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FOLLOWING THE PEERS: THE ROLE OF SOCIAL NETWORKS FOR HEALTH CARE UTILIZATION IN THE PHILIPPINES

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Abstract

This paper studies peer effects on the use of essential health care services offered by a microfinance institution in impoverished neighborhoods in the Philippines. I apply a novel IV identification strategy to overcome the well-known challenges in the estimation of peer effects in non-experimental, cross-sectional settings. The strategy uses structural information from social networks and the existence of overlapping peer groups for an unbiased estimation. I find positive and substantial peer effects in the communities. An increase in program uptake of 10% in the peer group leads to a 6.6% increase in individual health care utilization. I estimate hazard models to further explore underlying mechanisms. Peer effects are found to be strongest immediately after first exposure to the intervention and to fade out over time. While the strength of the relationship with the peer does not seem to matter for the adoption decision, the peers' structural position in the network does. Interestingly, peers with fewer connections seem to have a particularly strong influence on individuals with a central position in the network.

Keywords

Peer effects, social networks, health care utilization, microfinance, developing country, Philippines.

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Following the Peers: The Role of Social Networks for Health Care Utilization in the Philippines

Roman Hoffmann

1 Introduction

Individual decision making is to a large extent influenced by social interactions. Social scientists have long been interested in understanding the nature and size of such peer effects in various fields. Examples include students influencing each other's school performance (Sacerdote 2001; Zimmerman 2003), effects of colleagues on employees' motivation and conduct at the workplace (Guryan et al. 2009; Falk & Ichino 2006; Mas & Moretti 2016), farmers learning from each other about how to use and benefit of new technologies (Bandiera & Rasul 2006; Conley & Udry 2001; Conley & Udry 2010; Duflo et al. 2008), and spillovers between firms and financial institutions (Guiso & Schivardi 2007; Leary & Roberts 2014; Kaustia & Rantala 2015)

Also for the design and implementation of health policies, peer effects can have important normative implications as they may lead to an amplification of the impacts and outreach of interventions. In particular for poor households in developing countries, for which the adoption of health products and services often remains sub-optimally low, social networks can play a crucial role (Perkins et al. 2014; Chuang & Schechter 2015). In this context, peers and kin often represent the only source of information and other resources possibly influencing decision making in various ways. For instance, individuals who have used a helpful health intervention can teach others about its benefits. At the same time, they can help overcoming reservations and fears by encouraging or nudging their peers to try out the intervention themselves (Jackson 2011; Dupas 2011b).

In this paper, I study peer effects on the utilization of essential health care services by poor households in the Philippines, a lower-middle income country. The services are provided as part of the health program of a microfinance institution (MFI), which offers regular check-ups and consultations to its clients. Microfinance refers to the provision of small-scale financial services, such as loans, saving accounts, or insurance, to poor households (Karlan & Morduch 2010). Commonly, microfinance clients from a neighborhood are clustered in microfinance groups who are liable for the actions of its members. In recent years, an increasing number of MFIs have started to provide complementary health services in addition to microfinance as a mean to compensate for deficits in public health care and to improve the health situation of their clients (Leatherman et al. 2012; Leatherman & Dunford 2010).

Despite the importance of this trend, there is little empirical evidence on the success of these health initiatives and the role of microfinance groups in influencing client's adoption of the provided services. In general, although MFIs serve more than 200 million borrowers, according to recent estimates (Microcredit Summit Campaign 2015), very little is known about the 'social fundaments' of microfinance group networks and how they affect individual decision making. This study is one of the few analyzing these groups, which have become a focal point in the life of client families all over the world (Banerjee et al. 2013).

This study is interested in whether an individual's adoption of the health services is influenced by her peers' adoption decision. The estimation of these peer effects is challenged with several econometric issues. For instance, the well-known reflection problem, which was first emphasized by Manski (1993) and further discussed by Moffitt (2001) and Blume et al. (2011), refers to the inability to disentangle endogenous peer effects from contextual effects in social interaction models. As peers may influence each other simultaneously, it is impossible to determine whether the peers' behavior is the cause of an individual's behavior, or vice versa. Besides simultaneity, further endogeneity issues may challenge the estimation: Peer groups do not form randomly, but are themselves the result of individual choices. For examples, friends often share similar characteristics due to homophilous peer selection (Mcpherson et al. 2001). This may confound the estimation of peer effects if it is not the social interaction, but the similarity in specific characteristics which determines the friends' outcomes in form of correlated effects. At the same time, peer groups may be exposed to the same environmental shocks, which may affect the outcomes, even if the peer group members did not interact with each other. Health shocks in a neighborhood, for instance, could make people simultaneously decide to undergo a medical check-up, even without having directly influenced each other in their decisions.

In the recent years, an increasing number of studies have employed randomized controlled trial designs to study peer effects on the uptake of health innovations as they allow solving some of the aforementioned challenges (Kremer & Miguel 2007; Oster & Thornton 2012; Dupas 2011a). Commonly, these designs vary the access to an intervention randomly within networks to study how the exogenously created variation in the number of adopters or peers with access influences the individual adoption decision. Although methodically rigorous, such designs may face practical limitations, for instance if – like in my case – a treatment cannot be varied randomly within, but only across networks.

In this paper, I tackle the different econometric challenges with a novel instrumental variable (IV) identification strategy, which has not been used before for studying health care utilization decisions in a developing country context. The approach, which was first proposed by Bramoullé et al. (2009, see also De Giorgi et al. (2010) and Lin (2010) for other contributions), exploits variation in the network structure and the existence of partially overlapping peer groups for the unbiased estimation of peer effects. An overlap in peer groups exists if not all actors in a network are connected with each other and if some individuals are part of different peer groups. In this setting, exogenous characteristics' of second order peers, i.e. the friends of an individual's friends who she is not personally connected with, can be used to instrument the behavior of the directly connected peers. The idea of the approach is that second order peers can only influence an individual by influencing her peers' behavior in form of contextual effects allowing to break the reflection problem. In my estimation, I also control for the level of the (plausibly exogenous) instrumental variable for the individual and her direct peers. With this, I attempt to capture any similarity in background characteristics between the individual as well as her first and second order peers that may have resulted from homophilous peer group formation and which may confound the instrumental variable estimation. I further control for a rich set of background variables and neighborhood fixed effects in my preferred specification to minimize the potential bias due to environmental shocks.

Apart from the IV models, I exploit the variation in another dimension, the timing of the uptake of the program, to test for the robustness of my results. Using retrospective information on the adoption decision, I estimate discrete proportional hazard models, which allow me to explore some of the mechanisms moderating the peer effects. Here, I focus on three factors that have been shown to be relevant in other settings, namely the timing since first exposure to the health program, the strength of the relationship with the adopting peers, and their structural position in the microfinance group networks (Bandiera & Rasul 2006, Perkins et al. 2015; Shakya et al. 2014).

The data for this study was collected in interviews with 1064 clients of my partner organization, the Kasagana-Ka Development Center Inc. (KDCI), a small-scale MFI operating in the greater area of Metro Manila and the surrounding provinces. The clients of my partner organization were clustered in 70 microfinance centers, which form the basis for my social network analysis. The setting offers several advantages: Every group consists of a restricted number of clients and hence has a clearly defined network boundary. Also, only the KDCI clients and their families are entitled to use the studied health care services, making it impossible to mimic or learn from the behavior of others outside the network. As part of my main survey, I collected rich sociometric data, which relies on direct nominations of peers in the network. In contrast, much previous research is based on arbitrary criteria in defining what constitutes a peer group, such as geographical proximity, shared characteristics, or kinship, which may not well reflect the actual interaction patterns in the networks (Sacerdote 2001; Deri 2005; Conley & Udry 2001; Wydick et al. 2011; Charles et al. 2009; De Giorgi et al. 2010; Caeyers 2014b).

I find evidence for significant and large peer effects. According to my preferred specification, a 10% increase in the number of direct peers using the health services leads to an increase of 6.6% in the individual adoption probability. The results are robust to the inclusion of a broad variety of individual and contextual factors as well as neighborhood fixed effects. I furthermore test for the consistency of my results using the dynamic uptake information and discrete proportional hazard models, which largely confirm the previous findings. Having a larger share of friends who made use of the services previously significantly increases individual uptake. Like in other studies, peer effects are found to be strongest immediately after first exposure to the intervention and to fade out over time. While the strength of the relationship with the peer does not seem to matter for adoption, the peers' structural position in the network does: Although high status individuals, as defined by their standardized indegree, have on average a higher level of program uptake, they are more susceptible to the influence of their low status peers. This finding may result from the particular nature of the microfinance group networks: In these, it is often the most active clients who hold central positions in the network. These central actors have a higher initial propensity to use services and products that are offered by the MFI. Wanting to serve as a role model in the group, they may be more susceptible to external influences by their lower status peers in order to preserve their reputation as good clients in the group. I further discuss these findings and derive policy recommendations that are relevant for health interventions in other contexts.

The remainder of the paper is structured as follows. Sections 2 and 3 review the relevant theoretical and empirical literature on peer effects in developing countries. Section 4 introduces the linear-in-means model and discusses the used identification strategy. Section 5 describes the data and measurement. Section 6 reports the main results on the role of peer effects for the studied health care utilization decisions. Section 7 discusses the findings and concludes.

2 Theoretical Framework and Predictions

In economics, social network theory has developed as a rigorous and microfounded approach to analyze social interactions (Jackson 2011; Boucher & Fortin 2015). In particular, the approach is concerned with how networks endogenously form and how they in turn affect individual behavior and outcomes, the focus of this study. Individuals, who are embedded in social networks, which restrict their action space, are represented by nodes $i = \{1, \dots, s\}$ in graphs G. The nodes have relationships (ties) g with each other and can be characterized by their structural position in the network, i.e. the set of ties to other actors, their ties, and so forth. The identification strategy employed in this paper heavily builds on such structural information about the considered networks.

