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A description of within-family resource exchange networks in a Malawian village

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Abstract

In this paper we explore patterns of economic transfers between adults within household and family networks in a village in Malawi's Rumphi district, using data from the 2006 round of the *Malawi Longitudinal Study of Families and Health*. We fit Exponential-family Random Graph Models (ERGMs) to assess individual, relational, and higher-order network effects. The network effects of cyclic giving, reciprocity, and in-degree and out-degree distribution suggest a network with a tendency away from the formation of hierarchies or "hubs." Effects of age, sex, working status, education, health status, and kinship relation are also considered.

1. Introduction

Using Exponential-family Random Graph Models (ERGMs) and data from the *Malawi Longitudinal Study of Families and Health* (formerly the *Malawi Diffusion and Ideational Change Project*), we describe the patterns of wealth flows within household and family networks in a Malawian village. We graphically represent the observed economic resource transfers within household and family networks, and we use ERGMs to estimate the effects of individual attributes, relationship attributes, and network structures on giving patterns. We consider effects of age, sex, working status, health status, education level, and kinship relation. We also consider mutuality effects, the effect of cyclical giving patterns, and the degree distribution of the network. An important feature of the analysis is the estimation of these effects from partially observed household networks. Based on the sampling strategy in the survey design, the complete household networks were not observed. Our ERGM statistically corrects for the sampling, and estimates the parameters of the complete networks. We apply a novel framework to describe patterns of resource exchange in a single Malawian village. Ultimately, we hope that our analysis will provide a basis for the formulation of hypotheses regarding the social processes underlying these patterns, and will encourage investigation into the question of whether similar patterns might be found in other Rumphi villages.

2. Background

The UN estimates the adult HIV prevalence rate in Malawi to be 11.9%, with an estimated 930,000 adults and children living with HIV in Malawi in 2007 (UNAIDS 2008). The impact of the AIDS epidemic in Malawi is compounded by the extreme poverty of the country. Approximately two-thirds of the population lives below the nation's poverty line, and Malawi was ranked 165 out of 177 countries in the 2005 United Nations Human Development Report (United Nations Development Programme 2005). The population is predominantly rural (85%), relying on subsistence agriculture and a strong sense of family, community, and interdependence. Where health insurance, life insurance, and other structural supports are unavailable, there is a deep reliance on community, kin, and social obligations. A full description of the impact of the AIDS epidemic on individuals, families, and communities in rural Malawi must include a description of the economic support structure in which people are embedded.

Understanding the social and economic networks in which AIDS unfolds helps us understand the social response to AIDS in a context of extreme poverty. A number of papers have examined social and economic networks in the context of the AIDS epidemic in Malawi. Mtika (2003) showed that prime-age adults (aged 20-40) are key players in the family's economic support network, and that their transfer behavior depends on their health status. As prime-age adults are at the heart of the transfer support system, but are also the age group most likely to contract HIV/AIDS, Mtika warned that the AIDS epidemic will have economic and social repercussions throughout the family network. Weinreb (2007) found that economic transfers between family members are influenced by the overall network structure: the presence or absence of certain relations (e.g., siblings) can make a potential recipient more or less attractive to potential givers. Some kin categories are substitutable: the absence of a parent increases the likelihood of a transfer from an aunt or uncle. Such findings could be applied to predict how transfer dynamics shift when a family member dies of AIDS, or to predict the level of social and economic support that an AIDS orphan might receive from family members. Chao and Kohler (2007) examined transfer dynamics and underlying motivations through behavioral economic games. The authors found that wealthier participants gave less but reciprocated more, that participants in better physical health gave more, and that those in better mental health reciprocated more. They found that the expectation of reciprocity was a more dominant motive than altruism or fairness, and that transfer behavior was related to the perceived HIV status of both giver and receiver, as well as to the level of felt stigma for HIV. Weinreb (2002) found that lateral as well as vertical transfers play a role in intergenerational economic support networks in Malawi, and that working-age adults have a net loss of wealth to their parents, but also a net gain from aunts and uncles, suggesting the existence of an institutionalized network of resource transfer within the family. In addition, they found that gender and kin relationship determine the roles people play within the transfer network.

We contribute to the literature on Malawian economic resource networks by applying ERGMs to describe and graphically represent the observed pattern of resource transfer in a Malawian village. Our data comes from the 2006 round of the *Malawi Longitudinal Study of Families and Health*, a longitudinal study whose original sample in 1998 included married women aged 15-49 and their husbands. In 2006, respondents enumerated all members of their household and immediate kin, and reported on economic transfers to and from each person in this *Family and Household Listing*. We use an ERGM to describe within-household giving patterns in one Malawian village. By fitting an ERGM to the data, we estimate the effects of individual level covariates (such as age and sex), dyadic covariates (such as relationship), and other network characteristics (such as reciprocity and hierarchy) on giving patterns.

The best-fitting ERGM was selected by comparing models using likelihood ratio tests. We find statistical evidence that the network cannot be described by individual and dyadic covariates alone, but that higher network structures also determine the dynamics in this village. This finding indicates that peoples' propensities to give and receive depend on the giving behavior of others around them, not just on individual-level attributes. A full understanding of the social response to the AIDS epidemic should account for these higher level network structures.

