

Who benefits from network intervention programs? TERGM analysis across ten Philippine low-income communities

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ABSTRACT

Building social capital and strengthening social networks among members of low-income communities has been recommended as a potential pathway out of poverty. However, it is not clear how network-strengthening interventions and community-based programs interact with pre-existing networks and power structures. We examine the impact of one such intervention in ten low income communities in the Philippines. The intervention is a standardized program of a faith-based organization implemented in thousands of communities in multiple countries. It brings together low-income individuals in each community for 16 weekly sessions about health, income generation, and Christian values. An important but yet unmeasured goal of the intervention is the strengthening of social networks among the participants. We measured the social networks before and after the intervention and analysed their changes both separately and jointly for all ten communities with temporal exponential random graph models (TERGM). We modelled the post-intervention network structures conditioning on the pre-intervention networks, pre-intervention node attributes, and attribute changes through the intervention. We found social engagement (measured by social visits to others) to moderate most consistently the effects of the intervention across the ten communities. Those who were more socially engaged consistently strengthened their networks through the intervention. By contrast, some network mechanisms strongly diverged between the communities. In particular, religiosity was positively associated with gaining social links through this faith-based intervention in some communities and negatively in others. Similar communities may in some aspects react to the same intervention in opposite ways—a phenomenon that should be further explored through studies of larger numbers of comparable networks.

Introduction

People living in poverty who lack access to institutions and services need social networks just to get by in their lives. Many programs try to strengthen the networks of the poor but with little research-based evidence (Perkins et al., 2015). Faith-based organizations are large providers of such interventions (Summerskill and Horton, 2015; Green, 2016) and we would like to know who benefits most from them? Do programs that bring together members of low-income communities help socially isolated individuals access social support and resources? Specifically, we are asking what is the role of pre-existing social networks and what are the relationships between change in social networks and participants' self-reported health, wealth, and faith?

We focus on a program called “Transform” that has been

implemented in a standardized format in thousands of communities in multiple countries by International Care Ministries (ICM), a faith-based non-governmental organization. We collected complete longitudinal network data from before and after this 16-week intervention organized in ten low-income communities in the Philippines. The intervention brings together marginalized women and men in each community for weekly sessions that include training on health promotion, income generation, and Christian values. Conditioning on the participants' pre-existing networks, we analysed the ten community networks both jointly in a common model and also separately. We applied a version of temporal exponential random graph models (TERGMs) to this data to analyse the social network evolution among the intervention participants during the program and the interplay of networks and the participants' changing personal attributes.

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Background

Social support networks in low-income communities, wellbeing, and health

Social networks can improve well-being, health, and people's lives through several social mechanisms, including social influence, social engagement, access to resources, and actual and perceived social support (Smith and Christakis, 2008). Supportive social relationships are good for mental health, the functioning of the immune system, and an overall decrease in all-cause mortality risks (Cohen and Wills, 1985; House, Landis et al., 1988; Seeman, 1996; Cohen, 2004; Holt-Lunstad et al., 2010). People who have strong social networks of close confidants live longer than socially isolated individuals (Berkman and Syme, 1979; Blazer, 1982; House et al., 1982; Welin et al., 1985; Schoenbach et al., 1986; Case et al., 1992; Williams et al., 1992; Berkman et al., 2004; Hobbs et al., 2016). In reverse, health can also affect access to social support as health impediments can make people less willing or able to participate in social activities and affect their popularity as social companions (Schaefer et al., 2011) and many stigmatised diseases can cause "social death" (Tsai, 2013).

Most studies on these relationships appeared to have relied on data of separate individuals or separate links between pairs of individuals (from which extrapolation of network-level mechanisms is problematic, Jones and Handcock, 2003). For example, the roles of spouses (Gove, 1973; Zick and Smith, 1991; Lillard and Waite, 1995; Lillard and Panis, 1996; Korenman, Goldman et al., 1997) and parents (Sorkin et al., 2014) have been thoroughly explored but these relationships do not exist in a vacuum. By and large, individuals have multiple relationship dyads and these networks remain underexplored especially among the poor.

That is not ideal because community support networks are crucial for those who lack access to institutional support and cannot afford commercial services (Perkins, Subramanian et al., 2015). Marginalized individuals in low and middle income countries (LMICs) who lack financial and transportation means often depend on informal social relationships within their immediate neighbourhoods to access basic resources (Matous and Ozawa, 2010; Matous et al., 2013). However, the poorest community members may also suffer most from social exclusion as extremely low socio-economic status has been associated with fewer supportive social relations and poorer overall relationship satisfaction (Conger et al., 2010; Umberson and Montez, 2010; Martire and Franks, 2014).

Personal network studies in LMICs have often measured individuals' direct contacts (Kohler, 1997; Adams et al., 2002; Fonseca-Becker and Valente, 2006; Kohler, Behrman et al., 2007; Avogo and Agadjanian, 2008; Wutich and McCarty, 2008; Edmonds et al., 2012; Sandberg et al., 2012; Zhang et al., 2012; Moore, 2013), which is useful, but sociocentric data that capture connections between all individuals within a community allow researchers to further analyse collective mechanisms.

Importantly, social networks may play different roles in different communities and a typical limitation of many sociocentric studies is a low degree of their generalizability. It has been shown that different communities that may seem similar to an outsider can have strikingly different structures (Seeman et al., 1993; Entwisle et al., 2007; Helleringer and Kohler, 2007; Smith and Christakis, 2008; Sandberg et al., 2012; Zhang et al., 2012). However, available sociocentric studies still mostly focus on one or a few communities. Studies of multiple comparable networks in LMICs are rare, which limits the generalisability of results from each study (Perkins et al., 2015).

Faith-based community intervention programs

Jointly engaging community members in participatory programs has long been regarded as integral to community development in LMICs (Farnsworth et al. 2014). In particular, integrated community-based programs, which combine activities to stimulate change on both intra-personal and interpersonal levels have been recommended (Campbell,

2007; Singla et al., 2015; Shah More et al., 2017). As the vast majority of the global population is religiously affiliated (Karam et al., 2015), many of the organizations that deliver such interventions, especially in LMICs, are faith-based organizations (FBOs). FBOs have a particularly strong presence in neglected, underserved, and hard to reach populations where government programs may not be available, effective, or are not trusted by the targeted communities (Green, 2016). FBOs have been praised by some observers for reportedly providing low-cost culturally sensitive services and facilitating trusting relationships among the poorest who do not have the means to seek services or support outside of their communities (Bopp 2012).

A number of authors have proclaimed additional benefits of faith-based programs compared to secular community-development interventions, in particular those related to health. Firstly, religious affiliation and church attendance is correlated with physical and psychological health in many parts of the world (Kark, 1996; Oman, 1998). These associations have been explained by the positive role of social networks and social support provided by fellow church members as well as the role of prayer and health-related religious practices (Fiala et al., 2002). Secondly, religious institutions can reportedly influence their members' behaviour at multiple levels. Churches can discourage unhealthy behaviours by describing the body as the temple of God, stimulate communal support within the "church family", promote help and care for the sick (Summerskill and Horton, 2015), and reinforce social integration within the local community by encouraging local church attendance (Holt, 2006). Thirdly, a faith component that uses religious messages that fit the participants' existing beliefs can improve cultural targeting of interventions and thus help to get the message across (Resnicow et al., 2005). Finally, participants of faith-based health interventions report enjoyment of group-based spiritual activities (Yeary et al., 2011).

