparse networks are more likely to use than women in dense networks. These patterns in Figure 3 for Obisa thus reflect the implications of social learning. In contrast, the right graph in Figure 3 reflects a relation that is typical for social influence. Although the probability of having ever-used contraception again increases with the prevalence of use among network partners, the effect is rather minimal and not substantively important for networks with a density of 0.5. Only for relatively dense networks (i.e., density > 0.75) does the proportion of contraceptive users in the network have a relevant influence on the respondent's probability to use family planning. In addition, the lines no longer diverge for increasing levels of contraceptive prevalence in the networks as in the left graph, but rather intersect at a prevalence of about .7 that is indicated by the line *CC*. To the left of the line *CC* an increasing density of the network reduces the probability of having ever-used contraception, holding the prevalence of family planning users in the network constant. To the right of the line *CC* the social influence is towards modern contraception. In this case, an increasing density of the network, holding the prevalence of contraceptive users in the network constant, increases the probability of using family planning.

[Figure 2 about here]

These two regions for which our models are estimated in Table 2 are not distinguished by the characteristics of the networks of the respondents who live there, but rather by the extent of market activities (Table 1): in Obisa, more women are engaged in market activities than in OKW, and they buy and sell at a larger market. We find that social influence is important only where market activity is low. Where market activity is high, social learning dominates. Although the available data do not allow us to investigate in detail the interdependence of social interaction and market activities, the notion that higher market activities favor social learning is plausible. After all, the spread of information is an important aspect of markets, and market participants may focus more strongly on the information provided by their personal contacts than on the social acceptance regarding their family planning behavior. Our findings about the importance of market activity are consistent with provincial differences in the onset and pace of fertility decline in Kenya: the earliest declines occurred in Nairobi Province and in Central Province. Markets in both of these locations have long been more highly developed than in Nyanza (Bates 1981).

This finding also suggests predictions about the future of contraceptive use in South Nyanza. Even in areas where social interactions currently retard the diffusion of family planning, the dominance of conservative social influence may shift to a dominance of social learning, which will accelerate this diffusion if market development is sufficient. Thus we end by emphasizing the importance of network structure and market activities in fertility transitions.

Section 3.3 Social Networks and Changes in Contraceptive Use Over Time: Evidence from a Longitudinal Study in Rural Kenya from Behrman, Kohler and Watkins (2002)

A limitation of the analyses in the previous section, as well as of much of the demographic literature on social interactions, do not permit confident inferences regarding the causal effects of social networks because unobserved factors that may directly affect attitudes and behavior may also directly affect choices of the units of social interaction, as is discussed with regard to equation (1) above. In particular, most of the existing literature on social interactions and demographic behaviors assumes, usually implicitly, that it is acceptable to treat networks as if they were formed randomly. There are at least two reasons to expect that this assumption of random network selection often may be violated. First, empirical studies suggest a nonrandom selection of network partners. For example, using qualitative data collected as part of the KDICP, Watkins and Warriner (2003) showed that the networks with whom respondents discuss issues of family planning and AIDS are characterized by a tendency to discuss these topics with others who are perceived to be similar ("like me"); in addition, some network partners are deliberately chosen because they are believed to have relevant information or competence. Second, a theoretical consideration of learning under uncertainty suggests that social interactions about family planning are determined by the following factors: (1) the costs and benefits of social learning about family planning and fertility-related issues; (2) the various social constraints imposed on the ability to engage in interactions about family planning due to the availability of suitable network partners and the social acceptability of communications about contraception and fertility reduction within households and communities; and (3) the expected reduction of uncertainty about the benefits, side-effects (or other costs) of using family planning through interactions with others, which depends in part on network partners' knowledge, their possibly strategic communication of this knowledge, and the individuals' interpretation of the information they obtain from others. As a result of these processes of how social networks are formed, if the causal direction is unclear, what has been interpreted as the causal effects of social networks may simply be associations that are due to both contraceptive use and network partners' choices being determined, in part, by unobserved factors, such as preferences. Therefore we use our longitudinal data with special information on social networks once again to investigate the determinates of contraceptive use in high-fertility rural Kenya, in this case directly estimating the linear approximation in equation (1). We have four major findings (Table 3, along with additional results for men in Behrman et al 2002 that are not reported here in detail).

[Table 3 about here]

First and foremost, our analysis shows that social networks have significant and substantial effects even when we controlled for unobserved factors that may also determine the nature of the social networks. In particular, this study provides what we believe are currently the best available estimates about the effects of social networks on contraceptive use in high-fertility areas. *Second*, estimates of the effects of social networks that are based on the implicit assumption that they are determined randomly, as in previous studies, may lead to a substantial misunderstanding of the impact of social networks on individual behaviors. With our data, analyses that did not control for the possibility that both contraceptive behavior and social networks within which this behavior is discussed are partially determined by unobserved factors, such as preferences, appeared to misestimate the effects of networks. *Third*, the effects of social networks are not limited to women, even though in local stereotypes women are often characterized as gossiping much more than men. To the contrary, our estimates indicate that, if anything, men are likely to be more influenced by their network partners than are women. This finding may reflect cultural patterns of exogamy and patrilocality that result in men having known their network partners since childhood, whereas women alter their network partners after marriage. *Fourth*, the effects of social networks that we found contribute to a better understanding of social change. These effects are generally nonlinear and asymmetric. They are particularly large for having at least one network partner who is perceived to be using contraceptives; however, the inclusion of additional networks partners with the same characteristic generally has much smaller (and insignificant) effects (for women). This combination of nonlinearity and asymmetry suggests that the exchange of information constitutes the primary aspect of social interactions about family planning—social learning, not social influence. In addition, the nonlinear and asymmetric pattern of network influences is consistent with stereotypic diffusion models (e.g., Rogers 1995; Valente 1994). If there are just a few who initially adopt an innovation, they have a relatively large influence because they interact with a relatively large number of individuals who have not yet adopted it; in such cases, they provide these individuals with at least one adopter, the influence of whom is relatively large. Thus, adoption initially accelerates. As there are more innovators, however, the marginal influence of yet another adopter eventually starts to decline. Interaction processes therefore suggest that social networks are likely to have large effects on behavior as long as an innovation is not widely disseminated. As innovative behavior increases, the marginal effect of interactions is likely to be much smaller than in the early phase of the diffusion process.

The use of family planning has already increased rapidly worldwide and fertility has begun to decline almost everywhere in developing countries (Bongaarts and Watkins 1996). Although our data are particular to rural Kenya and our analysis is of specific interest to demographers who are interested in diffusion through social interaction, we believe the approach exemplified here is of wider use for those who are interested in social change. In particular, our results suggest that pervasive social change may be stimulated by early and small amounts of women's and men's gossip.