Complete within-household networks were not observed in our data set, as respondents reported on transfers to and from other household members, but not on transfers between non-respondent household members. Our model-fitting procedure statistically corrects for this sampling, and produces estimates of the model parameters for the complete network.

3. Data

The data come from the 2006 round of the *Malawi Longitudinal Study of Families and Health*, formerly called the Malawi Diffusion and Ideational Change Project (MDICP). This is a longitudinal demographic, health, and economic survey of respondents in three rural regions in Malawi.[3] The original sample in 1998 included married women aged 15-49 and their husbands. In each region a cluster sampling strategy was used. A total of 145 villages were selected, with the fraction sampled in each village inversely proportional to the village population. The target was 500 ever-married 15-49-year-old women plus husbands in each district, and the survey captured 1,541 women and 1,189 husbands. In 2006, the fourth wave of the survey, each respondent described his/her kin network in a *Family and Household Listing*, which included self, spouse, parents, parents-in-law, all children, anyone who slept in the household last night, and anyone who usually sleeps in the household. The demographic and health information of each living kin member was collected, as was information on economic resource transfers between the respondent and household members. Respondents were asked whether they had given or received money to/from each adult (age ≥ 15) kin member in the last two years.

In this paper we use information reported by respondents of the original cohort in a single Rumphi village to build and describe networks of resource exchange within this village. The Rumphi district lies in northern Malawi. Its population includes various ethnicities, but is dominated by the Tumbuka ethnic group, who are mainly Protestant. Rumphi culture is mainly patrilineal and patrilocal, and is tolerant of polygamy. Like the rest of Malawi, infrastructure in Rumphi is poor, and families support themselves through subsistence agriculture, cash earnings, and sales of corn, tobacco, and other crops (Miller, Zulu, and Watkins 2001). For our analysis, we selected a small village in Rumphi with a high proportion of households sampled. The village includes 17 households, of which 12 are represented by respondents who were successfully interviewed in 2006. Some polygamous households contain more than two respondents. Very small households with fewer than four members were excluded from the analysis, as these households provided relatively little transfer information, and may exhibit different transfer patterns than larger households. For family members who died in the last two years, transfer information was collected, but not covariate information, so we excluded these family members from the analysis.

Each household contains at least two respondents (more in polygamous households). We used reported names, relationship to respondent, age, and sex to match members reported by one respondent to those reported by another respondent in the same household. Since the spellings of names varied dramatically, we made all the matches by hand, and included the relationship, age, and sex variables to improve accuracy. In some households only one of two respondents was successfully interviewed in 2006, resulting in missing data.

[3]See http://www.malawi.pop.upenn.edu/ for details on survey design, sampling strategy, and data collection.

The study received ethical approval from institutional review boards at the University of Pennsylvania and the University of Malawi (University of Pennsylvania Population Studies Center 1998).

4. Methods

We model the network of economic resource transfers using an Exponential-family Random Graph model. Such a network can be represented graphically by a point for each social actor, with arrows depicting flows of money from one actor to another. The points are referred to as *nodes*, the arrows as *edges* or *ties*, and a pair of points is called a *dyad*. In a directed network such as ours, each observed dyad has four possible states: a mutual tie, a single tie from node A to node B, a single tie from B to A, or no ties. The *in-degree* of a node, in our case, is the number of transfers received by that node, while its *out-degree* is the number of transfers given. Mathematically, the resource transfers can be expressed as a sociomatrix: a square matrix Y with the same number of rows as there are social actors, and $Y_{ij}=1$ if money was transferred from actor i to actor j, and 0 otherwise. The probability distribution of such a network can be concisely expressed by an ERGM (Strauss and Ikeda 1990), which takes the form

$$P(Y=y) = \frac{\exp\{\eta \cdot g(y)\}}{\kappa(\eta, Y)}. \tag{1}$$

Here κ is a normalizing constant ensuring that the probability distribution sums to 1. The vector of observed network statistics g(y) may include the total number of edges, the number of ties between two people of the same sex, the number of reciprocal ties, and others. For more details on the selection and interpretation of such terms, see Morris et al. (2008). By including terms which represent the underlying network structure, we can fit a model which describes the distribution from which the observed network was generated. The distribution describes the social forces that influence resource transfer. The parameter vector η is estimated by the maximum likelihood estimate (MLE). As the normalizing constant in equation (1) above is often analytically intractable, MLEs can be obtained by maximizing a Markov Chain Monte Carlo (MCMC) approximation to the likelihood (Geyer and Thompson 1992).

Note that the ERGM is for a complete network. In our case, the complete network of transfers was not observed. Although respondents reported on transfers to and from other household members, they did not report on transfers between non-respondent household members. Dyads for which neither actor is a respondent are missing by design. In addition, some data is missing due to non-response, when respondents were not successfully interviewed in 2006. Inference for ERGMs based on sampled network data has been developed by Handcock and Gile (2010). The probability of a partially observed graph can be expressed as the sum of probabilities of all graphs which have the same values on the observed dyads, but any values on the unobserved dyads. From this basic principle a likelihood function is obtained, and is maximized to estimate the parameters. This approach is implemented in the **statnet** software, which fits ERGMs, while statistically correcting for missing dyads (Hunter et al. 2008).

We consider the following structural statistics as terms in the statistical model for our data:

1. An edges term, which reflects the density of the network.
2. The size of the household, which is likely to affect within-household transfers by limiting the largest possible degree, and which may affect tie density.