The ultimate desired social outcome of community-based faith interventions has been stated as building community competency and social support structures that sustain the program benefits after external resources have been withdrawn (Eng et al., 1985). In general, community-based initiatives are often expected a priori to strengthen the targeted community through collective activities, more intense social interactions, and the building of social capital (Matous, 2013). However, community-based development programs have also been criticised for reinforcing existing social inequalities within the communities by allowing the most central community members to exploit such initiatives to their benefit (Cooke and Kothari, 2001). The potential for aggravating social inequities by external social interventions has been highlighted by a number of authors (Razzaque et al., 2007, O'Neil et al., 2014; Antai et al., 2009; Black and Surkan, 2015; Blanchard et al. undated; Braveman et al., 2017).

The literature distinguishes faith-placed and faith-based interventions (Stewart 2016). Faith-placed programs come from outside of the religious context and are only implemented in faith settings, without adding specific components of that particular religion (Schoenberg 2015). Faith-based interventions are conducted for and by individuals belonging to a certain faith, not researchers or external health professionals, and the program typically includes the spiritual doctrine of that faith (Robinson-Edwards, 2018). There are also some community-based programs outside of faith-based or faith-placed settings that only incorporate some religious messages to increase their acceptance (Joseph 2017). The community-based program analysed in this study is a prototypical case of a faith-based intervention.

Caution has been called for around faith-based programs. In faith-based interventions, increased religious attendance has often been reported but religious attendance should not be automatically interpreted as improved social support. Religion-linked social controversies include family planning, immunisation, genital mutilation, gender, and end-of-life issues (Tomkins et al., 2015). Churches want to save souls, which may include evangelism and mandating the adoption of beliefs of the delivering organization (Campbell, 2007).

In summary, religious institutions invest large amounts in community-based interventions with strong normative components and it would be useful for policy makers to understand better the outcomes of such large-scale programs (Bryan et al., 2020). However, only a small number of rigorous assessments of the outcomes of faith-based interventions have been conducted and these predominantly focus on African-American churches in the United States (DeHaven 2003, Campbell 2007). The real impacts of faith-based community interventions on shaping the lives of the poor in LMICs are still not well understood (Karam et al., 2015). We do not know, for example, whether faith interventions benefit those who do not subscribe to their religious message. Rigorous testing and continued exploration of the differential impacts of faith-based interventions, particularly those involving poor community members, are warranted.

The Transform approach

This study examines a program provided by International Care Ministries, which is a non-profit Christian organization that implements standardised large-scale community-based poverty alleviation programs across the Philippines and other countries. During the time of this study in 2015, 975 communities received the Transform program annually, representing approximately 30,000 families. Since 2009, around 1.5 million individuals have participated in Transform. The intervention program is precisely specified and has a common structure with programs of several other FBOs involving millions of people around the world, which makes it an important model to study (Bryan et al., 2020). Households are identified and screened for eligibility using a poverty screening scorecard loosely based on the Poverty Probability Index for the Philippines, including indicators such as the quality of construction materials of the dwelling, access to electricity, clean water and sanitation, and household income (PPI, 2014). The 30 lowest-scoring households in each neighbourhood are invited to join the program, however all screened households are allowed to sit in as visitors.

The Transform program is delivered through weekly group sessions, which is a common format of faith-based interventions reported in the literature (Bopp, 2012). The core components of the program focus on three themes, “Values”, “Health” and “Livelihoods”, taught during fifteen 90-minute weekly meetings. A graduation ceremony is held in the 16th week. Trained staff teach the health and livelihood lessons, that target specific health issues such as child malnutrition or tuberculosis and livelihood needs such as business skills, saving, and gardening. A local church representative teaches the “Values” component. While this component is based on Christian beliefs it does not teach specific catholic or protestant doctrines but instead emphasises general spiritual values of Christian teachings.

Methods

We use sociocentric longitudinal network data from the 16-week Transform intervention in 10 communities. The 10 communities analysed in this study were randomly selected from 39 low-income communities that were scheduled to receive the Transform program in the Negros Occidental region in the Philippines (Fig. 1).

We apply TERGMs to this data to analyse the interplay between the networks of the intervention participants with their faith and health. The fitted TERGM serves as a reference point quantifying how the pre-intervention network structure and actors’ original and evolving attributes predict their post-intervention networks. Similar to the approach taken by Robins and Alexander (2004), we examine how closely the TERGM approximates the complex reality, which aspects of the network are modelled relatively faithfully, and in which aspects complex endogenous tendencies make the reality diverge far from the model.

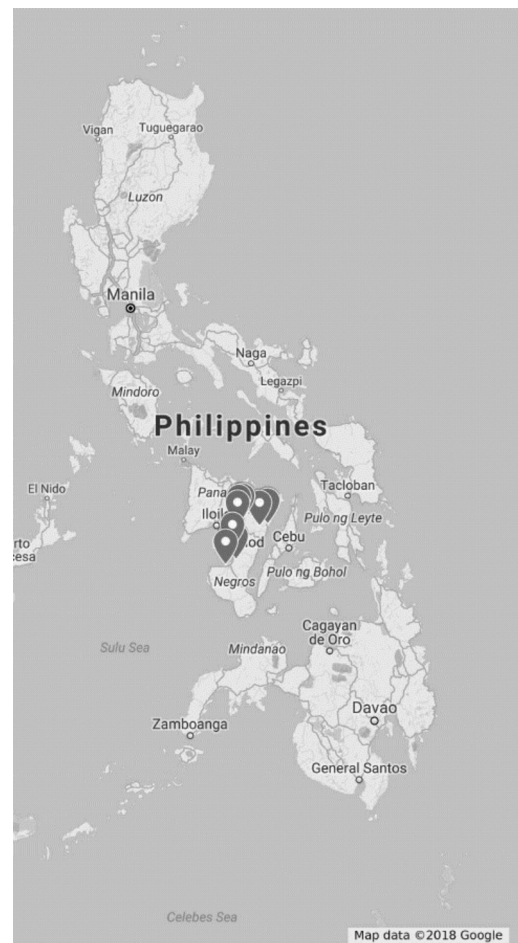


Fig. 1. The location of the surveyed communities.

Survey and sample description

Local community organizers submitted the names of potential Transform participants in July 2015. These households were screened based on a poverty scorecard introduced above and the poorest households were prioritized. One member of each household was invited to Transform. The invitees were the individuals who self-identified to be the main person responsible for health and financial decisions in their household; 85 % of them were women. There were 379 individuals who qualified for the program (37.9 per community) but not everyone participated in the program and in both surveys before and after (see the numbers of valid observations in Table 1).

The pre-intervention and post-intervention data were collected in September 2015 and February 2016, respectively. The same survey instrument was used for both surveys, covering general household demographics of all household members (age, gender, marital status), human capital (education level and general health), financial capital (household income, consumption, savings), and physical capital (state of shelter, access to water and sanitation, ownership of appliances and vehicles), and food security items.