Section 4. Social Networks and *Mortality* and *Death* -- the Diffusion of Worry about HIV/AIDS

Individuals facing the tsunami of the AIDS epidemic in eastern and southern Africa know well that HIV is primarily transmitted in their context by sexual intercourse and that reducing risky sexual interactions can help to protect them from infection and death. Whether correct or incorrect, the subjective perceptions of one's own HIV/AIDS risk and of one's sexual partner's risk have been shown to be important correlates of whether an individual adopts risk-reduction strategies (Cerwonka, Isbell, and Hansen 2000; Estrin 1999; UNAIDS 1999; Weinstein and Nicolich 1993). The process through which these risk perceptions are formed, however, is only poorly understood (e.g., Smith 2003).[7] In Kohler, Behrman and Watkins (2007), we therefore investigate the determinants of subjective HIV/AIDS risk assessments, focusing in particular on the hypothesis that individuals assess their risk of infection through interactions with others in their social networks. We begin by drawing on qualitative data to provide insights into the process by which it appears that risk perceptions are formed in social networks, and then turn to our quantitative evidence.

Section 4.1 Qualitative Evidence on the Content of Conversations About AIDS in Informal Social Networks in Malawi

The first round of our survey, in 1998, had confirmed that respondents talked about AIDS with others in their social networks Survey data, however, are inadequate for learning what people were saying to each other. For example, it could have been that there was no uncertainty about AIDS—perhaps all agreed or disagreed about the level of risk that they faced. Or perhaps the conversations did no more than transmit epidemiological information, such that HIV is transmitted sexually and invariably fatal, without comments evaluating the accuracy or appropriateness of the information, or that nothing was said in these conversations to support our assumption that social influence was being exerted in these conversations.

We thus conducted semi-structured interviews and ethnography in order to examine the validity of the assumptions with which we approached our quantitative analyses. Here we draw on the ethnographies, the term we use to describe a large set of field journals (currently 700) collected since 1999. We asked a total of 23 high school graduates living in or near the MDICP survey sites to pay attention to public conversations they heard about AIDS during the course of their everyday activities, such as walking to the well for water or having a beer in a local pub. They were then to write as much as they could recollect, and in as much detail as possible, in a field journal, which was then given to an intermediary and sent to us (more detail, including some of the journals, is available at www.malawi.pop.upenn.edu and in Watkins and Swidler 2005).

We begin by summarizing a journal that displays the great diversity in natural conversational settings and in topics covered in the conversations (the journal is identified by the journalist's pseudonym and the year; in this case the journalist is a woman then in her late twenties who had been divorced and widowed).

> *The journal begins on the 14th of June, 2001, when the journalist, Alice, visits her cousin, who is a nurse at a hospital about an hour's bus-ride away. The cousin, who is pregnant, tells Alice that three months after her marriage her husband began coughing, then a headache, then diarrhea, then both diarrhea and shingles, all of which involved stays in the hospital. The cousin herself had become thin. The cousin requested that they both be tested, and both were HIV positive. Later, Alice returns for the husband's funeral, where she talks with her cousin and her cousin's mother. The cousin warns Alice, a widow, to be careful whom she marries, and to be sure to have a blood test beforehand. On the way home from the funeral, Alice meets a man at the bus stop who has been to see a brother ill with tuberculosis; he tells her that the TB ward is full, they all have AIDS (presumably including his brother). Another man at the bus stop joins the conversation, asking why it is that women appear to have AIDS more than men. This generates a lengthy discussion about differences in men's and women's behavior and bodies, whether or not it is possible to use a condom in marriage, medications, and about the history of AIDS, with all of these topics*

[7] For a general discussion of the need to better understand the formation of expectations, including risk perceptions, see Manski (2004). Some of the few studies that have explicitly addressed the determinants of AIDS risk perceptions in sub-Saharan Africa or other developing countries are Bernardi (2002); Bühler and Kohler (2003); Bunnel (1996); Helleringer and Kohler (2005); Kengeya-Kayondo et al. (1999); London and Aroyds (2000); Smith (2003); Smith and Watkins (2005); Watkins (2004).

> *introduced not by the journalist but by the men, none of whom Alice knows. Two weeks later Alice returns for the funeral of her cousin's newborn baby. Walking back from the funeral to the bus stop, a neighbor of her cousin asks Alice why her cousin is so thin, and then comments that people are saying she has AIDS because although she herself was innocent, her husband was promiscuous and, as a woman, she could not refuse to have sex with her husband. On the bus, a woman starts a conversation with Alice about AIDS, which is then joined by the third person on their seat, an old man. Again, the others introduce the topics, which cover AIDS as God's punishment, AIDS as witchcraft, AIDS as a government plot, and AIDS as a result of youth who disobey the advice of their parents. A few weeks later Alice goes to the funeral of her cousin, where she overhears others explaining that her cousin was the innocent victim of her husband. (Alice 2001)*

Although funerals are frequent in rural Malawi—the 1998 survey round showed that on average respondents went to 3-4 funerals a month—the scarcity of facilities of HIV testing in rural Malawi meant that few would have been tested. Nonetheless, by that time people knew the symptoms of HIV, which they combined with local knowledge about the medical history of the deceased and his or her sexual biography to conduct a "social inquest" on the cause of death (Watkins et al 2006). Seeing someone sicken and then die of something that was believed to be AIDS is likely to have influenced the formation of individual's own perception of risk, the variable that in our quantitative analysis below is summarized as "worry" about infection.

In one incident, a young man tells several friends that he has reformed his behavior. They ask why, and he explains:

> "*Only because I have seen for myself, some of my friends have died because of this disease AIDS, and I do care for my life. AIDS troubles a lot!* I didn't say anything. He kept on, saying, *For example, there was a certain army pensioner who was living up there in my village…. He was very sick indeed, going to the hospital, no treatment, private hospitals—just wasting money and then he came home and was sick until he became like a very little young child. I was going to see him during the whole course of his suffering. You could liken him to a two-year-old child when he lay down sick…. And the way I had seen him suffering, that's when I came to my senses, that indeed AIDS troubles a great deal before one dies*." (Simon 2002)

The young man attributes his behavior change to seeing a neighbor who he knew had many sex partners decline physically, but we know from other journals that this witness had himself been promiscuous. Thus, it is likely that while watching his neighbor waste away he imagined himself as "a two year-old child." We do not know whether the reforms he claimed to have made happened at all, or persisted, or occurred too late. We do know that many in Malawi have had similar experiences watching those with whom they can identify die, as well as hearing about other deaths they did not witness. If we are persuaded by the literature in psychology that "people disproportionately weight *salient, memorabl*e or *vivid* evidence even when they have better sources of information" (Rabin 1998: 30, citing Kahneman and Tversky 1973), then anecdotes about people who are known in the community are likely to weigh heavily in the process of risk formation, as well as to provide particularly compelling motivations for change.

Rarely is information about HIV or AIDS unaccompanied by comment. The information is often evaluated in terms of its credibility. For example, one conversation turned to the possibility of infection when a man gets his hair cut from a barber. A woman says going to a barber is dangerous, that she heard a radio program that if a person with HIV is cut, "the virus sticks to the teeth of the shaver and if other people come to be shaved …definitely the other people will contract the virus and start suffering from AIDS." Another participant, however, evaluates this information by offering a counterfactual: he says "then if what the government was saying through the radio, that Barber shops can also facilitate the spreading of the virus which causes AIDS, was true, a lot of people would have contracted it, almost every man starting from a young boy and men and some of the women and girls.” (Simon 040217).