3. The number of ties in which the giver has completed high school. Those with higher education are more likely to have higher income jobs, and may be more inclined to make transfers.

4. The nodal covariates age (categorized), sex, working status, health status, and whether the potential giver and receiver are regular members of the compound. As with education level, these nodal covariates could influence giving and receiving.

5. The number of transfers between spouses, or between parents and children. Spouses may be more likely to make transfers to each other than to other family members.

6. A reciprocity term (the number of mutual ties). People may be more likely to give transfers to those they have received transfers from in the past.

7. Degree distribution terms, or an underlying parametric model for the degree distribution (both in-degree and out-degree). A network of economic transfer may be predisposed to a particular degree structure. For example, it may be that needy people receive ties from all other family members, and therefore have high in-degree nodes. Alternately, it may be that, within families, each needy person has a single person who looks after him, thus making high in-degree nodes unlikely.

8. A term capturing cyclic giving patterns, such as the number of cyclic triples in the network. A cyclic triple is a pattern in which A gives to B, B to C, and C back to A. The value of the cyclic triple term reflects the level of social hierarchy in the network. In a hierarchical society, we expect to find fewer cyclic triples than in a non-hierarchical one.

The terms described in (1)–(6) above are *dyad-independent*: the occurrence of a transfer on one dyad depends only on nodal and dyadic covariates. Models including only dyad-independent terms can be analyzed with logistic or log-linear regression. The terms described in (7) and (8) are, however, dyad-dependent: they capture dependency patterns among individuals in the network. A significant coefficient estimate for the degree distribution or cyclic triple term suggests that the independence assumption required by logistic or log-linear regression is violated, and that higher-level network structures are influencing individual behavior. The direction of these coefficients can motivate hypotheses about network structures, which could then be tested on a larger data set.

A challenge that sometimes arises when fitting ERGMs is model degeneracy, which occurs when the fitted model places most of the probability mass on a small number of possible networks. Model degeneracy is an indication of a poor model fit, and models including terms such as the number of triangles and degree counts are often degenerate. While degree counts can give rise to degenerate models, parametric forms for the degree distribution have been found to avoid this problem. For this reason, we chose a geometrically weighted statistic to model the in-degree and out-degree distributions. Including all degree counts in a model can result in a fitted model which puts a large probability mass on networks with high degrees. The geometrically weighted degree distribution gives successively lower weight to higher degree nodes, and is given by:

$$u(y, \varphi_s) = e^{\varphi_s} \sum_{i=1}^{n-1} \{1 - (1 - e^{-\varphi_s})^i\} D_i(y),$$

where $D_i(y)$ is the number of nodes with exactly i ties. More discussion on the geometrically weighted degree distribution can be found in Snijders et al. (2006), and a thorough discussion of model degeneracy can be found in Handcock (2003). We tested geometrically weighted in-degree and out-degree distribution terms, with the scaling parameter set equal to two.

We fit several models to the data, and compare them with likelihood ratio tests. We first fit a model to the data including the terms (1) through (6) described above. In this model, ties depend only on the covariate values of the dyad. Model 2 includes the number of cyclic triples within households, and Model 3 includes a parametric in-degree distribution term. Model 4 includes a parametric out-degree distribution term. Since our data set only includes ties within households (but not between households), we fit only models with a zero probability of between-household ties. This is accomplished computationally by fixing the edges coefficient at -1000, and fixing the coefficient for the number of within-household ties at 1000. Since the edges coefficient is fixed, we need to allow for tie density estimation by including the reference category of a categorical variable. Therefore, we estimated coefficients for all four gender combinations of a dyad (male to female, male to male, etc.), rather than omitting one as a reference category. Model-fitting, plotting, and simulation were all performed with **statnet** software (version 2.3) (Hunter et al. 2008) in the **R** statistical software environment (version 2.7) (R Development Core Team 2007). For more details on **statnet** software, see Goodreau et al. (2008).

After selecting the best-fitting model, we simulated 15 networks conditional on the observed dyads. The simulated networks are included in the appendix.

5. Results

Our network includes 10 households, 85 social actors, and 188 observed dyads. Table 1 displays descriptive statistics for the variables included in the analysis of our village. The corresponding statistics for all of Rumphi are shown in column 2. Recall that households with fewer than four members were excluded from the analysis. In our village, household sizes range from five to 19. We see that most people rate their own and their family members' health very positively. The distribution of the health rating relative to others of the same age and sex indicates that people rate their own and their family members' health status with an optimistic bias. Most individuals have less than a high school education, and most were employed in the past 12 months. Recall that only adults (age $\geq$ 15) are included in the network, as respondents were not asked about transfers to and from children. Most variables are missing values for very few or no individuals, but nine people are missing age values. Members of our village are younger than those in Rumphi as a whole, with a mean adult age of 34 rather than 40. Our village shows more recent mobility than Rumphi, and a slightly different health status distribution. However, distributions of all other variables, including household size, education level, illness status, and marital status, are comparable to the distributions for the entire Rumphi sample.