Respondents’ self-reported general health was measured on 1–5 Likert scale with categories standing for “very poor”, “poor”, “neutral”, “good”, “very good” (Ware et al., 1996). Self-reported health classified into these five categories is one the most used health status measures globally (Krause and Jay, 1994). A rigorous assessment across numerous longitudinal studies has shown that this self-rated health measure predicts mortality with impressive consistency even after controlling for common covariates that are known to predict mortality (Idler and Benyamini, 1997). Trust in neighbours was also measured on a

Table 1
Data description.

	n	mean	s.d.	median	min	max
PRE-INTERVENTION						
Total household income	272	4208.19	3352.01	3200	0	29800
Income per person per day	272	29.41	21.51	25	0	132
Perceived health problems (lower is healthier)	271	2.27	0.94	2	1	5
Importance of faith	266	3.86	0.50	4	2	5
Do you attend church weekly (1 = yes)	266	0.49	0.50	0	0	1
Trust in neighbours (higher means more trust)	272	3.87	0.84	4	1	5
Catholic (1 = yes)	270	0.6	0.49	1	0	1
Protestant (1 = yes)	270	0.35	0.48	0	0	1
POST-INTERVENTION						
Total household income	291	4008.88	3015.46	3000	0	16500
Income per person per day	291	30.23	23.96	25	0	230
Perceived health problems (lower is healthier)	290	2.05	0.84	2	1	5
Importance of faith	291	4.02	0.50	4	3	5
Do you attend church weekly (1 = yes)	289	0.51	0.50	1	0	1
Trust neighbours (higher means more trust)	290	4.01	0.66	4	2	5
Catholic (1 = yes)	289	0.68	0.47	1	0	1
Protestant (1 = yes)	289	0.28	0.45	0	0	1

five-point scale (no trust, tentatively trust, neutral, moderately trust, very trusting), as was the importance of faith (faith is important in my life: strongly disagree, disagree, neutral, agree, and strongly agree). The survey also asked whether the participant attended church weekly (yes/no; see Table 1).

The social network instrument asked the respondents whether they knew other members of their community Transform group, using a roster of all group participants. For each alter, the respondents were asked whether they knew the person well enough to discuss personal matters such as personal health issues together. These relationships do not necessarily depict actual mobilized support but signify relatively close personal relationships (as perceived by the respondent) that could potentially access support, should the need arise. The surveys were implemented by hired and trained third-party facilitators. To compensate the respondents for their time, each attendee was given three kilograms of micronutrient fortified rice.

Analysis

Temporal Exponential Random Graph Modelling (TERGM) aims at explaining current network structure, but also captures “memory” effects by treating previous network observations as exogenous covariates. There have been a few versions of TERGMs (Wasserman and Pattison, 1996; Robins and Pattison, 2001; Leifeld et al., 2018), and our model is based on TERGM proposed by Robins and Pattison (2001). We modelled post-intervention network structures (X) conditioning on the pre-intervention network structure (X'), pre-intervention node attributes (Y'), and attribute changes through the intervention ($Y_{\Delta} = Y - Y'$), where (Y) represents post-intervention attributes. We model the endogenous network processes post-intervention (X), and exam how pre-intervention network (X'), attributes, and changes of the attributes $\{Y', Y_{\Delta}\}$ relate to (X). We discuss the merits of other possible approaches to analyse this type of data in the discussion part of the paper.

Our TERGM can be expressed as

$$\Pr(X = x, X' = x', Y' = y', Y_{\Delta} = y_{\Delta}) = \frac{1}{\kappa} \exp \sum_Q \theta_Q z_Q(X, X', Y', Y_{\Delta})$$

where lower case labels represent realisations of networks or attributes.

$z_Q(X, X', Y', Y_{\Delta})$ are graph statistics counting the numbers of sub-graphs or network configurations of type (Q). The configurations can be derived from dependence assumptions among network ties or attributes where within each configuration of all tie- and attribute-variables are considered as dependent on one another conditioning on the rest of the network. Note that not all $\{X, X', Y', Y_{\Delta}\}$ are required for all configurations. For example, the endogenous post-intervention network processes can be represented by $z_Q(X)$, while the “memory” effect of pre-intervention network can be captured by $z_Q(X, X')$. Similar applies to the attributes $\{Y', Y_{\Delta}\}$.

θ_Q are parameters associated with z_Q . Positive and significant parameter estimate suggests the corresponding configurations happen more than we would expect from random occurrence. Negative estimates mean the opposite. For example, a positive and significant Sender effect for people with higher income pre-intervention suggests that they felt that they had many partners to confide in post-intervention.

κ is the normalising constant ensuring a proper probability distribution. As κ is not tractable, estimations of parameters rely on Markov Chain Monte Carlo (MCMC) simulations. We use an algorithm proposed by Snijders (2002) implemented in MPNet software (Wang et al., 2013) to estimate our models. A model is considered converged if the observed statistics are centred at the model distribution, represented by *t-ratios* that are smaller than 0.1 in absolute values. *t-ratios* are also used in model goodness of fit (GOF) tests, where a graph distribution is simulated from the converged model. GOF is assessed on statistics representing effects included in the model and statistics reflecting other aspect of the network structure, such the standard deviation and the skewness of the degree distribution and the global clustering coefficient. We consider that a model can provide adequate fit to an observed graph statistic if the *t-ratio* is smaller than 2.0. The GOF *t-ratios* can also be considered as *z-scores* comparing the model distribution with the observed data (Robins and Alexander, 2004).

We have conducted the analyses both for all communities separately and jointly. Similarly to Matous and Wang (2019), in the overall joint model, we combined all community networks into the same matrix, and used structural zeroes to prevent links between separate community networks in the TERGM. We use separate density parameters for each community to model the difference in network densities. The aim of the overall joint analysis was to examine whether there were any general measurable trends across the ten diverse communities, rather than exploring the particularities of each community.

For the overall dataset, it was possible to obtain convergence only for a basic model specification composed of baseline density effects for each community and interactions between nodal attributes and network activities. Inclusion of more complex higher order effects in the model, such as stars or triadic closure effects prevented model convergence. This model specification is similar to the p_2 model where the existence of network ties is considered interdependent within dyads, as well as the attribute values of the nodes and other ties within dyads (van Duijn et al., 2004). We use this model as a referencing graph distribution that captures the similarities and the differences in the tendencies for participants with different attributes or outcomes to form personal ties through the intervention. We follow the model selection strategy described by Van Duijn, et al. (2004) using backward selection based on Wald tests that identifies significant covariates. For higher-order effects, such as stars (AinS, AoutS), closure (ATA-T) and shared partners (A2PA-T), we follow the hierarchy of model specifications (Pattison and Snijders, 2012) where lower order insignificant effects are kept in the model if higher order effects are significant.

We present both the full model with all covariate effects and the parsimonious model derived by backward selection. Besides the baseline

density and reciprocity effects, the full model includes *sender*, *receiver*, and *difference* effects for each nodal attribute. The *sender* and *receiver* effects test whether nodes with higher attributes values tend to send or receive more ties, if the corresponding parameter is positive. The *difference* effects can be seen as dyadic attribute effects capturing heterophily between nodes within a dyad where positive parameter estimates suggest the greater the difference in attribute values, the more likely the tie exists; negative effects suggest homophily. Two models are presented in Table 2, where Model (a) is a complete model with all attribute effects included, while Model (b) is the final model which only includes significant variables. The model GOF comparison consists of a simulated sample of 1000 graphs from 100 million MCMC steps and was similar for both Model (a) and Model (b). The complete GOF test results are presented in the Appendix, while the full list of configurations can be found in MPNet manual (Wang et al., 2013) and Robins et al. (2009).

Effects of interest

The perceived availability of social support, especially emotional support, has direct effects on health and buffers the negative effects of stress (Cohen, 2004; Holt-Lunstad et al., 2010). It has been theorized already in the 1970s that what matters is the feeling that one is cared for in a supportive network (Cobb, 1976). Accordingly, the perceived number of available private confidants is a long-accepted measure of social and emotional support in health studies and is known to predict lower mortality (Berkman et al., 1992). In network studies, levels of social isolation and social support as perceived by ego have been found most relevant for health (Smith and Christakis, 2008). Therefore, we focus on the reported number of social contacts represented as the number of outgoing ties in the network as the main measure of perceived social support for each network actor. The number of reported confidants on private and health issues, or the actors’ outdegree is modelled by “sender” effect, also called “activity” effects in the ERGM framework. In the body of this manuscript, we focus on the reporting of the sender effects to reflect how the intervention program affect individual’s perceived access to supportive confidants. The complete models are presented in the appendices.