Theoretically, peer effects in health care utilization can stem from different sources. For instance, they can result from pure imitation or conformity which is the tendency of people to adjust their behavior to the behavior of their peers. In formal economic models, conformity is usually expressed as a desire to imitate social contacts with different individuals having heterogeneous tastes for imitation (Bikhchandani et al. 1992; Bikhchandani et al. 1998). Given an environment with imperfect information, learning from others is another possible form of social interaction (Banerjee & Fudenberg 2004; Conley & Udry 2001). By observing others or communicating with them, individuals can acquire information about the availability of health services and their benefits. Indeed, studies found substantial evidence that information provided by others and shared experiences can have a strong impact on adoption decisions (Magnan et al. 2015; Dupas 2011b; Krishnan & Patnam 2014). Others have also emphasized the importance of learning on how to effectively use a technology, which has been shown to be a crucial driver for the diffusion of more complex technologies (Oster & Thornton 2012). Finally, peer effects may stem from behavioral complementarities and external effects. For instance, there could be a utility gain if others are also using the health services simply because it is more pleasant to participate in the check-ups with a group of friends.

Importantly, peer effects do not necessarily have to be positive. For instance, Kremer and Miguel (2007) find particularly pronounced social interaction effects on take-up of deworming medicine for families with better education. This group's prior beliefs about a deworming drug were very positive, but then rapidly decreased once they acquired more information about the costs of utilization through their social networks. If social learning is possible, individuals may also strategically try to make use of their peers and wait for them to experiment with a product first to then learn from their experiences (Dupas 2011b; Besley & Case 1993). Furthermore, people can have nonconformist tastes inducing a desire to not behave like others in their peer group – a motivation which is commonly found in status or conspicuous consumption (Bagwell & Bernheim 1996). Finally, complementarities and external effects may as well result in a negative peer effect. For instance, the risk of being in contact with someone in the network who is infected with an undetected disease is lower for clients who are connected to many adopters of the health care services. This positive externality reduces the individual's need to make use of the services and may hence result in a diminished take-up. In the end, how peers affect individual decision making is an empirical question. Besides analyzing whether positive or negative peer effects exist, this study also considers mechanisms that influence under which conditions peer effects are most likely to occur.

As a first mechanism, I study the role of the *time since exposure* to the intervention. Previous empirical research has suggested that peer effects are strongest shortly after the first introduction of an innovation, as individuals had little chance to themselves experiment with it or to acquire information through other channels (Oster & Thornton 2012). An attenuation of peer effects over time has also been observed in settings where conformity motivations are more important (Sacerdote 2001). On the other hand, having a large number of potential adopters in the network may induce incentives to strategically delay adoption and to free-ride on the experiences made by others (Bandiera & Rasul 2006). Apart from the time factor, research in the field has suggested that the size and direction of peer effects critically depends on characteristics of the relationship. In particular, *tie strength* and the *status* of the peer in the network are often emphasized as important moderators of social interaction effects (Perkins et al. 2014; Shakya et al. 2014).

Since Granovetter's seminal study on the strength of weak ties (Granovetter 1973), researchers have analyzed the role of relationship strength for various outcomes in networks. While it is commonly argued that weak ties are better suited for the dissemination of information as they often constitute local bridges to structurally distant and loosely connected parts of the network (Burt 2000), strong ties are of greater importance for emotional support, access to valuable resources, and uncertainty reduction as they heavily rely on close reciprocal relationships and mutual trust (Krackhardt 1992). Health is an intimate topic, which is commonly only a matter for discussions in the close social environment. Accordingly, strong ties have often been considered to be more relevant for health-related outcomes and decisions than weak ties, or as Putnam (2000, p.323) puts it: "Strong ties with intimate friends may ensure chicken soup when you're sick". [1] Indeed, using social network data from India, Shakya et al (2014) show that individuals are more likely to own latrines if their peers own latrines as well; and this effect is more pronounced among close friends (see also Bond et al. (2012) on political mobilization). I analyze whether tie strength influences the size of peer effects in my settings expecting that stronger ties are more influential than weaker ties for the adoption decision.

Besides characteristics of the relationship, the actor's position in the network has received much attention in social network theory and research. In this respect, the concept of the *key player* is central (Zenou 2015). A key player can be defined as an actor in the network who is particularly important or influential for the outcome at hand, in my case the utilization of the health care services. For the empirical identification of key players, centrality concepts, which are based on specific features of an individual's position in the network, play an important

[1] On the other hand, especially in poor communities, strong social ties can also represent a source of mental distress, as some studies have reported (Kunitz 2004). In settings, where little access to formal health services exists, individuals have to rely heavily on their informal networks which may result in burdensome obligations and liabilities for the households.

role. Depending on the particular research setting, different centrality measures are appropriate (Marsden 2002; Jackson 2011). For instance, betweeness centrality, which is the number of shortest paths between all pairs of nodes in a network that pass through an actor, captures the importance of an individual as an intermediary who can control the transmission of resources, such as information. This concept forms the basis of the *structural holes* idea as developed by Burt (1992). In this study, I conjecture that for the uptake of the health services, the status or popularity of the adopting peers is particularly relevant, which I operationalize with the actor's number of incoming ties, i.e. her indegree centrality (Marsden 2002). It has been argued that people have a greater tendency to imitate popular individuals and that information transferred by high status peers is more influential for adoption decisions (Ibarra & Andrews 1993; Valente & Pumpuang 2007). Following this argument, I expect a stronger reaction in adoption behavior if higher status peers have started to use the program first.

3 Empirical Evidence: Peer Effects on Health Care Utilization

The empirical evidence on the role of social networks for health behavior and the adoption of health technologies in developing countries is somewhat mixed, which in part results from the diversity of research designs employed and the different contexts studied. Oster and Thornton (2012) find strong evidence for peer effects on the uptake of menstrual cups among school girls in Nepal. In their identification, the authors make use of a randomized distribution of the cups which created an exogenous variation in the share of friends exposed to the intervention. Other studies have likewise reported positive peer effects on various health behaviors in developing countries, such as Godlonton & Thornton (2012) for the learning of HIV test results in rural Malawi, Dupas (2014) for the adoption of insecticide treated bed nets in Kenya, An (2015) for cigarette smoking in China, Munshi & Myaux (2006) for contraception decisions in rural Bangladesh, Adhvaryu (2014) for the adoption of anti-malarial treatment in Tanzania, and Shakya et al. (2014) for latrine ownership in rural India. On the other hand, some studies also found no or even negative effects of peers on individual's health behavior, such as for the uptake of deworming drugs (Kremer & Miguel 2007) or investments in preventive health products (Meredith et al. 2013).

Few studies so far have considered the role of peer effects for the uptake of intangible health services. These can be described as a special case of an experience good in which consumers only learn of potential benefits after having used the services.[2] Like with more tangible experience goods (e.g. menstrual cups, deworming medicine), social learning can be a rational strategy prior to adoption. Deri (2005) studies the effects of social networks on health service utilization of immigrants in Canada. By using language group and geographic variation of the migrants, she finds peers to have a significant impact on individual utilization decisions. Likewise, Devillanova (2008) finds social networks to significantly increase health care utilization among undocumented immigrants in Milan. Similar results are reported from developing

[2] Health services, such as the ones offered by my partner organization, could even be described as a form of credence good. For this category of goods and services, it is hard for consumers to ascertain potential utility gains even after having used them (Dulleck & Kerschbamer 2006).

countries. For instance, Leonard et al. (2009) show that households deliberatively collect information in their networks about health facilities in their neighborhoods and use this information when choosing whether or not they want to visit new health care providers.

In the recent years, researchers have increasingly employed randomized controlled trial designs to study peer effects. Examples are the studies by Kremer & Miguel (2007), Oster & Thornton (2012), or Dupas (2014). Exposing some randomly selected individuals in a network to a controlled stimulus allows gaining an unbiased estimate of peer effects. In particular, new social media platforms enable researchers to conduct so called large scale *networked experiments* with ten thousands of observations (Aral & Walker 2012; Aral 2016). As it is often not possible in these settings to perfectly enforce compliance, so called encouragement designs are frequently used (Eckles et al. 2016). In these, a randomly selected sub-sample is encouraged to use a product or service, for instance by distributing vouchers as treatment. Even though not all of the selected participants may adopt, the initial randomized assignment can be used as an instrument to obtain an estimate of the local average peer effect.

Although randomized controlled trials represent an extremely powerful method for studying social interaction effects, they face some practical limitations. In many settings, it is not feasible to set an experimental stimulus for some, but not all members of a network. The health care services considered in my study, for instance, were accessible for all clients of my partner organization in a neighborhood. Also, data restrictions are a common problem. Often, it is not possible to track participant's behavior over time, constraining the researchers to cross-sectional data, which comes with additional challenges in the econometric identification.

Recently, new directions have been adopted in the empirical estimation of peer effects based on non-experimental, cross-sectional data (Fletcher 2014). In this paper, I employ an instrumental variable strategy which exploits characteristics of second order friends (i.e. the peers' peers) as instruments for direct peer's behavior (Bramoullé et al. 2009, De Giorgi et al. 2010, and Lin 2010).[3] This approach has been used only by few empirical studies so far, none of which is concerned with the adoption of health products or services. For instance, De Giorgi et al. (2010) study peer effects in education decisions. They find individuals to be more likely to choose a major when many of their peers made the same choice. On the individual level, this social influence resulted in inefficiency as peers can divert students from majors in which they have a relative ability advantage. Using the same approach, De Melo (2014) find significant endogenous peer effects on student outcomes, which may likewise result in negative outcomes, such as an amplification of educational inequalities. Caeyers (2014b) considers the spread of information about a development program in rural Tanzania among the elderly and disabled. Using information about the geographically nearest neighbors as relevant peer group, the author estimates that an additional informed neighbor in a set of 10 sampled nearest neighbors leads to a 7.7% increase in the probability that a household is informed about the program. Peer effects on health-related outcomes have been identified by Lin (2015), who showed that peers strongly influence risky behaviors among adolescents, namely the con-

[3] Note that this approach was strongly inspired by the spatial econometrics literature, which uses information about the spatial distribution of locations and spatial autoregressive models in the identification (Lee 2007; Lin 2010).

sumption of alcohol, cigarette smoking, physical fighting, and the skipping of school. Similarly, Fortin & Yazbeck (2015) find positive but small peer effect in fast food consumption using the Add Health Data from secondary schools in the US.