People also share their personal worries with others. For example, while walking together to a funeral one woman tells two others that she is worried that her husband will give her AIDS, for he had been having an affair with the deceased, a known prostitute who was believed to have certainly died of AIDS. Now, she says, she doesn’t know what to do. The participants discuss the pro’s and con’s of divorce: the conversation ends when one of the participants advises her to have a blood test before she takes a hasty action.

In addition to providing insight into the process by which perceptions of risk are formed in social networks, as well as the uncertainty that rural Malawians are facing, an important feature that distinguishes our study from earlier investigations of the effects of social interactions on AIDS risk perceptions is that these data show that many determinants of risk assessment are unobserved in our survey data, such as an individual’s exposure to seeing someone die from AIDS, or being advised to have a blood test before taking the serious step of ending a marriage. These unobserved factors are not only likely to affect variation in perceptions of risk, but also the size, composition, and selection of individuals’ social network partners (see Section 3 for a related discussion). Some individuals, for example, are likely to have less tolerance for risk and, because of systematic patterns in the selection of their social networks, are more likely to associate with others who have less tolerance for risk (for a discussion of these aspects of social network selection, see also Behrman, Kohler, and Watkins 2002; Manski 2000; Watkins and Warriner 2003). Based on considerations above about individuals having unobserved characteristics such as those related to risk aversion and social interaction that are likely to affect both their worry about HIV/AIDs and their social networks related to information about HIV/AIDS, parallel to our studies of the impact of social networks on fertility control in Section 3, we posit that prior social networks are not likely to be random in the sense of being independent of disturbance terms in relations for the estimation of risk perceptions and AIDS-related behaviors at time *t*. Therefore we use an empirical specification of the relation determining risk perceptions and AIDS-related behaviors in which there is explicit recognition that, in addition to observed right-side variables (including social networks prior to time *t*, there are unobserved factors.

Section 4.2 Quantitative Evidence on the Impact of Social Networks on Responses to AIDS

<u>Description of Key Quantitative Data</u>: Quantitative data on social networks and HIV/AIDS are summarized in Table 4 for Kenya and Table 5 for Malawi. Not surprisingly, concerns about the risk of AIDS infection are widespread in both rural Kenya and Malawi. The MDICP survey measured this perceived AIDS risk with a question frequently used in research on risk perceptions: “How worried are you that you might catch AIDS?” Responses to this question ranged from “not worried at all” to “worried a lot.” Between 36% and 40% of women in Kenya responded in the 1996/1997 and 2000 surveys, respectively, that they perceived themselves to have a moderate or high risk of becoming infected with AIDS. For Malawi, 61% and 47% of women perceived a high risk of AIDS in 1998 and 2001, respectively; moreover, their responses are highly and positively correlated with a question about the subjective likelihood that the respondent will become infected with HIV/AIDS in the future. Respondents are generally also aware of several mechanisms by which HIV/AIDS is transmitted and several ways of protection. For instance, in 1996/1997, more than 90% of women in Kenya knew that AIDS can be transmitted by sex, and 48% knew about possible transmission by injections. Similarly high levels of knowledge prevail in Malawi.

[Tables 4 and 5 about here]

Some of the survey responses suggest considerable talk about AIDS in social networks, reinforcing the perception that such conversations are frequent from the qualitative data that are summarized in Section 4.1. The survey network module began with a question, "How many people have you talked with about AIDS?" Very few had talked with no one. The networks are quite dense (most members know each other as well as the respondent) and highly gendered (men talk with men, women with women (Watkins and Warriner 2003; Zulu and Chepngeno 2003). Responses to other questions provide insight into some topics of their conversations. For example, respondents report on the extramarital partnerships of their network partners and their best friend; a study of a subsample of MDICP respondents shows that they learn about these relationships directly from one of the couple, indirectly from others who have talked with one of the couple, or from observation ("I saw them coming and going" (Tawfik and Watkins 2007). More than 85% (Kenya) and 87% (Malawi) of women know of at least one recent death that they suspected was caused by AIDS, and more than 30% (Kenya) and 16% (Malawi) know about more than five such cases.

As noted in Section 2, our quantitative data are, to our knowledge, unique because they include detailed accounts about women's and men's interactions about the HIV/AIDS epidemic with social network partners (besides their spouses) that allow us to investigate the role and importance of these interactions. We describe there how the data were collected and what data were collected. The specific question regarding the risk perceptions of the network partners was phrased as "How worried is *name of network partner* about getting AIDS?," with the same response categories as for the respondent. Over three-quarters of the women had talked with at least one person about AIDS, and over two-fifths of the women had talked with at least one person who believes that he or she is at moderate or great risk of becoming infected with AIDS (Tables 1 and 2). In addition to talking with network partners about AIDS, husbands and wives discuss with each other their risks and how they can prevent infection.

On average, women report that they had talked with 3.9–4.8 network partners about AIDS, and men report slightly more interactions, ranging from close to 4 to about 7 network partners. Detailed information about interactions is available for about 2.4–3.6 network partners. In general, the respondents report more interactions with network partners who perceive a high AIDS risk as compared with network partners who assess their risk as low. Neither the size of these networks nor having talked with at least one network partner about AIDS depend strongly on the respondent's risk perception (Kohler, Behrman and Watkins 2007, Table3), whereas—as we expect based on the our hypothesis that social interactions are important determinants of risk perceptions—network partner's assessments of HIV/AIDS risks are associated with the respondent's own risk perception. We represent social networks by the extent to which each respondent's network partners are reported to be worried about AIDS. This perception is measured via a categorical variable with four options in Kenya (categories are none (1), some (2), moderate (3), and great (4)) and with three options in Malawi (categories are none (1), moderate (2), and great (3)). The essential variable representing social interactions about HIV/AIDS is therefore the number of network partners with whom the respondent has interacted about HIV/AIDS classified by the respondents' perceived network partners' risk perceptions. Although in what follows we will refer to the network partners' perceptions of risk, this perception is reported by the respondent.

<u>Econometric estimates of impacts of social networks on worry about HIV/AIDS</u>: A first-order linear approximation to the model for the perceived risk of AIDS is given by equation (1), but with Y_{it} now defined to be the perceived AIDS risk of individual i at time t; f_i now defined to be unobserved fixed factors that are assumed to affect risk perceptions and AIDS-related behaviors by individual i (e.g., the persistent part of preferences, unobserved current community characteristics, expectations regarding future prices, and interfamilial and community resources on which the individual can draw); and e_{it} is an i.i.d. disturbance term that affects the perceived AIDS risk of individual i at time t due to, for example, new information about AIDS prevalence provided by the death of a family/community member from AIDS, new information about the behavior or the spouse, or price shocks that are deviations from the long-run secular price trends. To obtain consistent estimates of the coefficient a, which measures the

impact of social networks on risk perceptions and AIDS-related behaviors, it is necessary to break the correlation between the term representing social networks and the compound disturbance term including both fixed and random elements. For this purpose, in our estimation strategy for this study, we combine both fixed-effect and instrumental-variable estimation and follow an approach motivated by recent progress in estimation techniques for dynamic panel models (e.g., Arellano and Honoré 2001).