We empirically tested the relevance of available and potentially theoretically meaningful actor attributes for the creation and maintenance of communal social support networks in relation to this faith-based intervention focused on health improvement and income generation. These attributes included self-reported measures of trust and

social engagement with other community members, overall health, income, and the importance of faith and religious engagement. Health, income, and faith variables were included because they directly targeted by the three substantive modules of the intervention program. Socio-economic status, faith, and religious participation have also been reported to predict access to social support networks (Ellison and George, 1994; Weyers et al., 2008; Lim and Putnam, 2010; Merino, 2014; Letki and Mieriņa, 2015; Holt, Roth et al., 2018).

Social engagement and trust within the local community, although not an explicit component of the training, were included because they may be potentially important drivers and outcomes of social support networks in a community (Fischer, 1982; Putnam, 1995). By backward selection, we gradually eliminated the attribute effects that were clearly not significant until we obtained parsimonious models with only significant effects (plus any related lower-order effects as a control, if applicable). We assessed that the GOF of the parsimonious models was comparable to that of the complete models. We pursued this selection strategy both for the overall model and the separate community models. The parsimonious specification varies between the communities for the separate models.

Results

Table 1 shows the descriptive statistics for the sample before and after the intervention. The overall changes in personal attributes are small compared to standard distribution of these variables in the sample.

The changes in networks seem more substantial. The average density of networks across the 10 communities increased from 0.47 to 0.67 (see Fig. 2 for illustration). The average outdegree increased from 12 to 19. For reasons explained in the methods, we focus the reporting of results in this section on sender effects in Table 2. The sender effects capture ego’s reported discussants of private health matters used as a proxy for perceived access to social support. The full models with receiver variables and interaction variables of nodal attributes is in the appendix. The positive and significant Reciprocity and Pre-Intervention network effects show that the links tend to be reciprocated and more likely to exist where a relationship existed already before the intervention.

For brevity, we present results only for sender effects in the main body of the paper. Complete information about the models is in the Appendix. In Table 2, joint model (a) presents the sender effects of the complete model with all tested attribute effects, and joint model (b) presents the effects only of the parsimonious model from which

Table 2
TERGM Sender effects.

Sender effects associated with nodal attributes and their changes	Joint model (a)		Joint model (b)		Separate models		
	p.e.	s.e.	p.e.	s.e.	Positive	Negative	N.S.
Number of sessions attended	0.021	0.004	0.024	0.004	4	2	4
PRE-INTERVENTION ATTRIBUTES							
Male	-0.006	0.160			2	0	8
Trust in neighbours	0.453	0.044	0.501	0.027	5	1	4
Perceived health problems	0.273	0.044	0.274	0.039	4	0	6
Household income	-0.026	0.014			3	1	6
Attend church weekly	0.316	0.079	0.255	0.063	2	1	7
Importance of faith	0.067	0.044			3	3	4
Social visits to others	0.140	0.008	0.138	0.006	9	0	1
CHANGE IN ATTRIBUTES							
Trust in neighbours	0.498	0.035	0.529	0.026	4	2	4
Perceived health problems	0.314	0.035	0.324	0.031	5	1	4
Household income	-0.021	0.010			4	2	4
Attend church weekly	0.091	0.060			2	2	6
Importance of faith	0.145	0.037	0.093	0.022	2	3	5
Social visits to others	0.102	0.005	0.101	0.004	8	1	1

This summary table reports results only for sender effects because of their substantive importance. The full fitted models are in the Appendix. Significant effects in the joint models are indicated with bold font where the parameters in absolute values are greater than twice the magnitude of the associated standard errors. The “Separate models” section on the right-hand side of the table summarises the number of positively significant and negatively significant result for each sender effect across the ten communities.

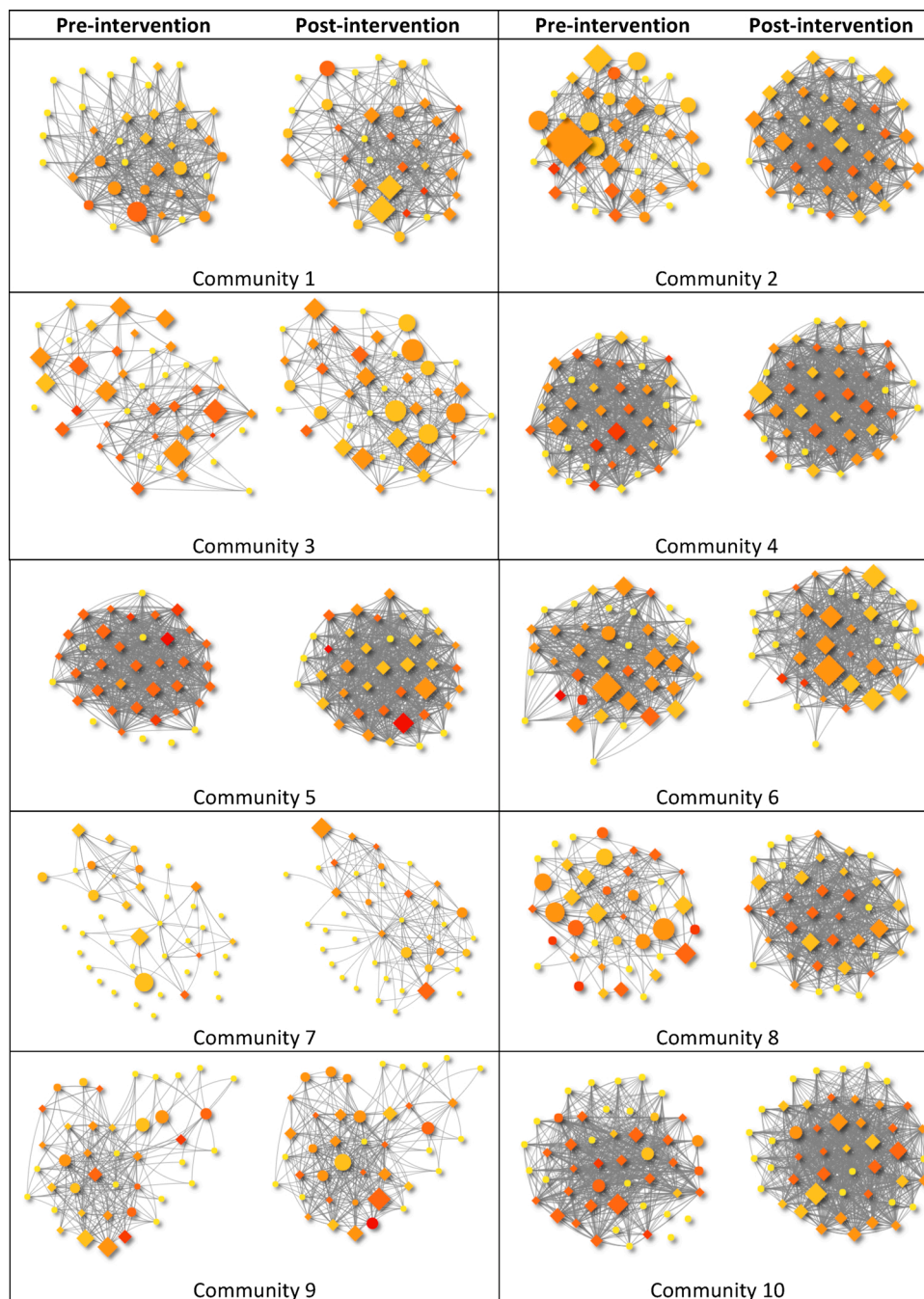


Fig. 2. Pre- and post-intervention networks. Node colour represents health condition (red report sever health problems), node size represents income; diamond shape nodes represent importance of faith greater than 3 out of 5 (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article).

insignificant effects were omitted. Comparison of the two models shows that one sender attribute (change in household income) that was originally significant became insignificant when other insignificant variables were omitted. All other significant sender effects remained significant. In the right-hand side of the table, results of the separate (parsimonious) models are summarised in terms of the number of significantly positive and significantly negative results across the ten communities.