4 Identification Strategy

I analyze peer effects using a dual identification strategy. First, I employ the described structural IV approach, which uses second order peers' background characteristics as instruments for peers' behavior. In a second step, I estimate discrete-time proportional hazard models. These exploit dynamic information about timing of adoption and allow me to test for the consistency of my findings.

4.1 Empirical Model: The Linear-In-Means Model

Following the pioneering work of Manski (1993), I empirically estimate a structural linear-in-means model which defines the behavior of an individual ego i as a function of the behavior of her peers (endogenous peer effects), the characteristics of her peers (exogenous peer effects), her individual characteristics, and an error term. In this study, I am mainly interested in the individual's use y_i of the health services provided by my partner organization and the influence of peers' utilization on the individual adoption probability, i.e. the endogenous peer effect.

Clients of my partner organization are nested in microfinance groups of size s which form the basic networks for the analysis. Furthermore, I assume that each individual has a close reference group R_i of size r_i from the more large-scale network of clients. In my setting, the reference group is defined by all peers j of an individual who have a connection with i based on the nominations in a social network questionnaire (see Section 4). Networks are assumed to be symmetric. Following the linear-in-means approach, let the structural model be as follows:

$$y_{ni} = \alpha_n + \beta \frac{\sum_{j \in R_i} y_{nj}}{r_i} + \delta \frac{\sum_{j \in R_i} x_{nj}}{r_i} + \gamma x_{ni} + \epsilon_{ni} \tag{1.1}$$

where y_{ni} is a dummy indicating whether a client i in network n used the health services. The coefficient β measures the endogenous peer effect of the average program uptake in the immediate peer group. Note that a client is not part of her own peer group, i.e. $i \notin R_i$. The contextual peer effect is captured in the coefficient δ and α_n represents network effects. For now, I assume that no correlated effects due to self-selection into the peer group or common shocks exist. This assumption will be relaxed later.

Apart from the endogenous peer effect β, I also consider the influence of various plausible contextual and individual characteristics x_{nj} and x_{ni}: Membership duration, education level, health knowledge, health status, wealth, insurance status, experienced social support, religiosity, and the number of children in the household. For instance, having a peer group with worse health (under control of the individual health condition) may make an individual more likely to utilize the health program as she learned from her peers' bad condition. At the same time, friends who know a lot about health (under control of individual health knowledge) may convince an individual of the importance of medical check-ups and hence increase her adoption probability. In addition, I include a measure for individual's and peers' utilization of health services that are offered by organizations other than my partner organization. This allows me to take indirect effects on ego's behavior into account, e.g. observing peers who underwent regular check-ups, even if these were offered by other organizations, may induce ego to use the health services. For each actor in the network, the characteristics of the first and second order peers are averaged over all peers. I furthermore control for a rich set of structural and socio-demographic background variables on individual level.

The model above can be neatly rewritten in matrix notation. First, I define an identity matrix I_s with ι_s being a vector of ones for each network. Second, based on the network information from each neighborhood I construct a weighted adjacency or interaction matrix G_n of $s \times s$ dimension with sender in rows and receiver in columns. The matrix is row-normalized with its cells taking the value $G_{ij} = {}^{1}/_{r_i}$ if j is part of $i's$ reference group and $G_{ij} = 0$ otherwise. Please note that G_n is symmetric with all diagonal cells of the matrix G_{ii} set to zero. I can rewrite the adapted linear-in-means model in matrix notation for each neighborhood:

$$y_n = \alpha_n \iota_n + \beta\, G_n y_n + \delta G_n x_n + \gamma x_n + \epsilon_n \tag{1.2}$$

or in reduced form:

$$y_n = \alpha_n \iota_n (I_n - \beta\, G_n)^{-1} + (I_n - \beta\, G_n)^{-1}(\gamma + \delta G_n) x_n + (I_n - \beta\, G_n)^{-1} \epsilon_n \tag{1.3}$$

4.2 Instrumental Variable Estimation

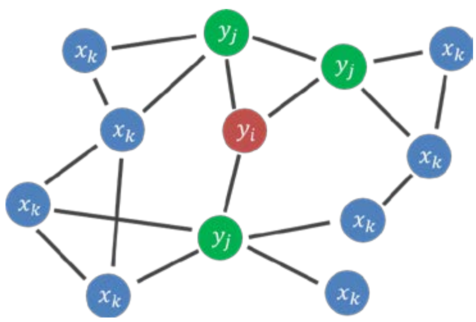
The identification of the endogenous peer effect is challenged with several well-known econometric issues (Manski 1993; Moffitt 2001; Blume et al. 2011; Durlauf & Ioannides 2010). First, an individual and her peers may influence each other simultaneously, which Manski refers to as reflection problem. Furthermore, correlated effects due to self-selection into the peer group and common shocks may exist. The following IV identification strategy allows me to minimize the reflection and endogeneity problems in the analysis.

Before applying the IV identification, I first estimate the social interaction model using ordinary least squares (OLS). The estimates can serve as benchmark, but are likely to be biased because of the aforementioned issues. Commonly, it is believed that the OLS estimates cumulate the impact of endogenous effects and correlated effects and hence over-estimate the true effect. Yet, as it has been suggested by De Giorgi et al. (2010), this interpretation is based on the implicit assumption that both effects influence the outcome in the same direction, which is not necessarily the case in my setting. Individuals in the network can be members of different peer groups exerting heterogeneous correlated effects. Since each of the effects can have different signs, it is not possible to predict whether OLS would over- or underestimate the true peer effect. Moreover, if non-linearities and interactions in the structure of the correlated effects exist, it is even more difficult to assess the direction of the potential estimation bias. De Giorgi et al. (2010) underpin their argument with simulations showing that OLS is equally likely to over- or underestimate the true peer effects given a heterogeneity in the correlated effects across individuals. Furthermore, as has been highlighted by Guryan et al. (2009) and formalized by Caeyers (2014a), OLS estimates may be downward biased due to the exclusion of individuals from their peer group's average outcome calculation, what Caeyers refers to as 'exclusion bias'.

To overcome the biases in the OLS estimation, I extend my estimation in a second step by applying a two-stage least squares (2SLS) instrumental variable identification strategy (Bramoullé et al 2009, De Giorgi et al. 2010, and Lin 2010). The approach exploits variation in the structure of the networks and overlapping peer groups to identify causal peer effects. Bramoullé et al (2009) show that if the matrices I_n, G_n, and G_n^2 are linearly independent, i.e. some of the peers' peers are not friends with ego, then both endogenous and contextual effects can be identified. Here, G_n^2 describes the second-order row-normalized interaction matrix which assigns a value greater than zero to all actors in the network n that can be reached by i within two steps (i.e. second order peers). The linear independence condition is fulfilled if peers have friends who are themselves not friends with ego, i.e. reference groups do not overlap. In this case, the characteristics of network members who are not part of ego's direct reference group, but who can be reached through her direct friends in two (or more) steps can serve as valid instruments to predict peers' behavior $G_n y_n$.

In my estimation I control for the level of the instrumental variable for the individual x_n and her direct peers $G_n x_n$ to account for similarities in background characteristics between the individual and her first and second order peers. Such similarities that may result from homophilous peer group formation may threaten the exogeneity of the used instruments $G_n^2 x_n$ if not properly controlled for. In addition, I control for properties of the network (e.g. density/clustering and size) and the individual network positions (e.g. degree centrality), which may be correlated with the adjacency matrixes G_n, and G_n^2. The intuition of the identification strategy is illustrated in Figure 1: The characteristics of ego's peers' peers' $G_n^2 x_n$ (blue nodes, generic identifier k) can influence ego's behavior (red node) only by influencing the behavior of her direct peers (green nodes) in form of contextual effects.

Figure 1 - Illustration of identification strategy



The identification strategy rests on several assumptions. First, for the identification to empirically hold, contextual effects have to exist on the aggregate level. Characteristics of second order peers can only be relevant instruments if they are correlated with peers' average behavior (relevance assumption). To raise the relevance of my instruments, I restrict my sample to individuals whose second order peer group is at least half as big as the first order peer group (82% of total sample). Through this, I want to avoid cases in which the behavior of a large number of direct peers is instrumented with the background characteristics of very few second order peers which may create noise in the first-stage estimation. Second, I assume that second order peers influence ego only through her peers' behavior and not any other channel under control for ego's own characteristics x_n and the characteristics of her direct peers $G_n x_n$ (exclusion assumption). This assumption may be violated if correlated effects are present, e.g. due to common shocks to the entire network, which affect both ego's decision to use the health services and the instruments. Hence, the presented IV estimation allows solving the reflection problem, but does not fully rule out potentially remaining endogeneity.

To address this issue, I do not only control for a rich set of individual and contextual background characteristics in my models, but also take neighborhood fixed effects into account. Single centers are categorized in larger neighborhood units which are located in close proximity and are all supervised by the same staff member, a so called socio-economic officer, who is likely to exert a strong influence on the uptake decision of the center members. In total, this categorization yields 15 neighborhood clusters.[4] To control for fixed effects, I demean the data by subtracting the neighborhood average from each variable, i.e. each term in equation (1.2) is multiplied by a factor $D_n = I_n - \frac{1}{n_n} \iota_n \iota_n$. Because of the demeaning, the constant network effect cancels out in the structural model:

$$D_n y_n = \beta D_n G_n y_n + \gamma D_n x_n + \delta D_n G_n x_n + D_n \epsilon_n ; \tag{2.1}$$

and in the reduced form model:

$$D_n y_n = D_n (I_n - \beta G_n)^{-1} (\gamma + \delta G_n) x_n + D_n (I_n - \beta G_n)^{-1} \epsilon_n \tag{2.2}$$

To further check for the robustness of my results, I exploit dynamic information on the uptake of the health program among the clients using discrete-time hazard models. These more flexible models also allow me to explore some of the mechanisms influencing the strength of the peer effects in different settings and under different conditions.