The fixed-effect estimation alone may not be fully satisfactory because it relies on the assumption that the social network prior to time t, N_{it-}, does not depend on the *lagged* disturbance terms $e_{i(t-1)}$ (or higher-order lags). Our estimation strategy for this study allows for such feedback from lagged disturbances affecting HIV/AIDS risk perceptions on the current social network size and composition by combining fixed-effect and instrumental-variable (IV) estimation. In particular, since the differenced version of relation (1) does not include the individual fixed effect, f_i, variables that are correlated with the fixed effect but uncorrelated with Δe_{it} can be used as instruments. Of particular relevance are variables that describe the opportunities and constraints for social interactions about AIDS.

Two aspects of these opportunities and constraints are observed in our data. *First*, our data include measures such as the number of funerals attended in the last year. Because people talk informally at funerals about the symptoms and sexual behavior of the deceased, the village average number of funerals constitutes a measure of the local opportunities for conversations about AIDS. *Second*, an additional important indicator of the constraints and opportunities for social interactions is related to the composition of a respondent's social networks at the beginning of the panel. This composition differs among individuals because respondents had differential opportunities or incentives to interact about AIDS with others prior to the initiation of the panel. This differential "stock" of network partners at time t is likely to be correlated with the fixed effects, f_i, in relation (1). This differential stock of past interactions also leads to different opportunities for new interactions during the period between surveys. For instance, in exploration of the determinants of social network changes in the article being summarized here, we present evidence that the increase in network partners (or those who are very worried about AIDS among them) is inversely related to the initial number of network partners. This outcome is plausible because the probability of a chance conversation with a new individual in the course of daily life (e.g, while fetching water or going to the grain mill) ceteris paribus would seem to be greater over a given time interval the fewer network partners one has had in the past. Similarly, we find evidence that the change in the number of network partners between panels is positively related to events that plausibly increase opportunities to increase interaction (e.g., funerals and other events that lead to social gatherings).

If the stock of social network partners in the network at the beginning of the panel is correlated only with the individual fixed effect and not with the random term in the differenced version of relation (1), Δe_{it}, then the stock of social network partners at the beginning of the panel can be used as an instrument for the change in the social network composition between the survey waves, ΔN_{it-}. Hence, in this model the "stock" of network partners can be used as an instrument for ΔN_{it-} in estimates of the differenced version of equation (1). Moreover, the instruments can also include other "stock variables" at the beginning of the panel that are correlated with individual fixed effects (the effects of which are controlled in the fixed-effects estimates so that such correlations do not cause biases) but not Δe_{it}, such as age, schooling attainment, marital status, and household assets.

To demonstrate empirically the relevance of considering the endogeneity of social networks in inferences of social interaction effects, we implement the following four estimation techniques: (a) standard OLS analyses of equation (1); (b) fixed-effect estimation of equation (1), which in our case is equivalent to OLS applied to the differenced version of equation (1); (c) IV fixed-effect estimation of the differenced version of equation (1) that instruments for the change in the social network measures, ΔN_{it-}; and (d) Generalized Methods of Moments IV (GMM-IV) fixed-effect estimation, which uses a more efficient weighting of the moment conditions implied by the IV fixed-effect estimation (e.g., see Baum, Schaffer, and Stillman 2003; Hayashi 2000).[8]

[Tables 6 and 7 about here]

Our major findings are as follows (Tables 6 and 7). *First* and foremost, our analysis shows that social networks have significant and substantial effects on individuals' AIDS risk perceptions, even when we control for unobserved factors that also may determine the nature of the social networks. Thus, to understand the dynamics and diffusion of behavioral change in response to AIDS, it is essential to incorporate the impact of social networks. The failure to do so may lead to misunderstanding the dynamics of behavioral change. *Second*, this effect of social networks extends to the area of spousal communication about AIDS risk, and interactions with network partners—independent of network partners' risk assessments—tend to increase the probability of husband-wife communication about the disease. *Third*, the effects of social networks that we have found contribute to a better understanding of diffusion. These effects are generally nonlinear and asymmetric. They are particularly large for having at least one network partner who is perceived to have a great deal of concern about AIDS. The inclusion of additional network partners with the same level of concern or with less concern generally has much smaller or insignificant effects. An exception to this asymmetry occurs in the network effects on spousal communication: network partners, independent of their risk perceptions, have strong and significant effects. *Fourth*, social networks are associated with important social-multiplier effects that reinforce the effects of AIDS prevention programs. For women, for instance, about one-fifth of the influence of program efforts on respondents' HIV/AIDS risk perceptions is mediated through social networks.

These findings are of central importance for understanding the spread of HIV/AIDS because they document that social interactions constitute important determinants of how individuals and couples develop strategies for coping with the disease. In particular, this study shows that social networks exert systematic and strong influences on risk perceptions and the probability of spousal communication about HIV/AIDS risks in rural areas of two sub-Saharan African countries with high HIV prevalence, and that these influences are in addition to other factors such as program interventions that disseminate knowledge about the disease, provide access to condoms, and advocate changes in sexual behaviors within and outside marriage. Social networks are also likely to amplify program efforts aimed at increasing individuals' information about HIV/AIDS and their assessments of their own risks. Thus, social interactions are likely to have a substantial impact on the course of the epidemic and the magnitude of its consequences, and these should be taken into consideration in understanding and predicting behaviors in such high-prevalence contexts and in devising program interventions with respect to the HIV/AIDS epidemic.

Section 5. Conclusions

Specific lessons from our studies that probably in many cases care over to the study of networks in business and in other contexts include the importance of accounting for the endogeneity of network

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[8] The difference between the IV and GMM-IV estimator can be illustrated based on the linear model, in matrix notation, $y = \mathbf{X}\beta + u$ with $E(uu') = \Omega$. In this model, both the IV and GMM-IV estimator are based on the moment conditions $E[\mathbf{Z'}_i(yi-\mathbf{X}_i)\hat{\beta}]=E[\mathbf{Z'}_i u_i]=0$, where $\mathbf{Z}$ is the matrix of exogenous instruments and $u_i = y_i - \mathbf{X}_i\beta$. In addition, both estimators can be written as $\hat{\beta} = (\mathbf{X'ZWZ'X})^{-1}\mathbf{X'ZWZ'}y$, where $\mathbf{W}$ is a weighting matrix. The conventional IV estimator is then obtained by using a weighting matrix $\mathbf{W}$ that is equal to $1/n\ (\mathbf{Z'Z})^{-1}$, whereas the GMM-IV estimator is obtained by using a weighting matrix $\mathbf{W}$ that is equal to $1/n\ (\mathbf{Z'}\hat{\Omega}\mathbf{Z})^{-1}$, where $\hat{\Omega}$ is a diagonal matrix of squared residuals based from a consistent first-stage IV regression. The GMM-IV estimator is more efficient than the IV estimator in the presence of heteroscedasticity, and the resulting covariance matrix is consistent. For further discussion, see Baum et al. (2003).

partners in analyzing network effects, that networks are important even with control for endogeneity, that network effects may be nonlinear, that there may be multiple equilibria, that which networks may either reinforce the status quo or help diffuse new options and behaviors, that both the context (e.g., the degree of market development) and the density of networks matter (possibly interactively), and that multiple approaches, including both qualitative and quantitative analyses, can be informative in providing more in-depth understanding of what networks do and how they function.