We discuss first the overall parsimonious model (b). We can firstly see that, overall, participants who attended more sessions seemed to create more links. Next, we focus on the relation of the participants' pre-intervention attributes to reporting a higher number of supportive relationships after the intervention. People who trusted their neighbours, who reported worse health, who paid more social visits to others, and

who attended church weekly before the intervention, overall reported more supportive confidants after the intervention. (We do not see any significant gender difference.)

Controlling for these effects (and all the other accompanying effects of these attributes that improve the model fit and are listed in the Appendix), the next set of results quantifies the relation of the changes in these attributes during the intervention to the number of perceived contacts after the intervention. Those who felt sicker, who increased their frequency of social visits and who strengthened their faith during the intervention, reported more social support by the end of the intervention.

From the z-scores in the model GOF comparisons (fully reported in the Appendix), we find that the network density effects for each

community and the selected nodal attributes sufficiently capture the lower order stars (two- and three-star configurations), two-paths, and cyclic-closure. The model does not sufficiently capture the outdegree distribution, transitive closure, and other triadic configurations. In other words, the observed personal attributes did not sufficiently explain the emergence of actors who sent disproportionately many links (i.e. individuals who reported very high numbers of supportive confidants) and the high degree to which links tended to cluster in transitive triangles. The predominance of transitive triangles (as opposed to cyclical closure elements) is also a sign that the observed social support networks generally tended towards more hierarchical structures than the networks simulated based on nodal attributes without network endogenous effects beyond dyads.

Analysis of separate communities summarised in the right-hand side of Table 2 and fully reported in the Appendix further shows that there were some noteworthy differences between the communities. (There were also more insignificant results because the smaller separate samples have lower statistical power.) The most consistent finding across the communities was that overall activity before the intervention in terms of social visits was clearly associated with increased access to potentially supportive relationships after the intervention. This effect was positively significant in nine out of ten communities, insignificant in one, and negatively significant in none. Secondly, perceived health problems were significantly positively associated with perceived access to potentially supportive relationships in four communities and negatively associated in none. Furthermore, increase in overall perceived health problems was associated with increased access to supportive relationships during the intervention. Finally, the only other effect that had the significant impact in a consistent direction in at least half of the communities was trust in neighbours. Trustful perceptions of the community before the intervention were generally associated with more gains from the intervention.

The most divergent results across different communities was in terms of faith. Importance of faith before the intervention was significantly positively associated with access to support in three communities and negatively associated in three communities after the intervention. Divergent results were also obtained for change in faith and church attendance during the intervention.

Discussion and conclusions

Summary of results

We have analysed the interplay between self-reported social networks, faith, and health of the poor in ten Philippine communities that underwent a typical example of a network intervention, which has been delivered to thousands of communities around the world. Although the changes in observed individual attributes were small immediately after the intervention, changes in networks were clearly visible. The reported number of potentially supportive partners increased from a mean of 12 to 19. We have also found a clear positive effects of the participants' local social engagement (measured by social visits the participants paid to other community members) on network relational gains from the intervention. Furthermore, there appears to be an overall general trend for people who perceive to have more health problems and whose health further worsened during the intervention to gain more supportive relationships through the intervention (but these respective trends are statistically significant only in four and five separately analysed communities).

The overall model also suggested that this faith-based network intervention may have benefitted more those who received well its religious message. However, the analysis of separate communities showed that this tendency varied significantly across the communities. While those who frequently attended church before the intervention and those whose faith strengthened through the program reported in the end significantly more supportive relations in some communities, the

tendency was significantly opposite in others.

Overall, this type of intervention might be less useful to those who are by local standards relatively less social engaged and healthy. It is possible that such people may have better social support networks elsewhere and do not need to rely on other, mostly very poor, community members. (We asked one binary question about the presence or absence of any supportive relationship outside of the community but almost everyone provided a positive answer to that question and therefore this variable did not shed more light on the situation.)

These findings are interesting considering that we did not survey concrete instances of actual received support, which could be expected to be lower for people who needed less support. Instead, we asked about relationships that are strong enough for the respondents to share their personal issues such as health problems, which we used as a proxy for potential access to support when needed. The respondents who had been better off during the intervention perceived to have fewer close and potentially supportive relationships. This finding does not mean that the respondents whose situation has improved received less support because they had fewer opportunities to need support.

It is also necessary to note that our study analysed the program as a whole package in the standard form in which it is delivered around the world. We cannot untangle how each aspect of this intervention contributed to the observed outcomes and whether these outcomes could be achieved with a simpler intervention design. For readers less interested in networks and more interested in the substantial impacts of separate components of the intervention, we recommend Bryan's et al. (2020) study. Our focus was on changing networks and our analysis showed that they changed significantly. The evidence is thinner on how stronger networks might significantly bring benefit to their members. This question is more directly tackled by Hung and Lau (2019) for this program and by numerous studies for other contexts (which are cited in the beginning of this paper).

Practical implications for social network interventions

The practical motivation for this study was to contribute to the evidence base for global policy makers and practitioners to help them design better social programs in LMICs that take into account and, where appropriate, leverage social networks and belief systems of their intended beneficiaries. Outcomes of social interventions are shaped by, and may also shape, the social structures of the targeted communities (Eng et al., 1985). Social networks may amplify the effects of external interventions, increase their efficiency and effectiveness, or derail them and exacerbate existing inequalities (Perkins et al., 2015).

Awareness and sensitivity to the pre-existing relationships and prevalent spiritual beliefs within the targeted communities can help finetune the delivery of resource-constrained development programs. "Northern" researchers aiming to support the advancement of living conditions and social welfare of people in LMICs may consider "non-scientific beliefs" as in conflict with their agenda. However, capitalizing on the strength of FBOs might allow them to reach thousands of people in contexts where other kinds of institutional support may be lacking.

In terms of faith, in particular, our findings were highly divergent and suggested a strong role of each community's context. To avoid manipulating or trivializing people's spiritual beliefs to pursue a development agenda, efforts to better understand the local cultural and social context of each community through extensive formative research and the involvement of knowledgeable local advisors will be necessary. In diverse and pluralistic societies, more than one format for impact-oriented social network interventions may be needed. The religious format of the intervention assessed in this article worked for some participants and some communities better than for others. Needs and preferences of those who do not fit the belief system of the promoting organizations must also be considered.

Further research

Although we focused only on one specific program, this case is representative of an important sector (Bryan et al., 2020). An increasing number of organizations that claim to be strengthening local communities are looking for ways to rigorously assess the outcomes of their programs. This is often motivated by increasing demands from their funders to see quantitative evidence of the proclaimed impacts of social programs that they have sponsored.

This is an opportunity for social network researchers to gain access to massive exogenous network interventions. Embedding rigorous social network instruments into social impact assessment protocols of large organizations will allow us to explore how social change propagates or get hindered by social networks. It will also enable the implementing organizations to monitor early signs of who might be left behind in their network interventions.