The residency status of parents of respondents shows evidence of the Tumbuka's patrilocal practices. Only one of 12 living parents of female respondents lived in the same compound as their daughter; all others lived in different villages. In contrast, four of the five living parents of male respondents lived in the same compound as their son. Although more transfers were reported from parents to married sons than to married daughters (64% vs. 48%), the difference was not statistically significant. A larger sample may detect a significant difference. It could also be the case that transfers occur more frequently to married sons than daughters, but that our measure was not fine enough to detect this. Our outcome measure is a transfer of money that occurred any time over the last two years.

Figure 1 shows plots of household networks. The vertex color shows the relationship to the (female) respondent. A household may have more than one female respondent, where the husband has multiple wives, as in household 6. Transfers of money are depicted as black arrows, and reports on no transfers of money are depicted as light gray arrows. The absence of an arrow between two nodes indicates that transfer information between those two people was not collected. There is a great deal of structurally missing data, since information was only collected on transfers between the respondent and other household members. The reported non-transfers plotted in light gray allow us to distinguish actual non-transfers from missing dyads. Household members for whom covariate values were not obtained were excluded from the analysis and are not displayed. For example, women did not always report on their co-wives and their co-wives' children.

Table 2 shows the parameter estimates for each of the four models. Coefficients in Model 1 should be interpreted as follows: the odds of a transfer occurring from a person who has completed some high school to another person is estimated to be $e^{0.1}$=1.11 times the odds of a transfer occurring where the giver has not completed some high school. This effect is in the direction we expect, although it is not statistically significant. The odds of a transfer occurring to a receiver aged 26-39 is estimated to be $e^{-1.54}$=0.21 times the odds of a transfer occurring to a receiver who is aged 15-26 (the reference age category). The other covariate attribute parameters are interpreted similarly. We see that transfers are significantly more likely to occur between married couples and from parents to children, as we might expect. Transfers are more likely to occur from children to parents, although this effect was not significant. Transfers are most likely to occur from males to males (controlling for other variables in the model), followed by female-to-female transfers, then male-to-female transfers; with female-to-male transfers being the least likely. However, the significance levels for these coefficients must be interpreted with care. We did not omit one gender pairing as a reference category because we did not estimate an overall density parameter. Thus, the gender pairing coefficients are estimating a density effect as well as gender pairing effects, and should therefore only be interpreted in relation to each other. For example, the odds of a male-to-male transfer is $e^{-2.74 - (-4.83)}$=8.08 times the odds of a female-to-male transfer. However, the 95% confidence intervals for the female-to-male and male-to-male transfer coefficients overlap ([-4.98, -0.50] and [-7.25, -2.41] respectively), so none of the gender pairing effects are statistically significant. Their high significance levels are solely due to the significant density effect within households. The model also suggests that people over the age of 26 are more likely to make transfers than those aged 15-25 (although this effect is not significant), that those aged 26-39 and 40-59 are less likely to receive transfers than those aged 15-25, and that people over the age of 60 are more likely to receive transfers than those aged 15-25. The odds of a transfer in which the giver is a regular member of the same compound is $e^{1.75}$=5.75 times the odds of a transfer in which the giver is not a regular member, and the effect of the receiver being a regular member is $e^{1.29}$=3.63. The odds of a transfer that will complete a mutual dyad is $e^{-0.37}$=0.69 times that of a transfer that will not complete a mutual dyad, again assuming other covariates are equal, but the effect is not statistically significant.

The cyclic triple parameter in Model 2 is interpreted as follows: the odds of a transfer occurring that will complete a cyclic triple is $e^{-0.13}$=0.88 times the odds of a transfer occurring that would not complete a cyclic triple, assuming that dyadic and nodal covariates of the two dyads in question are all the same. This suggests a hierarchical tendency in giving patterns in this village. Cyclic triples, in which A gives to B, B to C, and C to A, show no indication of hierarchy among the three participants. In terms of transfer behavior, the three are equally ranked. A transitive giving pattern (i.e., A gives to B, A to C, and B to C), would be more likely to occur in a hierarchical society, with A at a higher status level than B and

C. Networks with fewer cyclic triples than we would expect to see at random show evidence of social hierarchy.

The coefficient for the geometrically weighted in-degree distribution in Model 3 is trickier to interpret. This is a measure of heterogeneity of degree, controlling for the number of edges and for other variables included in the model. Let us suppose that we are holding the number of edges fixed in a graph, as well as other variable values. We then move a single edge from a node of degree k to a node of degree k+1. The ratio of probability of the graph before to the probability of the graph after the change is equal to:

$$\frac{p_{\text{before}}(Y)}{p_{\text{after}}(Y)} = \exp\{\eta \rho^{k}\},$$

where ρ=(1-exp(-2))≈0.86 in our case (Hunter 2007). A geometrically weighted in-degree coefficient of zero, controlling for the number of edges, indicates that all degree distributions are equally preferred probabilistically. A negative geometrically weighted in-degree coefficient indicates a preference towards similarity in degree among actors. Socially, this suggests a network in which actors have similar levels of participation in receiving patterns. A positive coefficient indicates a preference towards heterogeneity in degree, with some actors having a very high degree, and some having a very low degree. Socially, this would manifest as networks in which some people receive transfers from many others, while some actors receive no transfers. Our estimate of -2.83 implies a preference for similarity in degree among actors. This implies an exchange network in which most people are engaged in similar levels of receiving, rather than a network which has a small number of people receiving very large numbers of transfers, and many others receiving very few or no transfers. The coefficient for the geometrically weighted out-degree distribution term in Model 4 is interpreted similarly, so the network shows a preference for similarity in giving patterns.