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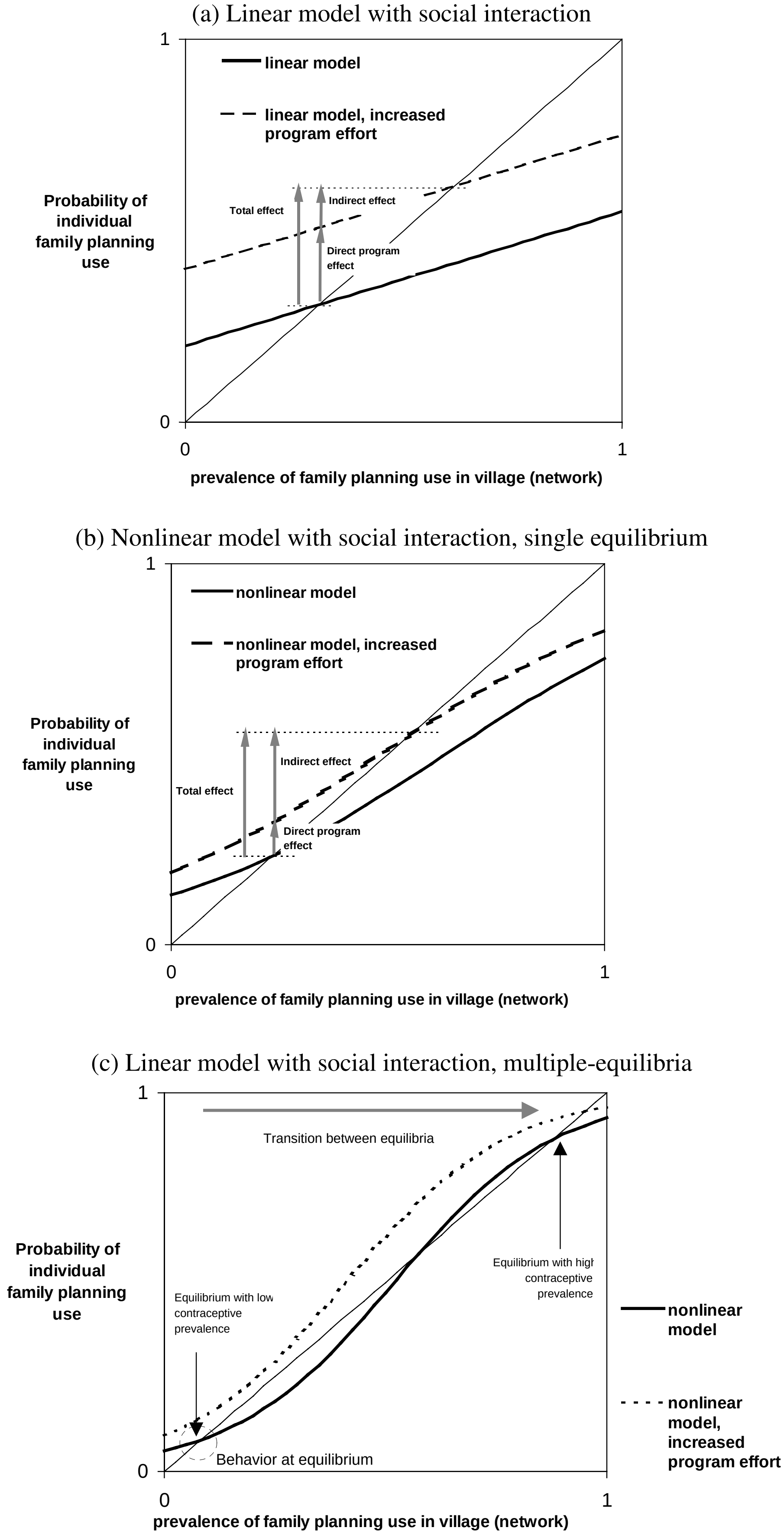

Figure 1: Linear and nonlinear model with social interaction

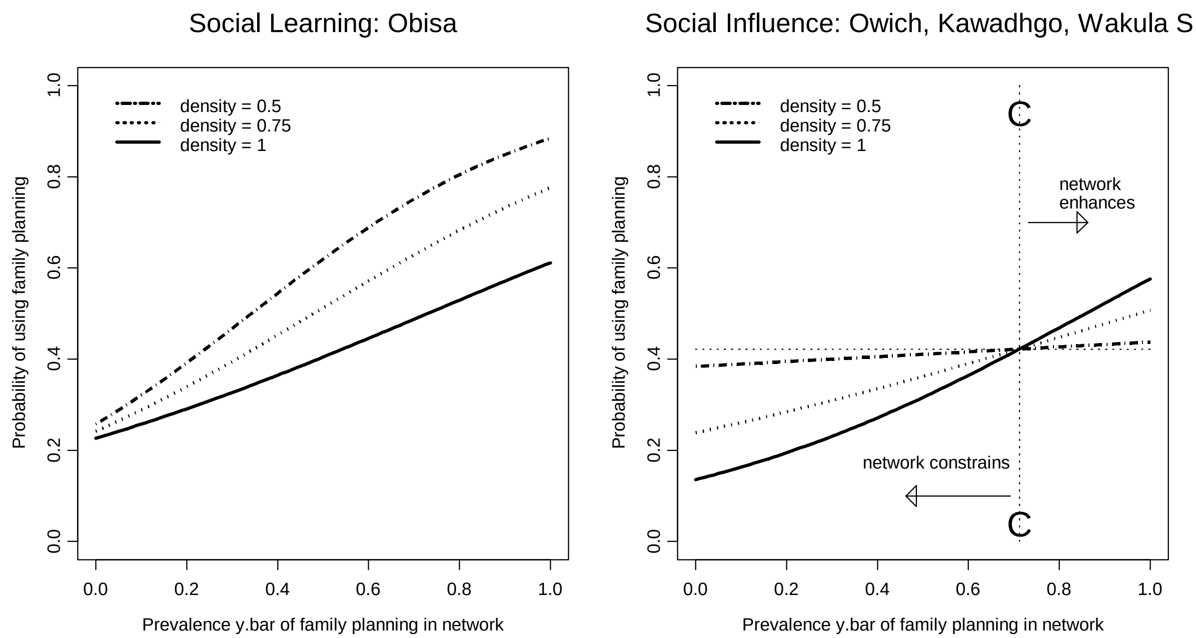

Figure 2: The effect of contraceptive prevalence in the network on the probability of adopting family planning for respondents with networks of different density (parameter values are derived from Model 3 in Table 2)