4.3 Discrete-Time Hazard Models

In the second step of my analysis, I am interested in the hazard of an individual i at time interval t to make use of the program as a function of her peers' past behavior, contextual variables, and the individual's characteristics. I estimate a discrete-time hazard function, which can be interpreted as the conditional probability of an event occurring during an interval t given that the event, in my case the first utilization of the health services, did not occur before (Jenkins 1995; Allison 2010)

[4] I also test for the robustness of my findings calculating fixed effects on the network level. However, this results in a very low relevance of the included instrumental variables in the first stage regressions making the IV approach infeasible.

$$\lambda_{it} = \Pr(T = t \mid T \geq t, \bar{y}_{R_{it}}, \bar{x}_{R_{it}}, x_i) \tag{3.1}$$

Where λ_{it} is the individual hazard rate, and $\bar{y}_{R_{it}}$ and $\bar{x}_{R_{it}}$ represent the peer group's mean program uptake and background characteristics. These variables are time-varying depending on 1) the timing of uptake in the peer group, and 2) the peer group composition at time interval t, which depends on the entry of the peers into the organization. A peer is only included in the peer group calculation if she was a client of my partner organization at time interval t. The individual characteristics x_i, such as the educational background or marital status, are assumed to remain stable over the observed period.

In my case, the considered time intervals t are quarters. The counting starts with the entry into the organization (or with the full initiation of the program in January 2009) and ends in April 2015 (t_{max}= 25). An observation is right censored if the client has used the health program during the study period. To estimate the models, the data is transformed into multiple period data with several episode observations per subject. Note that the analysis is based on retrospective information about the respondent's adoption of the program. The informational quality of the data is hence restricted. Full longitudinal information would allow to gain a more accurate picture, first of the role of changing individual characteristics for adoption decisions (e.g. changing health status) and second of the social dynamics within the network.

I use the complementary log-log function to model the individual hazard at time interval t, which is commonly applied in the literature (Jenkins 2004). The results are not sensitive to the use of alternative link functions, such as logit or probit. The cloglog model takes the event history form of:

$$\log(-\log(1-\lambda_{it})) = \lambda_0(t) + \alpha_n + \beta\bar{y}_{R_{it}} + \gamma\bar{x}_{R_{it}} + \delta\, x_i + \varepsilon_{it} \tag{3.2}$$

or as probabilities:

$$\lambda_{it} = 1 - \exp[-\exp\big(\lambda_0(t) + \alpha_n + \beta\bar{y}_{R_{it}} + \gamma\bar{x}_{R_{it}} + \delta\, x_i + \varepsilon_{it}\big)] \tag{3.3}$$

where $\lambda_0(t)$ is the baseline hazard function, which models the changing hazard over time and which takes a logarithmic functional shape in my preferred specification. I also estimate it using a non-parametric approach by including dummies for the single time intervals. As the findings remain largely consistent, I present only the results for the logarithmic baseline hazard here. Note that all models are estimated with fixed neighborhood effects and including the full set of additional individual and contextual controls to minimize the risk of bias due to unobserved correlated effects. Using the dynamic setting, I explore some potential moderators and mechanisms of peer effects by varying the baseline specification. More details on the model variations will be given in Section 6.3 together with the results.

5 Data and Measurement

5.1 Institutional Framework

This project was conducted in cooperation with the Kasagana-Ka Development Center Inc. (KDCI), a Philippine social development microfinance organization. KDCI is active in the greater area of Metro Manila and the surrounding provinces, where it mainly offers small-scale financial services and support. In total, the organization serves nearly 30000 mostly female clients who are clustered in centers as the smallest administrative unit of the organization in the neighborhoods. Each center convenes on a weekly basis at the house of one of the center members. The meetings are supervised by a socio-economic officer who is representing KDCI during the meetings.

As a reaction to health deficits in the poor communities, KDCI initiated a health program in 2009 together with partner organizations from the health sector. As part of the program, clients and their families are invited to medical check-ups, which are offered on an annual or bi-annual basis. During the check-ups, participants receive a full physical examination and take part in different laboratory tests. They are notified of the results of these tests at another follow-up meeting in which they receive a full diagnosis of their condition and an appropriate treatment plan. Furthermore, during the check-ups and follow-up consultations the participants are given additional information about appropriate health prevention and common disease threats in their environments. To attract clients, the medical check-ups are offered in locations that can be easily accessed from the centers and provided at a price 70 to 80 percent lower than the rates in local hospitals and clinics, according to a study conducted by KDCI (Sebastian 2012). Clients can choose from one of four check-up packages including different services (see Table A1 in the appendix). Besides a medical examination, the smallest package (A) includes a complete blood count, a urinalysis, a stool examination, and a chest x-ray at a price of PHP 310 (~$7.00). KDCI clients can avail health loans to cover the costs of the health services and the necessary medical treatments.

Many of the clients of my partner organization have no or only restricted access to the public health infrastructure. In the baseline survey conducted in 2014 by the author, more than 51% of respondents said that they never underwent a routine check-up in their entire life without experiencing any concrete disease symptoms. Even if symptoms occurred, many of the poor clients did not seek professional help. Self-treatment of symptoms, on the other hand, was found to be quite common among the respondents. Insufficient health monitoring and the low willingness to undergo medical examinations can have dramatic consequences for the poor for who health shocks and related expenditures represent an existential threat (Xu et al. 2003).

The essential health services provided by my partner organizations are meant to fill the gap by promoting care seeking and by reducing clients' barriers in the utilization of health care. Indeed, the rates of detected diseases show that the check-ups can be highly useful. Among the participants of an examination that was conducted in June 2013 in Tandang Sora, a district in Metro Manila, 85% were diagnosed with a medical condition. The majority of participants were not aware of their condition and its potentially harmful long-term consequences. In total, 17% were diagnosed with hypertension which may lead to fatal cardiovascular diseases, 13% were diagnosed with urinary tract infection, 10% with high cholesterol levels, and 6% with diabetes mellitus. Strikingly, 8% of patients had a positive pulmonary tuberculosis (PTB) test result. If untreated, PTB is a highly infectious disease, also revealing the important external effects of the offered health services for the communities. The findings mirror the test results from other areas of the city and underpin the need for more rigorous testing and health monitoring in the poor communities.

Despite their potential for improving the clients' health situation, uptake of the health program remains moderate. At the time of my main survey in 2015, only 30% of the respondents have ever made use of the services with the majority having used the examinations only once and not regularly as intended by my partner organization. The low uptake is unlikely to be due to financial reasons as the program is offered at rates that are affordable for the households. In addition, the costs can be covered through loans offered by the organization.[5] When asked for why they have not used the program, respondents often name a lack of time or an absence of pain as main reasons.

5.2 Data

The data for this study was collected among 1064 randomly selected KDCI clients from 70 centers which are located in Quezon City and Rizal province at the north to northeastern outskirts of Metro Manila. The centers form the basis for the microfinance group networks analyzed in this study. Each center represents a separate entity and serves only one neighborhood minimizing the chance of spill-overs from one center to another. This represents a major advantage of this study as it allows me to analyze *complete networks* of clients with clearly defined *network boundaries*. Importantly, the health program of my partner organization can only be used by its clients and their families, but not by outsiders to the organization.

Defining the set of peers who can potentially influence an individual is a major challenge in social interaction research. Often, peer groups are defined based on arbitrary criteria, such as geographical proximity, the sharing of common traits and characteristics, or kinship relations (Sacerdote 2001; Deri 2005; Conley & Udry 2001; Wydick et al. 2011; Charles et al. 2009; De Giorgi et al. 2010; Caeyers 2014b). This approach leaves considerable uncertainty as to whether the identified groups are actually relevant and whether or not sources outside the peer group may have an influence. Furthermore, other studies rely on egocentric network data, which restricts the analysis to small peer groups in the immediate environment of an individual (O'Malley et al. 2012; Smith & Christakis 2008). In this paper, I employ a sociometric approach, which enables me to combine the information from different actors in the network and to study the role of structural network features in influencing outcomes. The sociometric network data is based on direct nominations of peers by (almost) all members of the networks. When answering to the name generator questions described below, each respondent received

[5] As several studies have shown, poor households have an extreme price elastic demand for health products and services, even if these can lead to large health improvements, such as in the case of insecticide treated bed nets or rehydration salts (for an overview of studies, see Kremer & Glennerster 2011).

a complete list (sample frame) of all clients in her microfinance group reducing possible recall and identification biases in the nominations.

The KDCI centers are of different sizes normally ranging from 10 to a maximum of 42 members. Usually, centers emerge from a group of friends who form the core of each center. Over time, the centers grow larger as new persons enter. The new entrants are usually recruited by friends who are already clients of the organization. Many networks hence take the shape of a tree with a central core of old members and ramifications of newer members who form more isolated, peripheral peer groups.

Respondents were interviewed with an 18-page long questionnaire which contained several questions on client's background characteristics and her utilization of the KDCI health services. At the end of the questionnaire, respondents were shown a complete list of all members of their KDCI center and were given four *name generator questions* to assess their relationship to the other center members. Respondents were asked, i) who on the list they considered to be a personal friend, ii) who they met regularly (i.e. at least once every week for more than 15 minutes besides the regular center meetings), iii) who they considered to be one of their five best friends, and with iv) who they spoke about their personal, intimate problems, such as their health situation. Answers were carefully recorded by the interviewers and encoded in separate adjacency matrices G_n for each center.

5.3 Measurement

To measure the utilization of the health services, respondents were asked if they or someone else in their household underwent a check-up provided by my partner organization in the past resulting in a binary outcome measure. If the program was used by someone in the respondent's household, she was subsequently asked for the exact years and months when the program was used, which forms the basis for my dynamic analysis.

Our data allows me to distinguish between weak and strong ties. Considerable ambiguity exists in the literature as to what constitutes a strong tie. In his early study, Granovetter said that the "strength of a tie is a (probably linear) combination of the amount of time, the emotional intensity, the intimacy (mutual confiding), and the reciprocal services which characterizes the tie" (1973, p. 1361). I have integrated several aspects of this concept in my four name generator questions, which indicate increasing levels of friendship intensity. Other studies have relied on more simplistic definitions of friendship and strong ties. Some have used reciprocated nominations as basis for their definition of strong ties (Oster & Thornton 2012), others have used frequency of interactions as a surrogate for tie strength (Huszti et al. 2013) or have created additive indices combining the information from different relationships (Shakya et al 2014).