We performed likelihood ratio tests to compare each of the Models 2, 3, and 4 to the dyad-independent Model 1. We approximate the null distributions of the change in the deviance by chi-square distributions, with degrees of freedom equal to the difference in the numbers of parameters of the compared models. The likelihood ratio statistics were 1.21, 5.64, and 2.28 for Models 2, 3, and 4, respectively. Since the critical value for a chi-square distribution with one degree of freedom is 3.84, we conclude that Model 3 fits better than Model 1, but that Models 2 and 4 do not. Therefore, Model 3 was selected as the best-fitting model.

6. Discussion

In this paper we used Exponential-family Random Graph Models to describe the patterns of money transfer in a rural Malawian village. Our key finding is that the best-fitting model includes the geometrically weighted in-degree distribution term, showing that the best model for the data includes dependency structure rather than just individual and dyadic effects. Our exploration of cyclic giving points to an underlying network with a tendency away from social hierarchy. The degree distribution coefficients suggest networks with fewer hubs, so that giving and receiving are more evenly distributed among members. Although only the degree distribution terms proved significant, the others could prove significant with a larger data set. Our statistical power is limited due to the large amount of structurally missing data. Our work describes transfer patterns in this particular village, not for Rumphi as a whole. Our results can be used to formulate hypotheses about transfer dynamics in the entire region, and these hypotheses could be tested with a larger data set.

We also found evidence for individual and dyadic effects. We found that transfers are significantly more likely to occur between married couples, from parents to children, and to and from regular members of the compound. People aged 26-59 are less likely to receive transfers, and smaller households have a higher density of transfers. Gender may play a role in giving patterns, with male-to-male transfers occurring most frequently, and female-to-male transfers occurring least frequently, although these effects were not significant in our best-fitting model. As males are more likely to be engaged in earning money, these patterns are reasonable, and might be found significant with a larger data set. The effects of working status and education are in the direction expected. Our model suggests that illness of the recipient decreases the likelihood of receiving a transfer, but this effect was not statistically significant.

Our conclusions rest on the assumption that the network actors are a representative sample of the village. Since all households in this village include at least one married woman of childbearing age, this assumption seems quite reasonable. We must be more careful when assessing the representativeness of the transfer data. Transfers to and from respondent and each household/family member are reported, but no information is available on transfers between two family members if neither is a respondent. Therefore, transfer information is representative of transfers where at least one of the two actors involved is either a 23-57-year-old ever-married woman, or a husband of such a woman. The key assumption we make is that such transfers follow the same underlying process as transfers between any two adults in the household. Since we have included so many relevant predictors in our model, we believe this is a reasonable assumption. It is, however, possible that there is a generational effect, which would mean, for example, that transfers between very elderly people follow a different pattern.

The degree of measurement error must also be considered when evaluating the data on this network. Respondents were asked about transfers of money in the last two years. Some may recollect better than others, and some exchanges could be forgotten. In fact, the data did contain discrepancies between the reports of husbands and wives. We assumed that a transfer occurred if reported by at least one member of a couple. In addition, it is possible that respondents reported transfers based on perceived social norms of who should give/receive, rather than what actually happened. The fact that interviews were face-to-face rather than written may increase the likelihood of this kind of reporting bias. An exploration of the extent of measurement error is beyond the scope of this paper.

We note that a hierarchical linear model (HLM) could also be used to analyze the data. However, a classic HLM would not be able to capture higher level network structures, such as hierarchy and degree distribution. The ERGM approach we have used allows us to capture and measure these often overlooked sources of dependency. Building an HLM which incorporates network structure is a challenging and nontrivial problem, and is beyond the scope of this paper.

This paper has explored and described the economic network structure of a Malawian village. The network effects of transitivity and degree distribution suggest a network with a tendency away from social hierarchy and a tendency towards similarity in giving and receiving patterns. Transfer patterns are influenced by age, relationship, gender, and working status. Health status and education level showed the expected relationship to transfer behavior, although the effects were insignificant, probably because of our small data set. Our key result is that individual and dyadic effects are insufficient to describe the entire transfer network; higher level network structures, such as degree distribution, also play a role.