The graph is based on a behavioral model in which the probability of a woman choosing modern contraception is $\Pr(y=1|\bar{y}_{nw},x,D_{nw}) = F(\alpha(D_{nw})(-\phi+\bar{y}_{nw})+\beta x+\gamma)$, where F is the cumulative logistic distribution, and direction of the network effect towards using or not-using family planning is determined by a social utility term $\alpha(D_{nw})(-\phi+\bar{y}_{nw})$. If the proportion of network partners who use modern contraception $\bar{y}_{nw}$ exceeds a critical level ϕ, then $(-\phi+\bar{y}_{nw})>0$ and the social network favors the adoption of family planning; the term $\alpha(D_{nw})$, which depends on the density of a network, determines the strength of this social influence. If $\bar{y}_{nw}$ is lower than ϕ, then $(-\phi+\bar{y}_{nw})<0$ and social interaction influences a woman's decision towards not using contraception. The influence is stronger the more $\bar{y}_{nw}$ deviates from the 'neutral' level ϕ: when $\bar{y}_{nw}=\phi$, then network effects on contraceptive adoption are absent and the respondent's decision is not affected by the presence of social interaction. This behavioral model translates into our estimates in Table 2 when a linear model for $\alpha(D_{nw})$ is specified, where $\alpha(D_{nw})=\tilde{\alpha}_1+\tilde{\alpha}_2 D_{nw}$. Multiplying out the terms of $\alpha(D_{nw})(-\phi+\bar{y}_{nw})$ in this linear specification yields the following correspondence between the model parameters and the estimated coefficients in Table and comparing the terms of the model to the coefficients in the equation estimated in Table 2: $\tilde{\alpha}_1=\delta_1$, $\phi=-\delta_2/\delta_3$, and $\tilde{\alpha}_2=\delta_3$.

Table 1: Some summary statistics for women in the sample, and for women with a network of size three or four, by region (1996 data, currently married women only)

Sample	**Women with a network of 3 or 4 network partners**		**All women**	
Region	Owich, Kawadhgo and Wakula s.	Obisa	Owich, Kawadhgo and Wakula s.	Obisa
N	270	118	497	197
Characteristics of respondents				
ever used family planning	38.9%[c]	51.7%[b,d]	27.0%	37.6%[a]
currently using family planning	20.0%[c]	33.1%[b,d]	14.3%	25.4%[a]
age	32.3	34.1[b]	32.4	33.2
	(8.41)	(8.15)	(8.42)	(8.61)
children ever born	5.34	5.91	5.36	5.55
	(3.06)	(3.15)	(3.11)	(3.21)
% of respondents with at least secondary education	17.4%[c]	19.5%	12.5%	16.2%
% of respondents with metal roof on hut (an indicator of wealth)	25.6%	42.4%[b]	20.1%	38.6%
% of respondents going to the market at least weekly	40.5%	71.7%[b]	39.3%	76.5%[a]
% of respondents with family planning network[1]	–	–	82.1%	82.7%
(uncensored) size of network[2]	7.68[c]	5.71[b,d]	4.71	3.88[a]
	(4.95)	(3.82)	(5.00)	(3.81)
Characteristics of social networks (currently married women with networks of size 3 and 4 only):				
average proportion of network partners using family planning	0.578	0.585	–	–
average density of network among network partners[e]	0.846	0.782[b]	–	–
average proportion of network partners that are				
female	0.931	0.950	–	–
female relatives of respondent	0.683	0.671	–	–
friends only (unrelated to respondent)	0.193	0.194	–	–
younger than respondent	0.235	0.304[b]	–	–
living in same compount or village	0.556	0.522	–	–
living in Nairobi or Mombassa	0.019	0.013	–	–

Notes: Standard deviation in parentheses. (1) These respondents have listed at least one person with whom they have talked about family planning. (2) Uncensored network size is the respondent's answer to the question about how many persons they had talked to about family planning (more detailed questions about the family planning use and the interaction the respondent were only asked for at most four of these network partners). *Results of two-sided tests for equal means:* (*a*) the difference between Obisa, and Owich, Kawadhgo, Wakula S. (OKW) is significant at the 5% level for all women; (*b*) the difference between Obisa and OKW is significant at the 5% level for women with a network of 3 or 4 network partners; (*c*) women with a network of 3 or 4 network partners differ significantly (5% level) from the remaining women in OKW; (*d*) women with a network of 3 or 4 network partners differ significantly (5% level) from the remaining women in Obisa. (*e*) network densities below 0.5 are relatively rare. Only 16% of respondents in OKW, and only 11% of respondents in Obisa, have networks with a density $< .5$.

Table 2: Lostisitc regression of contraceptive use (ever used family planning) on individual and network characteristics (Sample: currently married women with a family planning network of size three or four)

	Model 1	Model 2	Model 3
for Owich, Kawadhgo and Wakula S.			
%users (δ_1)	1.619	1.596	-1.712
	(0.442)**	(0.442)**	(1.053)
density (δ_2)		-0.248	-2.756
		(0.531)	(0.787)**
density × *%users* (δ_3)			3.867[a]
			(1.268)**
for Obisa			
%users (δ_1)	2.271	2.290	4.495
	(0.623)**	(0.542)**	(2.197)*
density (δ_2)		-1.850	-0.337
		(0.831)*	(1.654)
density × *%users* (δ_3)			-2.814[a,b]
			(2.614)

Notes: The estimated model is specified as $\Pr(y = 1|X, \mathit{social\ network}) = X\beta + \delta_1 \cdot (\%\mathit{users}) + \delta_2 \cdot \mathit{density} + \delta_3 \cdot (\%\mathit{users}) \cdot \mathit{density}$, where y equals 1 if the respondent uses (has ever used) family planning, X is a set of individual characteristics, *%users* is the percentage of users of modern methods of family planning by the network partners, and *density* is the density of the social relations among the network partners. The individual characteristics included in X include age, age^2, number of children ever born, and dummy variables indicating whether the respondent has primary or secondary education. The standard errors, reported in parentheses, are adjusted for the clustering of respondents in villages using the Huber- White estimator of variance. *p-values:* * $p < 0.05$; ** $p < 0.01$. *Additional tests:* (*a*) The linear combination $\delta_1 + \delta_3$ measures the effect on the probability to use family planning due to a change in *%users* in a network with $\mathit{density} = 1$. A Wald test of the null hypothesis $\delta_1 + \delta_3 = 0$ is rejected at the 1% level for OKW, and for Obisa at the 5% level. (*b*) The linear combination $\delta_2 + \delta_3$ measures the effect on the probability to use family planning due to a change in *density* in a network with $\%\mathit{users} = 100\%$. A Wald test of the null hypothesis $\delta_2 + \delta_3 = 0$ is rejected at the 5% level for Obisa in Panel A.