In my study, a weak link between two nodes i and j is present if for any of the four relationship questions (i to iv) either i named j, or j named i, or both. This results in a symmetric network with adjacency matrix $G_{ij} = G_{ji}$. A strong link, on the other hand, exists if at least one of the individuals nominated the other person as either being one of her five best friends or as someone she shares personal, intimate problems with. An actor's status in the network was measured with her indegree centrality $\frac{1}{s}\sum_j g_{ji}$, which is equal to the number of incoming friendship nominations standardized by the size of the center. The calculation of the centrality measure is based on both weak and strong ties.

I use four background characteristics of second order peers as instruments in my IV estimation, which are all strongly correlated with the uptake of the health services among the direct peers: The average membership duration measured in months since entry into the organization, education level measured in years of education, health knowledge assessed with a question battery on 28 relevant health topics (Hoffmann & Lutz forthcoming), and the subjective health condition, which is included in the models as a dummy variable indicating if a respondent perceived her health as being rather good or bad. I also include variables that measure the value of these four characteristics for the considered individual ego and her direct peers to control for similarity between ego and her peer group.

In addition, I consider a broad set of other plausibly relevant individual and contextual characteristics: Insurance status, the number of own children in the household, religiosity assessed with a measure for subjective religiosity (four-point scale) as well as the frequency of church visits (seven-point scale), and social support in the community which was measured by asking respondents if they knew someone in their surrounding who they could ask for help or advice if a health concern arose. Wealth was measured with an asset-based wealth index. The single items for the index were weighted with empirical weights derived from principal component analysis (Vyas & Kumaranayake 2006). Furthermore, I control for dummies if ego and her direct peers underwent check-ups in the past 12 months that were offered by an organization other than KDCI.

Various structural and socio-demographic individual background characteristics are controlled for in my models to raise the precision of the estimation and to reduce the risk of bias due to omitted correlated effects. As structural variables I control for the absolute number of first and second order peers in the network, the standardized indegree of the individual, the proportion of strong ties in the network, as well as the network size. As socio-demographic variables I control for the relationship and marital status, the respondent's age, the size of her household, the parental educational background, and the distance of the respondent's home to the closest public health facility, which can either be a hospital or a primary health care unit. The geographical information on the location of the health facilities was kindly provided to me by the National Mapping and Resource Information Authority in the Philippines.

6 Results

6.1 Descriptive Statistics

In terms of structural characteristics my sample of networks is quite heterogeneous. While some of the microfinance group networks are dense and characterized by a large number of connections, other networks express lower degrees of connectedness. On average, networks have a size of 21.3 and a diameter of 3.7, which is the longest path between two persons in a network. The size of the networks varies greatly with the smallest network in the sample consisting of only 6 and the largest of 42 clients. As sensitivity check I removed centers with a size below 10 (in total 3 centers) from the analysis.

Table 1 shows summary statistics on the individual ties in the network. Respondents have a mean number of 7.88 connections in their network. Among these, 4.51 are weak and 3.37 strong ties, on average. The high number of strong ties suggests that for many clients the microfinance networks represent a central focus of their social life (Feld 1981). Only few respondents (<1%) were isolated in the network, i.e. did not have a connection to any of the other clients. According to the standardized degree measure, clients are on average connected to 36% of others in the network with few respondents being connected to all other members of the center (degree of one). The few number of isolates and the strong overlap of peer-groups represents an advantage for my identification which exploits structural information from the existing ties in the network. The indegree variable, which measures how often the respondent was nominated as a direct contact by one of the others, has a mean value of 0.21 and a maximum of 0.83.

Table 1 - Summary statistics of individual relationship characteristics

	Mean	Standard deviation	Min	Max	N
Degree: # connections	7.88	4.39	0	34	1064
# weak ties	4.51	3.3	0	29	1064
# strong ties	3.37	2.37	0	20	1064
Isolated	0.09	0.03	0	1	1064
Standardized degree	0.36	0.20	0	1	1064
Standardized indegree	0.21	0.15	0	0.83	1064

Figure 2 shows three exemplary networks from my sample. Clients are depicted as nodes. Thin lines represent weak and thick lines strong relationships. The size of the nodes is based on their number of direct connections to others in the network. The graphs are arranged around the most central actors with the largest number of connections. There is great variation in the number of connections between the nodes with some peripheral actors just having one or two connections to other clients in the network. The color of nodes indicates whether clients have used the health services provided by my partner organization or not. Red nodes are users, blue nodes are non-users. As it also becomes visible in the depicted graphs, users often take more central positions in the networks (standardized degree of 0.45 compared to 0.25 for non-users) and are more likely to form cliques with other users (probability of having at least one user among the direct peers is 15% higher for users compared to non-users). The question is whether or not this pattern is due to peer effects or merely a result of correlated effects in the networks.

Figure 2 - Exemplary networks with different sizes and densities

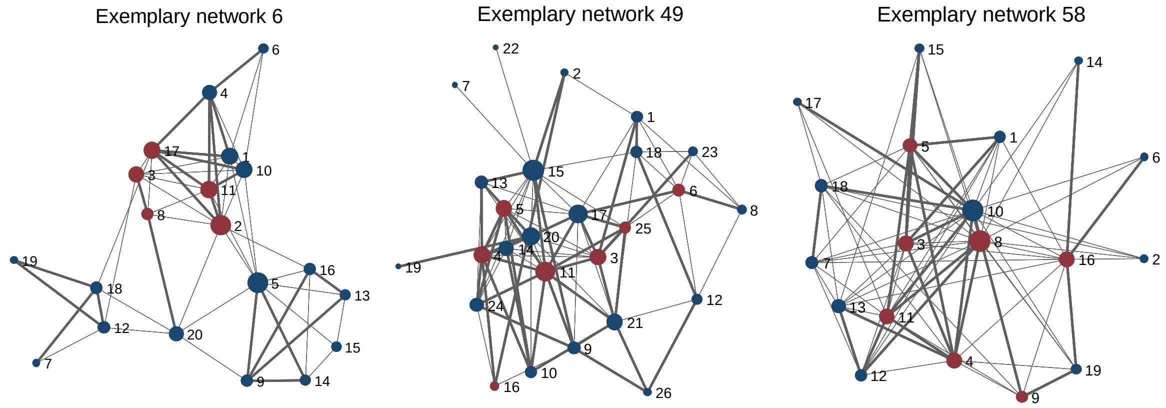


Table 2 provides further information about clients' utilization of the health services. The health program was used by 30% of the respondents or other members of their households. Despite my partner's promotion of a regular use of the essential health services, the majority of users have used them only once or twice. On average, the program was used 1.5 times with some having used it up to 6 times. The variable time to adoption, which forms the basis for the dynamic analysis in Section 5.3, measures how long users waited before making use of the program for the first time after becoming a client of the organization or after the introduction of the program (for those who were clients of the organization prior to the introduction of the program). The vast majority of respondents made use of the program for the first time in the past one (61.1%) or two years (20.0%). The average time to adoption is 44.3 months. Respondent's beliefs of the benefits of the program were assessed with an index ranging from 1 (very bad) to 5 (very good). On average, most clients evaluate the health examinations either as good or very good. Only few gave the program bad grades across the evaluated items (reachability and accessibility of check-up venue, waiting time, personal manner of medical staff, privacy during testing, price of services, and usefulness for health). On average, users value the program higher (4.05) than non-users (3.83). The difference is statistically significant ($p \leq 0.05$) according to a two-sided t-test (assuming identical distributions).

Table 2 - Summary statistics of program utilization

	Mean	Standard deviation	Min	Max	N
Used program	0.3	0.46	0	1	1064
Times program used (users only)	1.54	0.86	1	6	322
Time to adoption (users only)	44.27	25.65	0	98	322
Belief of non-users	3.83	0.49	2	5	742
Belief of users	4.05	0.51	2.57	5	322

Table 3 shows further differences in some key background variables between users and non-users of the program. On average, users have a higher membership duration ($p \leq 0.01$, t-test), have better health knowledge ($p \leq 0.01$, t-test), and are older ($p \leq 0.01$, t-test), wealthier (p≤0.05, t-test), more religious (p≤0.05, t-test), and more often married (p≤0.01, t-test) than non-users. As can be inferred from the higher standardized indegree measure, users were also more likely to be nominated as a peer compared to non-users (p≤0.01, t-test, for all tests I assume identical distributions).

Table 3 - Differences in background variables between users and non-users

	Range	Non-user (n=742) Mean	SD	User (n=322) Mean	SD
Membership duration (months)	2-101	38.78	[28.71]	58.05	[28.45]
Years of education	0-19	9.73	[2.85]	9.44	[2.89]
Health knowledge	1-28	15.34	[4.50]	16.48	[4.07]
Health status	0/1	0.77	[0.42]	0.77	[0.42]
Age	20-76	44.1	[10.06]	47.5	[8.95]
Wealth	0-5	1.76	[0.88]	1.9	[0.88]
Cognitive abilities	0-10	4.11	[1.41]	3.93	[1.51]
Religiosity	1-4	2.34	[0.67]	2.25	[0.65]
Marital status	0/1	0.67	[0.47]	0.73	[0.44]
Number of children	0-12	2.19	[1.60]	2.25	[1.91]
Standardized indegree	0-1	0.18	[0.14]	0.28	[0.17]

6.2 Structural Analysis: OLS and Instrumental Variable Estimation

Table 4 presents the linear probability models estimated with OLS, which give me a first intuition of social interaction effects in the considered setting. The estimation is based on equation (1.2) with $y_i = 1$ if a client underwent a medical check-up as part of the health program of my partner organization and 0 otherwise. The baseline model (1a) contains only the mean program uptake in the peer group as well as the basic background controls (not displayed). It is gradually extended in several steps by including additional relevant individual characteristics (1b), characteristics of the peer group which may exhibit contextual effects (1c), and neighborhood fixed effects (1d). Standard errors are clustered on network level (m=70).