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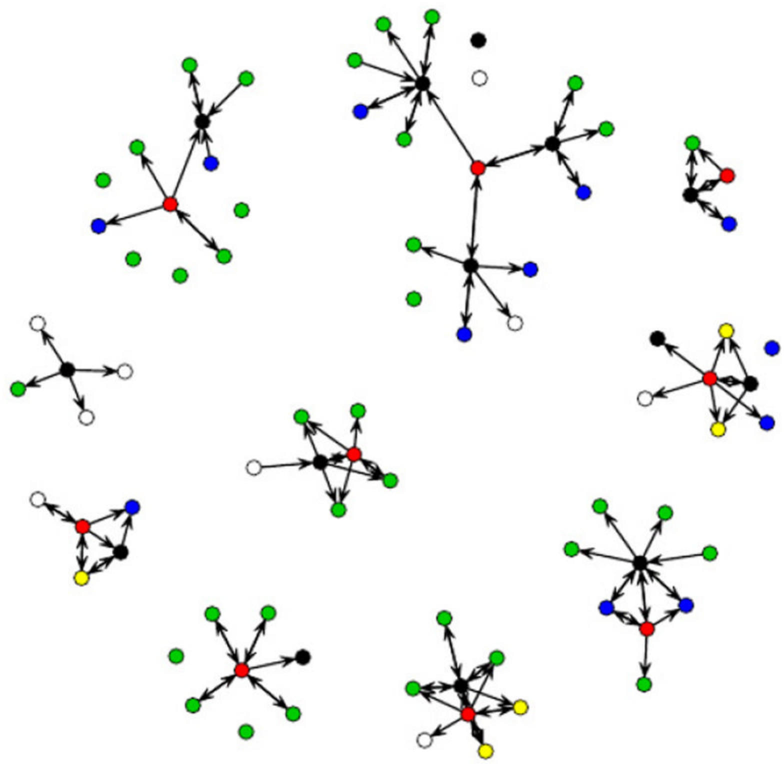
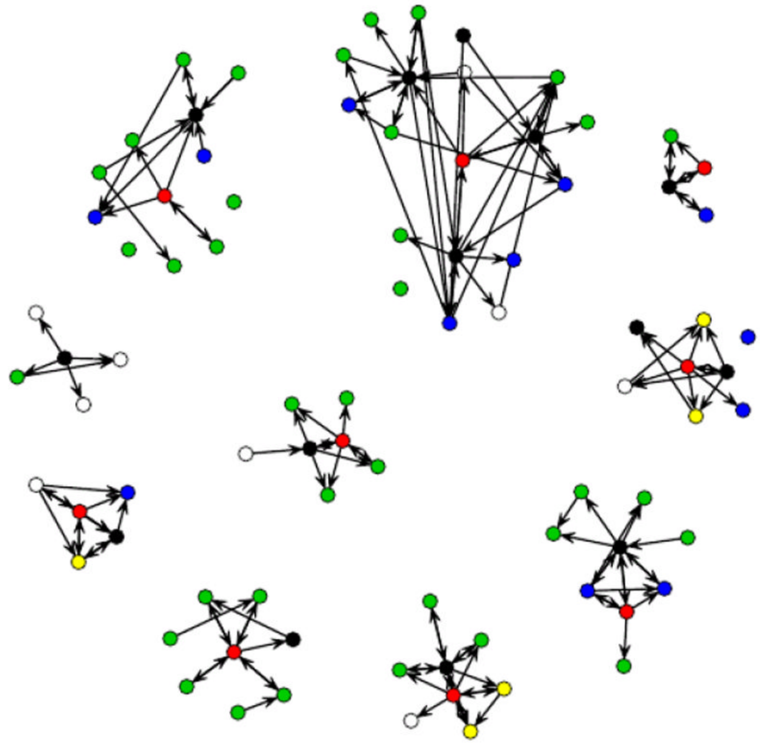
Appendix

The observed network is shown, as well as 15 networks simulated from the best-fitting model. These networks are simulated conditional on the observed dyads. For all plots, colors indicate relationship to the respondent as follows:

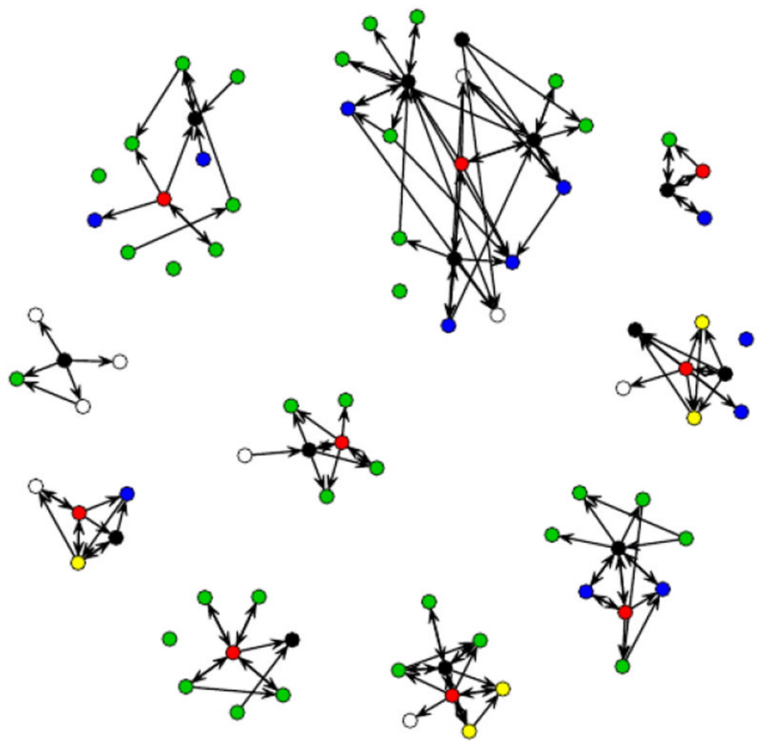
- female respondent (black)	- husband (red)
- child (green)	- parent (blue)
- parent-in-law (yellow)	- other (white)