In this case, our main motivation was to find whether there are any typical impacts of a standardised network intervention program that is expanding to diverse locations at a fast pace. For this purpose, we randomly selected ten communities in one region where this program was being implemented. Our original goal was to obtain a single simple baseline model that was applicable across all the surveyed communities to examine whether they have any fundamental aspects in common in the way they reacted to a standardized network intervention. This has proved to be a challenging mission within the exponential random graph modelling framework. After many months of exploring theoretically informed alternative specifications, we were not able to find a better-fitting converged model than the ones presented in this paper. Only the presented dyadic models could fit the common statistical regularities across all ten communities, although they had all superficially similar socio-demographic characteristics.

How different networks respond to the same network intervention might vary significantly. This prevented us from achieving our intentions for a single well-fitting model. We ventured to collect socio-centric data but the overall model does not fully utilize the power of the sociocentric data because it was not possible to include more complex effects, which resulted in imperfect model fit with the observed reality. In particular, the poor fit for outgoing stars, which are directly related to the substantial outcomes of this intervention, is a reminder to treat the results of the ten-community model with caution.

Therefore, our conclusions had to ultimately rely to a large degree on the ten separate single-community models, which provided a useful view of the divergent outcomes of the intervention in different communities. However, even with the separate models, not all desired effects could always be included for each network and not all networks fit perfectly. This fact calls for caution when making comparisons of ERGM models of different networks and, in addition to the insufficient number of networks we had, prevented us from applying meta-analysis to the separate models. (Fitting separate longitudinal ERGMs, Snijders and Koskinen, 2013, or Stochastic Actor Oriented Models, Snijders 1996, would also have been possible methodological options for such explorations but neither of these approaches is without limitations either.)

Nevertheless, the separate analyses enabled us to capture somewhat better the networks' endogenous tendencies for most communities (although not all) by including higher order triadic and star effects. Importantly, the similarity of results regarding pre-existing social engagement across ten randomly selected communities increased our

confidence in its general importance. In contrast, the large differences for other variables highlighted the difficulty of finding common network mechanisms for intervention responses across multiple communities, even if these communities appear superficially similar.

All these insights would have been missed, if the study included only a smaller number of non-representatively selected networks, which is common. Extending network studies to a larger number of meaningfully sampled networks is necessary to further increase the generalizability of network research. Apart from analyses for illustrative approaches of methodological advances, we would argue against cherry-picking from sets of networks only ERGM-convergent cases for publications, as such skewed subsets might not be representative of the full complex variety of real-world networks and bias our substantial understanding of the studied phenomena. We would also argue against completely abandoning this modelling framework if complex specifications with higher order effects cannot be fit.

While the presented TERGMs do not include all endogenous network effects, even the dyadic model controls for important network tendencies that are not captured in regression models or simple random graphs. This approach does not pretend that endogenous network effects do not exist but, using z-scores, specifically quantifies the degree to which their omissions shifts the model away from the observed reality.

It would be convenient and informative for future ERGM software developments to enable the analysts an automatic generation of separate GOF for each network in joint models, which would explain in which way each network case diverges from the whole. Such results could be discussed in relation to the context of each network. In many cases, "perfect-fitting" ERGM models will not exist for datasets containing a larger number of networks. In such cases, presenting the best-fitting converged model and discussing the particularities of the fit would provide some useful network-specific insights that would not be obtained from regression models.

Our longitudinal data before and after the intervention suggested some links between changes in support networks and changes in people's perceived health. However, such relationships are complex and more controls are needed to further unpack them. For example, someone's deteriorating condition may attract more supportive relationships but strengthening relationships within marginalized communities may also hypothetically trap their members in poverty (di Falco and Bulte, 2011). In future studies, we would like to vary across different treatment groups the parameters of the studied interventions to identify which aspects of these interventions are most critical to producing the desired outcomes and which observed statistical associations might have been spurious. We are also aiming to compare the outcomes of this intervention with randomly selected control group communities that will receive the intervention later. While attempts at randomized experiments in whole networks have started to emerge at the individual level (Matous and Wang, 2019), when feasible and contextually acceptable, we believe that a randomized control of network interventions at the level of whole networks will allow us to better understand causal mechanisms in social networks.

There are other limitations of the study that we are planning to address by measuring longer term impacts of interventions on a larger number of communities. This has become possible due to an increasing interest among institutions implementing social programs towards regularizing network data collection for monitoring and evaluation purposes.

Appendix A

Complete TERGM results

Significant effects in are indicated with bold font where the parameters in absolute values are greater than twice the magnitude of the associated standard errors. This is a conventional approach in the ERGM framework and correspond to approximately 5% significance threshold.

Effects	Model (a)		Model (b)	
	p.e.	s.e.	p.e.	s.e.
G1_Sender	-4.620	0.200	-4.643	0.109
G2_Sender	-3.304	0.185	-3.326	0.107
G3_Sender	-4.761	0.195	-4.812	0.106
G4_Sender	-3.042	0.195	-3.026	0.117
G5_Sender	-2.971	0.202	-2.951	0.127
G6_Sender	-3.558	0.194	-3.596	0.111
G7_Sender	-5.209	0.201	-5.170	0.121
G8_Sender	-2.938	0.193	-2.909	0.109
G9_Sender	-4.887	0.206	-4.935	0.118
G10_Sender	-2.953	0.196	-2.939	0.101
Reciprocity	0.656	0.080	0.572	0.065
Pre-Intervention network	0.984	0.063	1.002	0.056
Number of sessions attended				
Sender	0.021	0.004	0.024	0.004
Receiver	0.026	0.005	0.023	0.004
Difference	-0.029	0.004	-0.030	0.004
Male				
Sender	-0.006	0.160		
Receiver	0.072	0.165		
Interaction	0.054	0.169		
PRE-INTERVENTION ATTRIBUTES				
Sender				
Trust in neighbours	0.453	0.044	0.501	0.027
Perceived health problems	0.273	0.044	0.274	0.039
Household income	-0.026	0.014		
Attend church weekly	0.316	0.079	0.255	0.063
Importance of faith	0.067	0.044		
Social visits to others	0.140	0.008	0.138	0.006
Receiver				
Trust in neighbours	0.045	0.051		
Perceived health problems	-0.115	0.047	-0.041	0.020
Household income	-0.011	0.014		
Attend church weekly	-0.217	0.086	-0.116	0.057
Importance of faith	-0.009	0.049		
Social visits to others	0.055	0.008	0.055	0.006
Difference				
Trust in neighbours	-0.010	0.028		
Perceived health problems	-0.023	0.034		
Household income	-0.004	0.011		
Attend church weekly	0.138	0.053	0.118	0.049
Importance of faith	0.007	0.025		
Social visits to others	-0.003	0.007		
CHANGE IN ATTRIBUTES				
Sender				
Trust in neighbours	0.498	0.035	0.529	0.026
Perceived health problems	0.314	0.035	0.324	0.031
Household income	-0.021	0.010		
Attend church weekly	0.091	0.060		
Importance of faith	0.145	0.037	0.093	0.022
Social visits to others	0.102	0.005	0.101	0.004
Receiver				
Trust in neighbours	0.017	0.038		
Perceived health problems	-0.049	0.038		
Household income	0.001	0.011		
Attend church weekly	-0.047	0.064		
Importance of faith	-0.032	0.040		
Social visits to others	0.012	0.004	0.012	0.004
Difference				
Trust in neighbours	0.021	0.022		
Perceived health problems	-0.035	0.024		
Household income	0.014	0.008		
Attend church weekly	0.118	0.044	0.125	0.041
Importance of faith	-0.025	0.021		
Social visits to others	0.001	0.004		

The complete model shows that social support tends to be reciprocated. The pre-intervention network ties tend to persist across the intervention. The more sessions people attend, the more likely they send and receive ties. People who attended similar number of sessions are more likely to link to each other. The results suggest that the intervention program promoted links among participants. There is little evidence to suggest any difference between male and female community members in their network activities. People who had better trusting relationship with neighbours, who reported health issues, and who attended church weekly, sent more ties post-intervention. People who paid more visits to others, both sent and received more ties post-intervention. People who reported health issues and attended church weekly before the program were less likely to receive ties post-intervention. Post-intervention ties tended to form between people who visit church with greater difference in frequency. In regard to changes in people's attribute and how that affect their social activities, people who had greater increase in their trust to their neighbours, their health issues, household incomes, importance of faith and social visits to others were more likely to send ties post-intervention. People who visited others more

during the intervention were more likely to receive more nominations post-intervention. The greater the difference in their frequencies attending church during intervention, the more likely they form post-intervention ties.