Table 3: Females – fixed effect and random effect logit models for currently using family planning with different specifications of network partners' family planning use. Respondent's contraceptive use is measured at K1, K2 and K3

Method	**Fixed Effects Logit**	**Random Effects Logit**	**Fixed Effects Logit**	**Random Effects Logit**
At least one family planning user in network	0.72 (0.30)*	0.61 (0.25)*	0.69 (0.32)*	0.49 (0.26)+
Number of remaining family planning users in network	0.16 (0.12)	0.49 (0.10)**	0.07 (0.14)	0.49 (0.11)**
At least one non-user in network			0.01 (0.30)	0.27 (0.24)
Number of remaining non-users in network			-0.22 (0.16)	-0.19 (0.13)
Dummy for not married, time $t-$	-0.60 (0.52)	-0.64 (0.41)	-0.59 (0.52)	-0.66 (0.41)
Children ever born, time $t-$	0.10 (0.12)	0.06 (0.05)	0.12 (0.12)	0.06 (0.05)
Respondent has radio, time $t-$	0.41 (0.30)	0.38 (0.20)+	0.39 (0.30)	0.37 (0.20)+
Respondent has metal roof, time $t-$	-0.71 (0.37)*	0.08 (0.22)	-0.73 (0.37)*	0.08 (0.22)
Respondent has at least primary schooling		0.83 (0.31)**		0.85 (0.31)**
Respondent has secondary schooling		0.61 (0.28)*		0.61 (0.28)*
Age		0.41 (0.11)**		0.41 (0.11)**
$(\text{Age}/10)^2$		-0.59 (0.16)**		-0.59 (0.16)**
Dummy for survey wave Kenya 2	0.35 (0.24)	0.21 (0.22)	0.34 (0.24)	0.21 (0.21)
Dummy for survey wave Kenya 3	0.60 (0.29)*	0.44 (0.22)*	0.63 (0.30)*	0.45 (0.23)*
Constant		-11.36 (1.99)**		-11.35 (1.99)**
N (number of women, each observed at three surveys)	156	497	156	497

Notes: p-values: + $p < 0.1$; * $p < 0.05$; ** $p < 0.01$. Fixed effect logit model is based only on individuals who change their contraceptive behavior at least once between Kenya 1 and Kenya 3; women with constant contraceptive use in all three survey waves are dropped in the estimation We use the subscript "$t-$" to emphasize that the variable refers to the time prior to t, where t refers to the survey wave

Table 4: Summary statistics for the Kenya data ('nwp(s)' = network partner(s))

	Females		Males	
	Kenya 2	Kenya 3	Kenya 2	Kenya 3
N	701	882	523	599
Individual Characteristics at $t-$				
Age	32.8		43.4	
	(8.39)		(12.92)	
Not currently married	0.07	0.13	0.03	0.04
Children ever born	5.44	5.34	7.44	7.46
	(3.09)	(3.17)	(6.73)	(5.37)
Has radio	0.60	0.63	0.65	0.73
Has metal roof	0.26	0.41	0.27	0.41
Has at least primary schooling	0.79	0.82	0.90	0.92
Has secondary or higher schooling	0.14	0.14	0.28	0.33
Perceived AIDS risk, respondent				
Proportion perceiving no risk	0.25	0.20	0.28	0.21
Proportion perceiving small risk	0.35	0.44	0.38	0.53
Proportion perceiving moderate risk	0.26	0.27	0.23	0.22
Proportion perceiving great risk	0.14	0.09	0.11	0.04
AIDS network				
Prop. with at least one nwp in AIDS network	0.76	0.88	0.83	0.91
Uncensored size of AIDS network	4.88	6.20	6.54	9.43
	(5.88)	(6.96)	(7.80)	(10.7)
Censored size of AIDS network	2.38	2.91	2.70	3.26
	(1.61)	(1.42)	(1.52)	(1.27)
Proportion with more than 4 network partners	0.35	0.53	0.43	0.55
Proportion with at least one nwp who perceives moderate or great AIDS risk	0.42	0.43	0.48	0.48
Number of nwp who perceive moderate or great AIDS risk	0.91	1.06	1.09	0.93
	(1.28)	(1.24)	(1.37)	(1.19)
Proportion with at least one nwp who perceives no or small AIDS risk	0.47	0.70	0.55	0.77
Number of nwp who perceive no or small AIDS risk	0.98	1.61	1.19	2.07
	(1.27)	(1.40)	(1.36)	(1.47)
Communication with spouse about AIDS risk				
Proportion having talked to spouse	0.56	0.71	0.73	0.83

Table 5: Summary statistics for the Malawi data ('nwp(s)' = network partner(s))

	Females		Males	
	Malawi 1	Malawi 2	Malawi 1	Malawi 2
N	1179	1159	806	799
Individual characteristics				
Age	31.1	34.3	37.0	40.4
	(9.26)	(9.39)	(10.43)	(10.96)
Not Married	0.11	0.11	0.01	0.03
Children ever born	4.38	5.11	5.28	6.17
	(3.05)	(2.89)	(4.20)	(3.98)
Has radio	0.57	0.64	0.67	0.73
Has metal roof	0.07	0.10	0.08	0.11
Has at least primary schooling	0.64	0.67	0.79	0.83
Has secondary or higher schooling	0.05	0.06	0.14	0.15
Family planning variables, respondent				
Proportion currently using family planning	0.30	0.31	0.40	0.45
Proportion ever using family planning	0.52	0.61	0.60	0.70
Perceived AIDS risk, respondent				
Proportion perceiving no risk	0.17	0.29	0.27	0.42
Proportion perceiving moderate risk	0.21	0.23	0.19	0.21
Proportion perceiving great risk	0.61	0.47	0.53	0.37
AIDS program effort[a]	0.24	0.30	0.24	0.30
	(0.12)	(0.14)	(0.12)	(0.14)
AIDS network				
Prop. with at least one nwp in AIDS network	0.83	0.95	0.92	0.97
Uncensored size of AIDS network	4.33	5.84	6.24	7.04
	(5.14)	(5.57)	(6.46)	(6.92)
Censored size of AIDS network	2.53	3.42	3.08	3.56
	(1.50)	(1.09)	(1.26)	(0.95)
Proportion with more than 4 network partners	0.28	0.42	0.43	0.49
Prop. with at least one nwp who perceives great AIDS risk	0.61	0.52	0.67	0.47
Number of nwp who perceive great risk	1.46	1.06	1.77	1.05
	(1.49)	(1.28)	(1.59)	(1.35)
Prop. with at least one nwp who perceives moderate AIDS risk	0.31	0.45	0.32	0.43
Number of nwp who perceive moderate AIDS risk	0.50	0.71	0.54	0.71
	(0.87)	(0.95)	(0.94)	(1.03)
Proportion with at least one nwp who perceives no AIDS risk	0.26	0.57	0.30	0.58
Number of nwp who perceive no AIDS risk	0.48	1.12	0.68	1.24
	(0.94)	(1.23)	(1.20)	(1.32)

Note: (*a*) AIDS program effort is the village proportion of respondents who have been visited at home by a community-based distribution (CBD) agent or a Health Surveillance Assistant to give information about how people can protect themselves against AIDS.