Observed network



Simulated network 1



Simulated network 2

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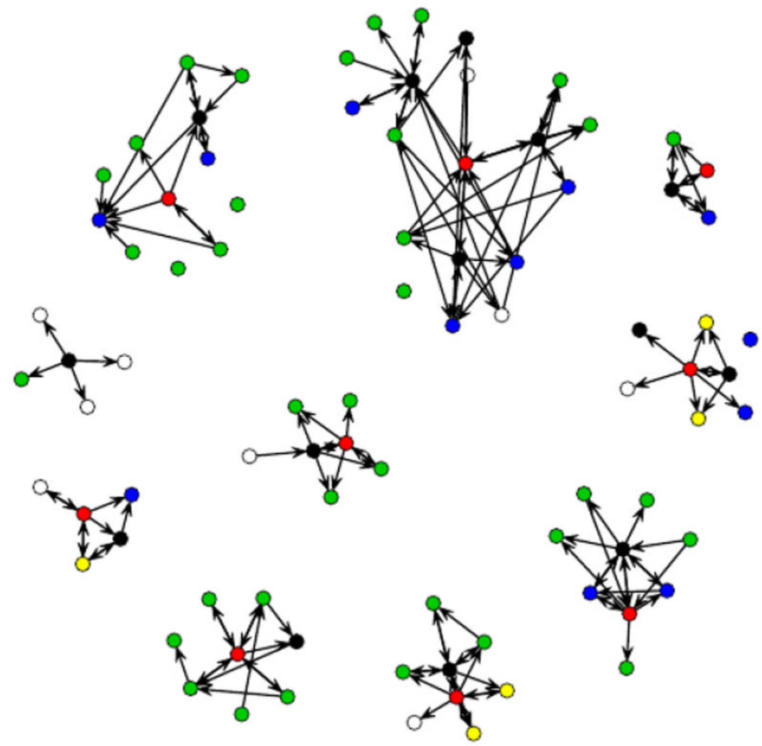
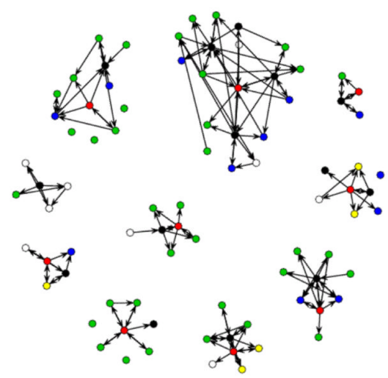
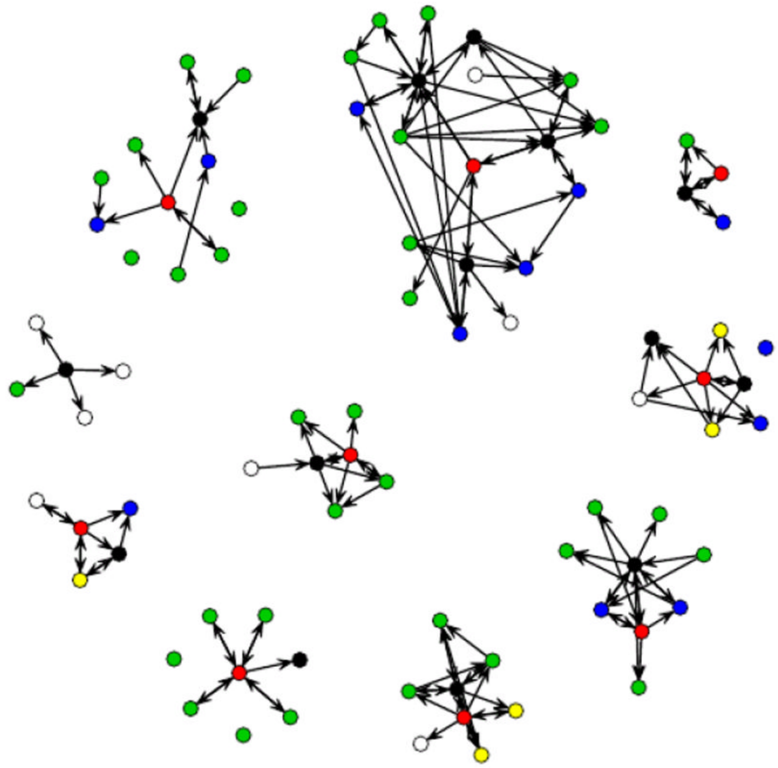