Across all models, I find statistically significant evidence for endogenous peer effects. According to the full model specification (1d) an increase of 10% in uptake in the peer group is associated with a 2.58% increase in individual adoption. While I observe substantial endogenous peer effects, I find only weak evidence for contextual effects on individual behavior: According to model 1c, having direct peers with higher education reduces utilization of the health services. However, once neighborhood fixed effects are controlled for, the effect becomes insignificant.

The endogenous peer effects estimated with OLS may be biased due to simultaneous peer influences and correlated effects. Table 5 presents the 2SLS estimates for the full model specification including all individual and contextual variables estimated both without (2a) and with neighborhood fixed effects (2b). The F-statistics of the models are clearly above the 5% error thresholds recommended by Stock & Yogo (2002) indicating that weak instruments are not a major concern. The first stage regressions are reported in Table A2 in the appendix. I provide further descriptive results in Table A3, which shows similarities in the distribution of some key variables between the first and second order peer groups. On average, the mean values of the groups are highly similar suggesting that I do not pick up any particularities in the way I construct the peer groups. The Hansen overidentification test is used to test for the exogeneity of the used instruments. According to this test, there is no evidence that the instruments influence ego's behavior in any other way than by influencing her direct peers' behavior.

Table 4 - OLS peer effect estimates

	Outcome: Individual program uptake							
	1a		1b		1c		1d	
Endogenous peer effect	0.327***	[0.059]	0.300***	[0.061]	0.311***	[0.065]	0.258***	[0.072]
Individual characteristics								
Membership duration(months)			0.003***	[0.000]	0.003***	[0.001]	0.003***	[0.001]
Years of education			-0.008	[0.006]	-0.006	[0.006]	-0.005	[0.006]
Health knowledge			0.004	[0.003]	0.003	[0.004]	0.003	[0.004]
Health status			0.025	[0.034]	0.021	[0.033]	0.026	[0.035]
Wealth			0.014	[0.016]	0.026	[0.016]	0.02	[0.016]
Other check-up			-0.027	[0.031]	-0.033	[0.032]	-0.031	[0.033]
Personal health insurance			0.058*	[0.032]	0.064**	[0.032]	0.060*	[0.032]
Children			0.006	[0.016]	0.006	[0.016]	0.002	[0.016]
Religiousness			0.009	[0.022]	0.013	[0.023]	0.008	[0.024]
Church visits			-0.01	[0.008]	-0.009	[0.008]	-0.009	[0.009]
Social support			-0.003	[0.032]	-0.002	[0.033]	0.005	[0.032]
Contextual characteristics								
Peers' membership duration					-0.001	[0.001]	-0.001	[0.001]
Peers' years of education					-0.018*	[0.010]	-0.016	[0.010]
Peers' health knowledge					-0.001	[0.007]	-0.004	[0.008]
Peers' good health status					0.101	[0.067]	0.101	[0.066]
Peers' wealth					-0.003	[0.033]	-0.007	[0.035]
Peers' other check-up					-0.009	[0.057]	-0.09	[0.060]
Peers' personal health insurance					-0.08	[0.059]	0.018	[0.062]
Peers' children					0.011	[0.015]	0.005	[0.017]
Peers' religiousness					0.038	[0.038]	0.032	[0.040]
Peers' church visits					-0.027	[0.019]	-0.029	[0.018]
Peers' social support					0.001	[0.064]	0.006	[0.066]
Constant	-0.456***	[0.129]	-0.469***	[0.163]	-0.364	[0.270]	-0.015	[0.017]
Additional controls included	Yes		Yes		Yes		Yes	
Fixed effects	No		No		No		Yes	
Observations	863		863		863		86	
Adjusted R^2	0.106		0.139		0.141		0.123	
AIC	951.562		929.63		938.998		934.794	

Notes: OLS coefficients in cells, standard errors in brackets. Standard errors are clustered on center level (m=70). Additional controls included in the model, but not displayed: Number of peers, number of second order peers, standardized indegree, proportion of strong ties, network size, network density, relationship and marital status, age, household size, parental education background, and distance to closest health facility. Fixed effects calculated for 15 neighborhood clusters. P-value: * p≤0.1, ** p≤0.05, *** p≤0.01.

Table 5 - 2SLS peer effect estimates

	Outcome: Individual program uptake			
	2a		2b	
Endogenous peer effect	0.628***	[0.195]	0.662***	[0.234]
Individual characteristics				
Membership duration (months)	0.004***	[0.001]	0.004***	[0.001]
Years of education	-0.005	[0.006]	-0.005	[0.006]
Health knowledge	0.003	[0.004]	0.003	[0.004]
Health status	0.021	[0.035]	0.023	[0.035]
Wealth	0.028	[0.019]	0.024	[0.019]
Other check-up	-0.031	[0.031]	-0.027	[0.032]
Personal health insurance	0.063*	[0.037]	0.061	[0.037]
Children	0.003	[0.014]	0.002	[0.015]
Religiousness	0.017	[0.022]	0.017	[0.023]
Church visits	-0.007	[0.009]	-0.007	[0.009]
Social support	0.007	[0.035]	0.01	[0.035]
Contextual characteristics				
Peers' membership duration	-0.002**	[0.001]	-0.002*	[0.001]
Peers' years of education	-0.006	[0.013]	-0.006	[0.012]
Peers' health knowledge	-0.007	[0.009]	-0.009	[0.009]
Peers' good health status	0.112*	[0.066]	0.111	[0.070]
Peers' wealth	-0.023	[0.035]	-0.033	[0.037]
Peers' other check-up	0.028	[0.064]	-0.134*	[0.076]
Peers' personal health insurance	-0.116	[0.075]	0.054	[0.066]
Peers' children	0.001	[0.017]	-0.004	[0.018]
Peers' religiousness	0.06	[0.046]	0.063	[0.050]
Peers' church visits	-0.021	[0.018]	-0.027	[0.019]
Peers' social support	-0.009	[0.067]	-0.018	[0.071]
Constant	-0.489*	[0.282]	-0.031	[0.021]
Additional controls included	Yes		Yes	
Fixed effects	No		Yes	
F-test excluded instruments	20.13		18.31	
Hansen J statistic	4.472		3.001	
P-val Hansen overid. test	0.2148		0.3915	
Observations	863		863	
Adjusted R^2	0.111		0.081	
AIC	968.25		975.295	

Notes: 2SLS Coefficients in cells, robust standard errors in brackets. Additional controls included in the model, but not displayed: Number of peers, number of second order peers, standardized indegree, proportion of strong ties, network size, network density, relationship and marital status, age, household size, parental education background, and distance to closest health facility. Fixed effects calculated for 15 neighborhood clusters. P-value: * p≤0.1, ** p≤0.05, *** p≤0.01.

The estimated 2SLS peer effects are significant and substantial. According to the fixed effects model (2b), an increase of 10% of program users in the direct peer group leads to a 6.62% increase in individual utilization of the health services. The effect is larger than in the previous models suggesting that the OLS estimates are downward biased, which may result from non-linearities and heterogeneity in the correlated effects (De Giorgi et al. 2010) or an 'exclusion bias' (Caeyers 2014a). The estimated effects could also represent a local average treatment effect (LATE) explaining the differences between the OLS and IV estimation. Such an explanation would hold if direct peers who are stronger influenced by their peer's characteristics (the so called compliers in this case) also exhibit a stronger endogenous peer effect on ego (Angrist & Pischke 2009).

The observed changes in effect sizes are comparable to other studies which report peer effects of similar size lending further support to my findings. For instance, using the same identification strategy, De Giorgi et al. (2010) report an average peer effect of 6.9% (restricted peer group definition) to 8.0% (wider peer group definition). Similarly, Caeyers (2014b) obtains a peer effect estimate of 7.7% and in De Melo (2014) peer effects in education outcomes range from 3% in science to 4.6% in reading in their full fixed effect specifications.

Like in the OLS models, I do not find much robust evidence for contextual peer effects on individual behavior. Again, having direct peers with a longer membership duration reduces utilization of the health services. In the fixed effects model, I do in addition observe that a higher utilization of health services provided by other institutions in the direct peer group is associated with a reduced individual take-up of the KDCI services. This may reflect a tendency of clients to follow their peers and to substitute KDCI health services with the services offered by other facilities. Among the individual characteristics, I observe that being a member of the organization for a longer time and having a personal health insurance are positively related with the propensity to make use of the essential health services. I test for the robustness of my results in the following section in which I base my identification on dynamic information about the timing of the first uptake of the medical check-ups.

6.3 Dynamic Analysis: Peer Effects on the Adoption Hazard

Table 6 shows the estimates of the discrete-time hazard models. The coefficients are exponentiated and can hence be interpreted as hazard ratios. All models control for the logarithmic time variable that reflects the baseline hazard and the full set of individual and first order peer characteristics. Instead of individual membership, I include a variable that measures the time difference between the respective time period and the survey in 2015.

In total, I estimate four model specifications. The first model 3a includes only the mean uptake of the program $\bar{y}_{R_{it}}$ in the peer group at time t. The models 3b interacts the mean program uptake with the baseline hazard to allow peer effects to vary over time. In the final two models 3c and 3d, the central explanatory variable, mean uptake in the peer group, is split up in two variables which capture the mean uptake among weak and strong ties and peers with a low and high indegree, which I define as individuals who are connected to more than 25% of the other center members (30.7% of all respondents, all results are robust to different status specifications). Please note that this specification requires that observations are connected to at least one weak and one strong tie, and to at least one peer with a low and one with a high indegree, respectively, which explains the drop in the number of cases.