Comparison between the observed networks and the TERGM distribution using Z-scores

T1 to T8 correspondent to standard labelling of triadic motifs. Model A and Model B have almost indistinguishable GOF. We present below the GOF results for Model A.

Statistics	Observed	Mean	S.D.	t-ratio
Arc	7876	7877.00	49.26	-0.02
Reciprocity	2512	2512.46	30.53	-0.02
In2Star	89804	88663.41	1013.47	1.13
Out2Star	124788	111351.85	1150.94	11.67
In3Star	719428	706416.46	12258.54	1.06
Out3Star	1408502	1138228.63	16950.54	15.95
TwoPath	183152	182719.65	2080.17	0.21
Transitive-Triad	157223	138396.12	2107.36	8.93
Cyclic-Triad	39959	39468.51	696.84	0.70
T1	15032	11239.19	349.66	10.85
T2	98854	80856.02	2098.19	8.58
T3	108683	97497.08	2083.34	5.37
T4	54835	48718.14	1036.06	5.90
T5	70565	57023.18	1100.31	12.31
T6	54972	50527.53	1100.26	4.04
T7	122881	123042.05	2150.47	-0.08
T8	162965	148108.44	2242.55	6.63
Sink	112	37.04	3.78	19.83
Source	0	0.10	0.32	-0.33
Isolate	1	0.17	0.41	2.01
G1 Sender	519	519.73	15.69	-0.05
G2 Sender	1079	1079.38	17.57	-0.02
G3 Sender	364	365.22	15.82	-0.08
G4 Sender	1267	1266.50	13.82	0.04
G5 Sender	1058	1058.20	13.50	-0.02
G6 Sender	794	793.88	14.21	0.01
G7 Sender	194	193.57	12.33	0.04
G8 Sender	899	898.61	15.94	0.03
G9 Sender	429	430.47	15.82	-0.09
G10 Sender	1273	1271.44	17.82	0.09
Pre-intervention network	3705	3704.38	24.81	0.03
Std. Dev. indegree distribution	9.51	9.21	0.10	2.98
Skewness indegree distribution	-0.38	-0.27	0.03	-4.24
Std. Dev. Outdegree distribution	16.13	13.96	0.09	23.69
Skewness Outdegree distribution	0.12	0.04	0.02	4.99
Clustering Coef. t/m	0.86	0.76	0.00	24.54
Clustering Coef. c/m	0.65	0.65	0.01	1.37
Clustering Coef. t/i	0.88	0.78	0.00	21.86
Clustering Coef. t/o	0.63	0.62	0.00	2.11
Number of sessions attended Sender	73418	73446.64	474.27	-0.06
Number of sessions attended Receiver	64420	64404.43	464.93	0.03
Number of sessions attended Difference	49454	49460.27	435.48	-0.01
Male Sender	6751	6744.17	44.96	0.15
Male Receiver	6673	6638.13	44.45	0.79
Male Interaction	5724	5685.18	41.42	0.94
PRE-INTERVENTION ATTRIBUTES				
Trust in neighbours Sender	25227	25228.19	156.96	-0.01
Trust in neighbours Receiver	22196	22123.76	153.46	0.47
Trust in neighbours Difference	15209	15333.08	130.89	-0.95
Perceived health problems Sender	14880	14883.93	99.82	-0.04
Perceived health problems Receiver	13000	12994.91	93.84	0.05
Perceived health problems Difference	10696	10818.09	84.08	-1.45
Household income Sender	25434.48	25541.47	232.81	-0.46
Household income Receiver	22602.39	22638.85	211.38	-0.17
Household income Difference	24420.75	24598.13	239.89	-0.74
Attend church weekly Sender	3379	3379.48	26.36	-0.02
Attend church weekly Receiver	2929	2928.08	25.64	0.04
Attend church weekly Difference	3374	3373.50	30.62	0.02
Importance of faith Sender	24048	24017.68	151.29	0.20
Importance of faith Receiver	21174	21102.80	149.52	0.48
Importance of faith Difference	13142	13273.40	126.34	-1.04
Social visits to others Sender	31352	31364.09	281.77	-0.04
Social visits to others Receiver	27320	27331.90	267.37	-0.04
Social visits to others Difference	36310	36502.22	326.59	-0.59
CHANGE IN ATTRIBUTES				
Trust in neighbours Sender	5073	5079.65	94.48	-0.07
Trust in neighbours Receiver	1852	1994.26	92.77	-1.53

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Statistics	Observed	Mean	S.D.	t-ratio
Trust in neighbours Difference	16137	16197.29	138.97	−0.43
Perceived health problems Sender	573	570.52	65.20	0.04
Perceived health problems Receiver	−909	−817.84	61.30	−1.49
Perceived health problems Difference	11558	11687.94	87.71	−1.48
Household income Sender	2549.10	2653.91	178.68	−0.59
Household income Receiver	88.89	85.66	168.29	0.02
Household income Difference	27547.79	27443.44	261.89	0.40
Importance of faith Sender	6310	6314.34	91.40	−0.05
Importance of faith Receiver	3148	3291.94	90.90	−1.58
Importance of faith Difference	12874	12982.38	129.84	−0.84
Attend church weekly Sender	1006	1006.19	25.95	−0.01
Attend church weekly Receiver	524	522.87	24.56	0.05
Attend church weekly Difference	4292	4291.56	35.87	0.01
Social visits to others Sender	21126	21136.00	338.45	−0.03
Social visits to others Receiver	15434	15437.68	351.35	−0.01
Social visits to others Difference	63184	63315.01	487.62	−0.27

TERGMs for individual communities

Significant effects in are indicated with bold font where the parameters in absolute values are greater than twice the magnitude of the associated standard errors (i.e., 5% significance threshold).