Table 6: Females: regression of respondents' risk perceptions on the number of social network partners with high, moderate and low risk perception and personal characteristics ('nwp(s)' = network partner(s))

	Kenya			**Malawi**		
	GMM FE-IV	Fixed Effect	OLS	GMM FE-IV	Fixed Effect	OLS
# of nwps with high risk perception, time $t-$	0.2199	0.1742	0.1618	0.1036	0.1193	0.1549
	(0.0440)**	(0.0318)**	(0.0237)**	(0.0242)**	(0.0188)**	(0.0131)**
# of nwps with moderate risk perception, time $t-$				-0.1315	-0.0639	-0.0487
				(0.0373)**	(0.0246)**	(0.0184)**
# of nwps with low risk perception, time $t-$	-0.0744	-0.0448	-0.0737	-0.2189	-0.1698	-0.1789
	(0.0429)$^{+}$	(0.0286)	(0.0212)**	(0.0366)**	(0.0229)**	(0.0183)**
children ever born	-0.0907	-0.0111	0.0115	0.0642	0.0003	-0.0055
	(0.0902)	(0.0412)	(0.0146)	(0.0481)	(0.0203)	(0.0082)
dummy for not married, time t	0.1913	0.1725	0.1894	-0.2154	-0.1804	-0.0942
	(0.1903)	(0.1814)	(0.0976)$^{+}$	(0.0966)*	(0.0972)$^{+}$	(0.0543)$^{+}$
Respondent has radio, time t	-0.1456	-0.1164	-0.0881	0.0399	0.0304	0.0278
	(0.1005)	(0.1027)	(0.0632)	(0.0538)	(0.0541)	(0.0343)
Respondent has metal roof, time t	0.0025	-0.0020	0.0430	0.1011	0.0867	0.0295
	(0.1240)	(0.1276)	(0.0670)	(0.0957)	(0.0927)	(0.0587)
AIDS program effort				0.4442	0.4760	0.3989
				(0.1733)*	(0.1750)**	(0.1255)**
Respondent has at least primary education			0.1417			0.0853
			(0.0784)$^{+}$			(0.0368)*
Respondent has secondary education			-0.1180			0.0721
			(0.0876)			(0.0692)
age			0.0216			0.0130
			(0.0274)			(0.0102)
(age/10) squared			-0.0475			-0.0149
			(0.0373)			(0.0129)
Dummy for survey wave Kenya 3 or Malawi 2	0.0363	-0.0190	-0.0206	-0.1073	-0.1114	-0.0964
	(0.0791)	(0.0617)	(0.0528)	(0.0512)*	(0.0374)**	(0.0333)**
Constant			1.9248			1.9322
			(0.4756)**			(0.1774)**
N	545	545	545	1138	1138	1138

Notes: Standard errors in parentheses. *p-values:* $^{+}$ $p \leq 0.10$; * $p \leq 0.05$; ** $p \leq 0.01$.

Table 7: Females: regression of respondents' risk perceptions on the number of social network partners with high, moderate and low risk perception and personal characteristics, allowing for nonlinear network effects ('nwp(s)' = network partner(s))

	Kenya			**Malawi**		
	GMM FE-IV	Fixed Effect	OLS	GMM FE-IV	Fixed Effect	OLS
at least one nwp with high	0.5383	0.4213	0.3336	0.1910	0.2520	0.3227
perceived risk, time $t-$	(0.1293)**	(0.0960)**	(0.0752)**	(0.0814)*	(0.0553)**	(0.0426)**
# of remaining nwps with high	0.0547	0.0641	0.0812	0.0693	0.0651	0.0870
perceived risk, time $t-$	(0.0740)	(0.0535)	(0.0401)*	$(0.0357)^{+}$	(0.0276)*	(0.0184)**
at least one nwp with moderate				-0.2476	-0.1176	-0.1017
perceived risk, time $t-$				(0.0903)**	(0.0557)*	(0.0409)*
# of remaining nwps with moderate				-0.0283	-0.0357	-0.0060
perceived risk, time $t-$				(0.0650)	(0.0415)	(0.0297)
at least one nwp with no or low	-0.0796	-0.1825	-0.1237	-0.3234	-0.1641	-0.2604
perceived risk, time $t-$	(0.1239)	$(0.0988)^{+}$	(0.0801)	(0.0930)**	(0.0573)**	(0.0443)**
# of remaining nwps with no or low	-0.1031	-0.0079	-0.0646	-0.1296	-0.1644	-0.1222
perceived risk, time $t-$	(0.0684)	(0.0467)	$(0.0356)^{+}$	(0.0605)*	(0.0349)**	(0.0290)**
children ever born	-0.0949	-0.0135	0.0109	0.0637	0.0009	-0.0060
	(0.0898)	(0.0417)	(0.0146)	(0.0485)	(0.0204)	(0.0081)
dummy for not married, time t	0.1156	0.1737	0.1952	-0.1984	-0.1796	-0.0905
	(0.1871)	(0.1814)	(0.0975)*	(0.0976)*	$(0.0977)^{+}$	$(0.0539)^{+}$
Respondent has radio, time t	-0.1006	-0.1031	-0.0858	0.0520	0.0341	0.0280
	(0.0997)	(0.1017)	(0.0630)	(0.0544)	(0.0543)	(0.0342)
Respondent has metal roof, time t	-0.0303	-0.0159	0.0392	0.0839	0.0822	0.0259
	(0.1234)	(0.1261)	(0.0669)	(0.0969)	(0.0926)	(0.0580)
AIDS program effort				0.4341	0.4792	0.3866
				(0.1746)*	(0.1750)**	(0.1260)**
Respondent has at least primary education			0.1406			0.0804
			$(0.0777)^{+}$			(0.0365)*
Respondent has secondary education			-0.1213			0.0631
			(0.0882)			(0.0685)
age			0.0234			0.0149
			(0.0275)			(0.0102)
(age/10) squared			-0.0503			-0.0174
			(0.0374)			(0.0129)
Dummy for survey wave Kenya 3 or Malawi 2	0.0274	-0.0282	-0.0312	-0.0961	-0.1135	-0.0888
	(0.0787)	(0.0618)	(0.0528)	$(0.0519)^{+}$	(0.0378)**	(0.0336)**
Constant			1.8864			1.8803
			(0.4778)**			(0.1783)**
N	545	545	545	1138	1138	1138

Notes: Standard errors in parentheses. *p-values:* $^{+}$ $p \leq 0.10$; * $p \leq 0.05$; ** $p \leq 0.01$.