Table 6 - Complementary log-log hazard models: Uptake of program over time

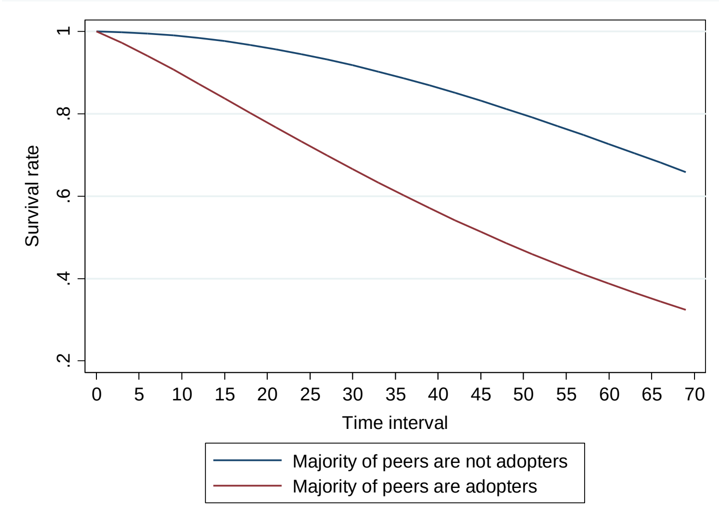
	Outcome: Individual program uptake							
	3a		3b		3c		3d	
Baseline hazard (log time)	1.650***	[0.199]	2.008***	[0.339]	1.662***	[0.220]	1.686***	[0.194]
Endogenous peer effect								
Program uptake (all)	8.744***	[2.352]	67.630***	[90.391]				
Program uptake * log time			0.550*	[0.197]				
Program uptake (weak ties)					2.920***	[0.731]		
Program uptake (strong ties)					2.680***	[0.465]		
Program uptake (low status)							3.591***	[0.997]
Program uptake (high status)							2.223***	[0.441]
Individual characteristics								
Standardized indegree	13.088***	[7.464]	12.739***	[7.185]	15.935***	[9.131]	9.259***	[5.842]
Time to survey (months)	0.978***	[0.008]	0.980**	[0.008]	0.975**	[0.010]	0.978***	[0.008]
Years of education	0.947**	[0.024]	0.946**	[0.024]	0.955*	[0.025]	0.950**	[0.024]
Health knowledge	1.035**	[0.017]	1.036**	[0.017]	1.040**	[0.018]	1.033**	[0.016]
Health status	1.119	[0.153]	1.127	[0.152]	1.097	[0.152]	1.085	[0.151]
Wealth	1.123*	[0.074]	1.128*	[0.075]	1.076	[0.068]	1.053	[0.066]
Other check-up	0.867	[0.107]	0.869	[0.105]	0.844	[0.113]	0.952	[0.134]
Personal health insurance	1.279*	[0.166]	1.280*	[0.163]	1.382**	[0.176]	1.276*	[0.176]
Children	1.028	[0.073]	1.033	[0.073]	1.007	[0.077]	1.044	[0.071]
Religiousness	0.965	[0.111]	0.968	[0.110]	0.947	[0.106]	0.962	[0.109]
Church visits	0.948	[0.037]	0.951	[0.037]	0.953	[0.037]	0.943	[0.037]
Social support	1.007	[0.148]	1.024	[0.148]	0.936	[0.147]	0.949	[0.136]
Contextual characteristics								
Peers' membership duration	0.988**	[0.005]	0.988**	[0.005]	0.987**	[0.005]	0.987**	[0.005]
Peers' years of education	0.921*	[0.041]	0.923*	[0.041]	0.977	[0.046]	0.937	[0.045]
Peers' health knowledge	1.002	[0.038]	1.005	[0.040]	0.983	[0.039]	1.047	[0.043]
Peers' good health status	1.279	[0.438]	1.274	[0.438]	1.627	[0.603]	1.556	[0.617]
Peers' wealth	0.906	[0.155]	0.907	[0.153]	0.925	[0.191]	0.872	[0.154]
Peers' other check-up	0.754	[0.226]	0.73	[0.225]	0.881	[0.238]	0.572*	[0.186]
Peers' personal health insurance	0.748	[0.243]	0.761	[0.243]	0.822	[0.293]	0.686	[0.262]
Peers' children	0.981	[0.075]	0.983	[0.075]	1.000	[0.082]	0.977	[0.079]
Peers' religiousness	0.756	[0.167]	0.751	[0.166]	0.617*	[0.157]	0.642*	[0.166]
Peers' church visits	0.958	[0.087]	0.961	[0.087]	0.999	[0.099]	1.037	[0.110]
Peers' social support	1.197	[0.315]	1.221	[0.323]	1.216	[0.357]	1.109	[0.351]
Additional controls included	Yes		Yes		Yes		Yes	
Fixed effects	Yes		Yes		Yes		Yes	
Observations	12540		12540		10368		10102	
AIC	2637.283		2635.099		2396.216		2379.75	

Notes: Coefficients are displayed as hazard ratios, standard errors in brackets. Standard errors are clustered on center level (m=70). Additional controls included in the model, but not displayed: Number of peers at time t, standardized indegree, network size, network density, relationship and marital status, age, household size, parental education background, and distance to closest health facility. Fixed effects calculated for 15 neighborhood clusters by including neighborhood dummies. P-value: * p≤0.1, ** p≤0.05, *** p≤0.01.

The baseline hazard is estimated in model 3a at a value of 1.650. An increase in the logarithm of time by one (i.e. in the membership duration or the time since introduction of the program) is associated with an increase in the hazard to use the program of 65.0%. As can be inferred from the time to survey variable among the individual characteristics, uptake of the program was overall lower in the first time after introduction of the program. The variable measuring mean program adoption among the direct peers reveals again a significant and substantial peer effect. Having 10% more peers in the network who used the program before raises the individual hazard to adopt by 87.44% confirming the previous findings.

In the second model the mean uptake is interacted with the baseline hazard indicating an interplay between the two variables: Peer effects seem to be strongest in early time periods after program exposure and become weaker as time progresses. Figure 3 shows the survival rates over time for respondents with a mean uptake in the peer group greater than 50% and those with a mean uptake below this threshold. Clearly, the chances of not being a user, i.e. the survival rates, are much lower in the group with a majority of adopters among the peers. As time progresses, however, the marginal peer effect in this group decreases leading to a flattening of the curve. For those respondents with fewer adopters in the peer group, on the other hand, uptake increases more steeply over time leading to a slight narrowing of the gap between the two groups.

Figure 3 - Survival functions over time by adoption in the peer group



In the next two models, the mean uptake variable is split to capture the uptake in different subgroups in the social networks: Uptake by weak vs. strong tie peers and peers with a high vs. low indegree. According to model 3c, both weak and strong ties exhibit a positive peer effect on individual adoption ($p \leq 0.01$) of almost equal size suggesting that relationship strength does not matter for the size of the peer effects in my setting. When I analyze the peer effects separately for low and high status peers, I find again a positive, and similarly strong effect for both subgroups in the network. Although the uptake in the low status group seems to be more influential (effect of 3.591 vs. 2.223), the two coefficients are not statistically different from each other ($p>0.1$)

Yet, if I interact the mean uptake of peers with lower and higher status with the individual indegree, I find evidence for an interesting interplay. For better illustration, I categorized the individual indegree into a binary variable with high status individuals being connected to more than 25% of the network. The results, which are reported in Table A4 in the appendix, do also hold if I use the continuous individual indegree variable. While individuals with a high standardized indegree generally express higher levels of take-up, I find low status peers' behavior to be more influential for high status individuals than the other way round (coefficient difference significant with $p \leq 0.1$). I also observe a significantly positive peer effect of smaller size ($p \leq 0.1$) of low status peers' behavior on low status individuals' adoption decisions. On the other hand, I do not find evidence that well-connected individuals are influenced by their high-status peers.

Why are high status individuals more susceptible to the behavior of their lower status peers? One possible explanation for this finding is that lower status clients are less well integrated in the microfinance group and less interested in the activities of my partner organization. Uptake by better connected, more active members in the network thus may have less of an effect on them compared to the other way round. The adoption of lower status peers, on the other hand, may serve as a strong motivator for higher status individuals who have already an a priori higher adoption probability and may perceive themselves as role models in the microfinance groups. To credibly maintain their status as good clients in the network they may hence be more susceptible to external influences from ties with lower status.

In the models, several of the included individual characteristics exhibit a robust effect on the use of the health services. Respondents are more likely to adopt if they have higher health knowledge and if they hold a personal health insurance. Furthermore, I find weak evidence that wealthier and less educated clients are more likely to make use of the program. Again, I do not find any substantial evidence for contextual effects. Like in the previous modes, the peer's average membership duration is negatively correlated with individual uptake. Besides, I find weak evidence for negative effects of peers' level of education and religiousness. However, these effects are not robust across models.

7 Discussion and Conclusion

In this paper, I study the role of peer effects for the use of health services and medical checkups that are offered as part of the integrated health program of a microfinance institution (MFI) in the Philippines. In the recent years, MFIs all over the world got increasingly engaged in the provision of health services in addition to their core financial activities (Leatherman et al. 2012; Leatherman & Dunford 2010). While this trend is increasingly shaping today's health care service landscape in many low- and middle-income countries, little is known about client's adoption of such programs and the role of the microfinance groups for individual uptake decisions.

I make use of a novel instrumental variable strategy to overcome reflection and endogeneity problems in the estimation of peer effects using non-experimental, cross-sectional data (Bramoullé et al. 2009). The approach exploits information on the structure of the networks and partially overlapping peer groups to reach identification. Besides, I consider the variation in another dimension, the timing of the program uptake, to check for the robustness of my results and to explore some mechanisms that moderate the strength of peer effects under different conditions.

Studying microfinance group networks offers several advantages for the analysis: First, as the microfinance groups are characterized by clear boundaries, I can use pre-defined sampling frames of the considered networks and do not have to rely on proxies, such as geographical proximity or shared characteristics, when defining the peer groups in the networks. Respondents were asked to directly nominate their interaction partners from the entire list of clients allowing me to collect sociometric information on the complete microfinance network. Furthermore, as only clients of my partner organization and their families are eligible to use the program, uptake cannot be strongly influenced by network outsiders reducing disturbing external influences.

I find evidence for substantial endogenous peer effects in the microfinance group networks. According to my preferred IV specification, an increase of program uptake by 10% in the direct peer group leads to an increase in the individual uptake probability by 6.6%. The results do also hold in the discrete-time hazard models, which show that an individual's decision to make use of the health services is strongly influenced by the percent of peers who have used the program before. Further analyses using the dynamic information reveal that peer effects differ over time. The social influence seems to be strongest briefly after the first exposure to the program and to gradually fade out over time. This is in line with findings from other studies, such as by Oster & Thornton (2012) or Sacerdote (2001). It becomes evident that there is an additional value to observing behavior over time in a dynamic setting, even if the information was collected only retrospectively.