	Community 1		Community 2		Community 3		Community 4		Community 5	
	p.e.	s.e.	p.e.	s.e.	p.e.	s.e.	p.e.	s.e.	p.e.	s.e.
Effects										
Arc	−3.888	3.305	−2.724	0.228	−2.46	1.069	−6.363	0.537	−10.39	2.264
Reciprocity	0.928	0.232	0.527	0.160	0.719	0.267			0.586	0.288
AinS	−0.556	1.500			−1.226	0.478				
AoutS	0.111	0.634			0.217	0.299				
ATA-T	0.824	0.357			1.191	0.187				
A2PA-T	−0.112	0.038			−0.136	0.024				
Male - Sender							3.171	0.327		
Male - Receiver										
Male - Intreaction										
Trust in neighbours - before - Sender			0.247	0.076	−0.447	0.125	3.388	0.261	2.856	0.516
Trust in neighbours - before - Receiver	0.738	0.179								
Trust in neighbours - before - Difference										
Perceived health problems - before - Sender			0.503	0.118						
Perceived health problems - before - Receiver	−0.830	0.218			−0.390	0.087				
Perceived health problems - before - Difference										
Household income - before - Sender	0.272	0.049								
Household income - before - Receiver										
Household income - before - Difference										
Attend church weekly - before - Sender	−1.186	0.364								
Attend church weekly - before - Receiver	−1.019	0.244								
Attend church weekly - before - Difference										
Importance of faith - before - Sender					0.675	0.120	−2.469	0.264	2.583	0.554
Importance of faith - before - Receiver	−0.332	0.124								
Importance of faith - before - Difference										
Trust in neighbours - change - Sender	−0.400	0.112			−0.441	0.112	2.534	0.210		
Trust in neighbours - change - Receiver	0.497	0.102								
Trust in neighbours - change - Difference							0.344	0.057		
Perceived health problems - change - Sender	0.886	0.122	0.969	0.097	0.157	0.058			−0.870	0.124
Perceived health problems - change - Receiver	−0.794	0.139			−0.210	0.085				
Perceived health problems - change - Difference										
Household income - change - Sender	0.098	0.036	0.144	0.017			−0.206	0.055	0.763	0.107
Household income - change - Receiver										
Household income - change - Difference									0.238	0.069
Importance of faith - change - Sender	0.263	0.091			0.606	0.119	−1.162	0.191		
Importance of faith - change - Receiver										
Importance of faith - change - Difference										
Attend church weekly - change - Sender	−1.015	0.276	−0.424	0.118						
Attend church weekly - change - Receiver										
Attend church weekly - change - Difference	0.575	0.159								
Social visits to others - before - Sender	0.209	0.032	0.189	0.023			1.216	0.102	1.500	0.189
Social visits to others - before - Receiver	0.081	0.020			0.065	0.013	0.158	0.042		
Social visits to others - before - Difference							−0.178	0.051		
Social visits to others - change - Sender	0.183	0.021	0.091	0.014	0.029	0.009	0.313	0.036	−0.280	0.033
Social visits to others - change - Receiver										

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	Community 1		Community 2		Community 3		Community 4		Community 5	
Social visits to others - change - Difference			0.038	0.010			0.066	0.022		
Number of sessions attended - Sender			0.165	0.017			-0.195	0.029	0.161	0.040
Number of sessions attended - Receiver	-0.032	0.015			0.030	0.014				
Number of sessions attended - Difference	-0.037	0.013	-0.049	0.015						
Before_Arc	1.227	0.184	1.033	0.182	1.770	0.169				

	Community 6		Community 7		Community 8		Community 9		Community 10	
Effects	p.e.	s.e.	p.e.	s.e.	p.e.	s.e.	p.e.	s.e.	p.e.	s.e.
Arc	-3.436	0.390	-4.582	0.746	-5.556	0.633	-4.684	0.357	-3.805	0.301
Reciprocity			1.465	0.401	1.297	0.233			0.577	0.206
AinS			-0.323	0.317						
AoutS			1.116	0.294						
ATA-T			0.830	0.172						
A2PA-T			-0.132	0.038						
Male - Sender					1.160	0.397				
Male - Receiver										
Male - Intreaction										
Trust in neighbours - before - Sender	1.716	0.220			1.196	0.199				
Trust in neighbours - before - Receiver										
Trust in neighbours - before - Difference										
Perceived health problems - before - Sender	0.707	0.124			0.498	0.186			0.386	0.143
Perceived health problems - before - Receiver										
Perceived health problems - before - Difference	-0.409	0.102								
Household income - before - Sender					0.147	0.041	-0.171	0.044	0.662	0.075
Household income - before - Receiver			-0.076	0.031						
Household income - before - Difference					-0.069	0.034				
Attend church weekly - before - Sender					2.264	0.296			1.236	0.270
Attend church weekly - before - Receiver										
Attend church weekly - before - Difference										
Importance of faith - before - Sender	-1.405	0.216			-0.781	0.127	0.452	0.079		
Importance of faith - before - Receiver	0.100	0.049								
Importance of faith - before - Difference	0.219	0.060								
Trust in neighbours - change - Sender	2.211	0.228			0.846	0.098			0.756	0.100
Trust in neighbours - change - Receiver										
Trust in neighbours - change - Difference									-0.136	0.063
Perceived health problems - change - Sender					0.530	0.143	0.358	0.089		
Perceived health problems - change - Receiver							0.308	0.097		
Perceived health problems - change - Difference									0.794	0.143
Household income - change - Sender							-0.226	0.044	0.184	0.049
Household income - change - Receiver										
Household income - change - Difference	0.069	0.028			0.112	0.034				
Importance of faith - change - Sender	-1.258	0.224							-0.440	0.093
Importance of faith - change - Receiver							-0.23	0.070		
Importance of faith - change - Difference							0.305	0.075	0.238	0.069
Attend church weekly - change - Sender					1.371	0.250			1.194	0.256
Attend church weekly - change - Receiver					-0.362	0.165				
Attend church weekly - change - Difference					-0.517	0.143				
Social visits to others - before - Sender	0.201	0.020	0.146	0.032	0.209	0.037	0.210	0.02	0.592	0.079
Social visits to others - before - Receiver	0.111	0.020					0.110	0.019	0.139	0.034
Social visits to others - before - Difference									-0.126	0.035
Social visits to others - change - Sender	0.214	0.021	0.105	0.017	0.204	0.027	0.124	0.011		
Social visits to others - change - Receiver	0.047	0.017			0.033	0.014	0.040	0.010		
Social visits to others - change - Difference			-0.068	0.020	0.070	0.017				
Number of sessions attended - Sender	-0.063	0.020					0.078	0.017	0.085	0.017
Number of sessions attended - Receiver	0.046	0.016							0.067	0.014
Number of sessions attended - Difference	-0.045	0.017			-0.071	0.013	-0.086	0.015	-0.067	0.015
Before_Arc	0.631	0.221	1.675	0.220	1.905	0.352	2.616	0.210	0.557	0.197

Correlations between variables

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1 - Male	1.000															
2 - Trust in neighbours - before	0.145	1.000														
	0.104	0.492	1.000													

(continued on next page)

(continued)

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
3 - Trust in neighbours - change																
4 - Perceived health problems - before	0.162	0.828	0.447	1.000												
5 - Perceived health problems - change	0.073	0.429	0.822	0.450	1.000											
6 - Household income - before	0.078	0.563	0.270	0.415	0.211	1.000										
7 - Household income - change	0.150	0.365	0.515	0.334	0.361	0.431	1.000									
8 - Attend church weekly - before	0.110	0.551	0.244	0.446	0.179	0.335	0.247	1.000								
9 - Attend church weekly - change	0.141	0.315	0.522	0.282	0.429	0.189	0.261	0.360	1.000							
10 - Importance of faith - before	0.143	0.895	0.492	0.791	0.435	0.573	0.378	0.520	0.296	1.000						
11 - Importance of faith - change	0.112	0.521	0.935	0.479	0.781	0.315	0.572	0.272	0.533	0.524	1.000					
12 - Social visits to others - before	-0.059	0.340	0.172	0.232	0.140	0.252	0.242	0.187	0.109	0.353	0.193	1.000				
13 - Social visits to others - change	-0.114	0.101	0.143	0.101	0.064	0.080	0.144	0.009	0.049	0.113	0.202	0.214	1.000			
14 - Number of sessions attended	0.176	0.214	0.420	0.234	0.347	0.055	0.244	0.264	0.341	0.224	0.450	0.049	0.092	1.000		
15 - Outdegree before	0.084	0.659	0.305	0.572	0.215	0.247	0.221	0.506	0.306	0.577	0.338	0.351	0.205	0.227	1.000	
16 - Outdegree after	0.024	0.404	0.644	0.370	0.538	0.168	0.284	0.291	0.503	0.366	0.654	0.202	0.347	0.356	0.473	1.000

Pearson correlation coefficients

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