While I do not find that behavior of strongly connected peers is more relevant than the one of weakly connected peers, the peers' structural position in the network matters. I find peers with fewer incoming connections than the individual, i.e. a lower structural status, to be more influential for the take-up decision of higher status individuals. This challenges the popular view that more central actors in the network are exhibiting a stronger influence on their peers (Ibarra & Andrews 1993; Munshi 2004; Valente & Pumpuang 2007; Perkins et al. 2014; BenYishay & Mobarak 2015). One explanation for the finding is that clients who are better integrated in the microfinance networks are more active and more interested in the provided services, as can be inferred from their higher a-priori uptake probability. These clients may want to serve as role models and develop a reputation as good clients (Fehr 2004; Kreps & Wilson 1982). If a larger number of their less well-connected (and arguably less active) peers starts using the services, they may feel more inclined to start using the services themselves as an expression of their strong interest. In other words: If even the less well-connected network members start using the services, the better integrated clients may face a stronger fear of loosing their face if they do not follow making them more susceptible to influences from their lower status peers. The finding could also reflect strategic motivations by the high status individuals who wait for their structurally more dependent peers to experiment with the program first to learn from their experiences (Cook & Emerson 1978; Yamagishi et al. 1988). However, as overall uptake is higher and average adoption times are shorter in the first group, this is not a likely explanation for the observed patterns.

The findings reveal the importance of understanding the exact mechanisms which underlay the observed peer effects. Although I have shown that peer effects can be substantial in the considered setting, it is unclear whether they are driven by pure imitation, learning, or the existence of externalities.[6] Importantly, without better knowledge about the actual mechanisms at play, it is impossible to calculate the social multiplier resulting from the interactions as the size of the multiplier fundamentally depends on the clients' preferences and utility functions (Graham 2015). Moreover, although low status peers are found to exert stronger influence on their higher status peers on the individual level, this does not necessarily translate into an overall greater influence. Although their influence is weaker, better connected individuals can reach out to more peers and hence may have a more substantial effect on the entire network.

Conducting research on social networks comes with various challenges ranging from the appropriate definition of the peer group to econometric difficulties in the identification. Also this study faces some limitations. First, using cross-sectional information I am unable to properly trace the dynamics of the social interactions in the networks. Even though I try to integrate more dynamic elements in the hazard model estimation, I have to rely on the retrospective information provided to me by the respondents. Also, my analyses are based on survey data, which might be prone to measurement and recall error. Second, this study rests on the assumption that I am able to adequately capture the relevant peer groups in the microfinance networks and that external influences from outside the network are minimized. Although my analysis takes advantage of the peculiar setting of the microfinance group networks, I cannot perfectly control for influences from outside the network which may have affected the results (see also Valente et al. 2013). This is a common challenge in social network studies, independent of whether they focus on networks in classrooms (e.g. De Melo 2014), dormitories (e.g. Sacerdote 2001), or villages (e.g. Conley & Udry 2001). Finally, although my used instrumental variable methodology is rigorous, I cannot fully exclude possible bias due to remaining endogeneity. In particular, the endogenous nature of the peer group formation process may have created unobserved similarities in preferences and background characteristics that may have influenced my results. In order to minimize remaining endogeneity, I estimate my models with neighborhood fixed effects and by including a variety of individual and contextual characteristics that are potentially relevant for the adoption decision.

Understanding the dynamics in social networks and their influence on program uptake is important for the promotion and anchoring of health interventions. Although my analysis is focused on the context in the Philippines, the findings of this study have broader applicability and come with several policy implications. As has been shown, the utilization of the health services is largely determined by the behavior of other clients in the network with peer effects being strongest shortly after the first introduction of the program. Social networks can hence be effectively used for client targeting and the promotion of health programs. In particular, based on my results, two groups should receive special attention: First, individuals with a very central position in the network as they can reach out to and influence many others; and second, weakly connected individuals, who are not strongly integrated in the microfinance group. Addressing the latter group may be useful because lower status individuals are overall less likely

[6] I included an index for peers' beliefs about the potential benefits and costs of the program to the models in some additional analyses not reported in the paper. If peer effects worked through the transmission of experiences and beliefs I would expect a reduction in the peer effect after controlling for the belief measure. However, I do not observe any substantial changes in the size of the peer coefficient serving as an indication that social learning may not be the primary underlying mechanism driving the peer effects in my setting.

to make use of the health services (net of peer effects) and a stronger promotion of the program among them may help increasing their uptake. At the same time, this may generate important indirect effects on individuals with a more central position in the network who are found to be most strongly influenced by the behavior of their lower status peers. In general, my results suggest that fostering the integration of clients in the microfinance groups and strengthening social ties between them is a useful strategy, which may positively affect the utilization of the services through social interaction effects. Ultimately, this can help raising the outreach of the considered health program and contribute to improving the health situation in the impoverished communities.

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Appendix

Table A1 - Medical check-up packages offered by the Kasagana-Ka Development Center

<table>
<tr><td>Package A
Recommended age:
34 years old and below</td><td>Package B
Recommended age:
35 to 39 years old</td><td>Package C
Recommended age:
40 years old and above</td><td>Package D
Recommended age:
15 years old and below</td></tr>
<tr><td>• Complete blood count
• Urinalysis
• Stool examination
• Chest x-ray
• Medical check-up</td><td>• Complete blood count
• Urinalysis
• Stool examination
• Chest x-ray
• Fasting blood sugar
• Lipid Profile
• Medical check-up</td><td>• Complete blood count
• Urinalysis
• Stool examination
• Chest x-ray
• Fasting blood sugar
• Lipid Profile
• Blood urea nitrogen
• Creatinine
• SGOT / SGPT
• Electro-cardiograph
• Medical check-up</td><td>• Complete blood count with blood typing
• Urinalysis
• Stool examination
• Chest x-ray
• Medical check-up</td></tr>
<tr><td>PHP 310</td><td>PHP 480</td><td>PHP 940</td><td>PHP 180</td></tr>
</table>

Table A2 - 2SLS first stage estimation

Instruments	Outcome: Mean uptake among peers 1		2	
Peers' peers' membership duration	-0.004***	[0.001]	-0.004***	[0.001]
Peers' peers' years of schooling	-0.041***	[0.008]	-0.018**	[0.008]
Peers' peers' health knowledge	0.012**	[0.006]	0.004	[0.006]
Peers' peers' health constitution	-0.245***	[0.051]	-0.222***	[0.052]
Constant	0.707***	[0.197]	0.029***	[0.010]
Additional controls included	Yes		Yes	
Fixed effects	No		Yes	
F-test excluded instruments	20.13		18.31	
Hansen J statistic	4.472		3.001	
p-val Hansen overidentification test	0.2148		0.3915	

Notes: First stage IV coefficients in cells, robust standard errors in brackets. Models include in addition all exogenous individual and contextual variables: Wealth, utilization of health service of another organization, health insurance, number of children, religiousness, church visits, and social support. Additional exogenous controls included in the model, but not displayed: Number of peers, number of second order peers, standardized indegree, proportion of strong ties, network size, network density, relationship and marital status, age, household size, parental education background, and distance to closest health facility. Fixed effects calculated for 15 neighborhood clusters. P-value: * p≤0.1, ** p≤0.05, *** p≤0.01.

Table A3 - Summary statistics of background characteristics for first and second order peers

	Peer characteristics				Peers' peer characteristics			
	Mean	SD	Min	Max	Mean	SD	Min	Max
Membership duration (months)	50.36	17.76	4	110.4	42.33	15.17	7.5	95.33
Years of education	9.69	1.67	3.5	15.25	9.62	1.32	3.6	13.25
Health knowledge	16.22	2.22	7.75	23	15.49	1.85	7.75	22.5
Health status	0.77	0.2	0	1	0.77	0.17	0	1
Age	45.68	5.08	26	62	44.73	4.46	27.67	62
Wealth	1.88	0.54	0.48	3.97	1.74	0.45	0.45	3.39
Cognitive abilities	4.12	0.7	1	7	4.07	0.56	2.25	5.83
Religiosity	2.29	0.31	1	3.5	2.31	0.27	1.25	3.33
Marital status	0.71	0.23	0	1	0.68	0.19	0	1
Number of Children	2.23	0.86	0	5.75	2.22	0.63	0.25	4.75
Belief about program benefits	3.95	0.27	2.86	4.76	3.88	0.21	3.21	4.71

Table A4 - Complementary log-log hazard models: The role of peers' and ego's structural position in the network

	Outcome: Individual program uptake			
	3e		3f	
Baseline hazard (log time)	1.722***	[0.200]	1.764***	[0.207]
Endogenous peer effect				
Uptake low status peers	3.765***	[1.054]		
Uptake high status peers	2.203***	[0.439]		
Uptake low status peers & low status respondent			2.619***	[0.887]
Uptake low status peers & high status respondent			8.630***	[3.283]
Uptake high status peers & low status respondent			2.878***	[0.693]
Uptake high status peers & high status respondent			1.407	[0.451]
Own characteristics				
Standardized indegree (dummy)	1.361**	[0.211]	1.423	[0.323]
Time to survey (months)	0.981**	[0.008]	0.982**	[0.008]
Observations	10102		10102	
AIC	2388.873		2385.504	

Note: Coefficients are displayed as hazard ratios, standard errors in brackets. Standard errors are clustered on center level (m=70). Model 3e reproduces model 3d including a binary measure for the standardized indegree. Model 3f presents the interactions between peers' and respondent's structural position in the network. All individual and contextual variables included, but not displayed: Wealth, utilization of health service of another organization, health insurance, number of children, religiousness, church visits, and social support. Additional controls included in the model, but not displayed: Number of peers, proportion of strong ties, network size, network density, relationship and marital status, age, household size, parental education background, and distance to closest health facility. Fixed effects calculated for 15 neighborhood clusters by including neighborhood dummies. P-value: * p≤0.1, ** p≤0.05, *** p≤0.01.

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