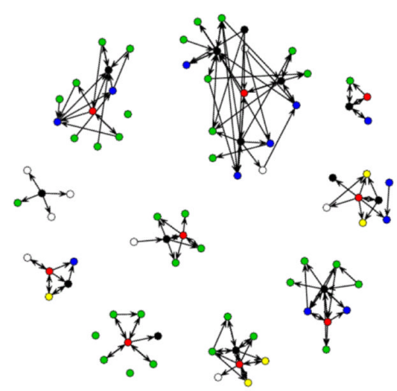
Simulated network 3



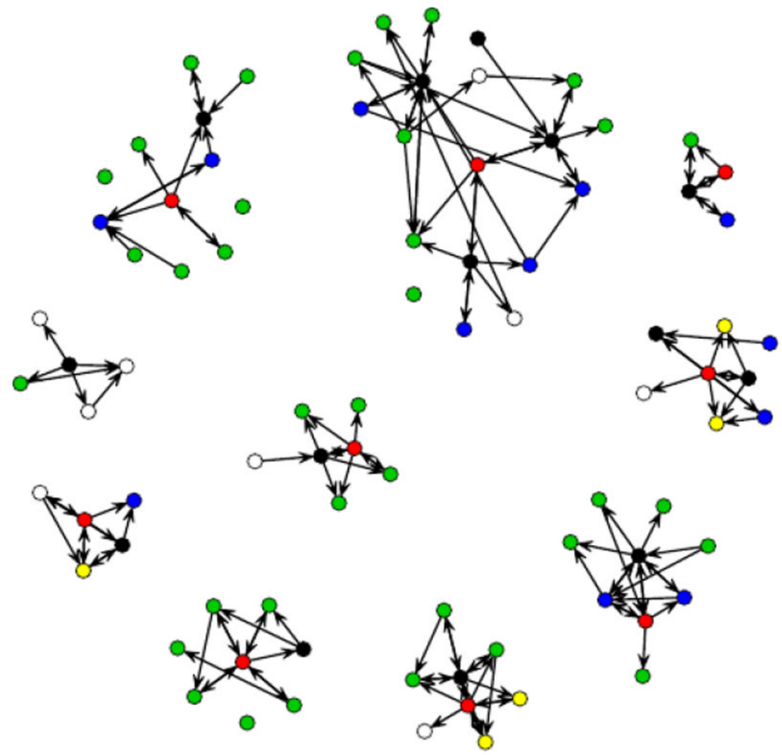
Simulated network 4



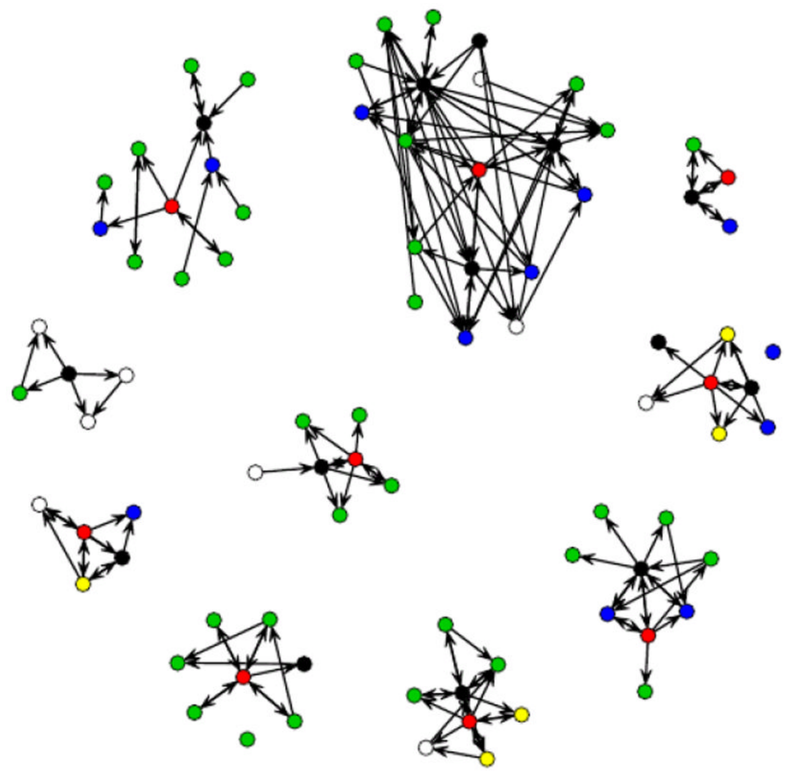
Simulated network 5



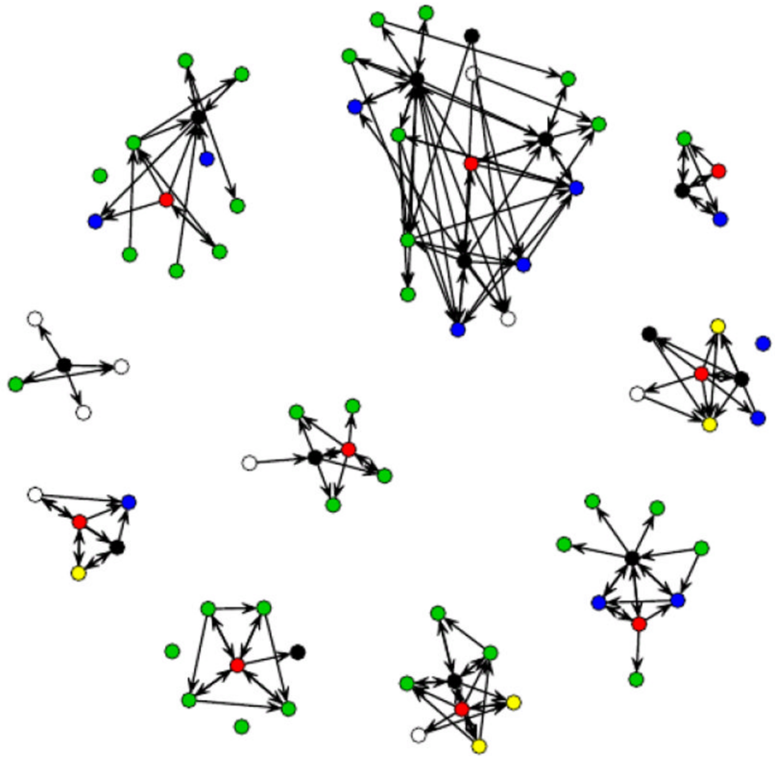
Simulated network 6



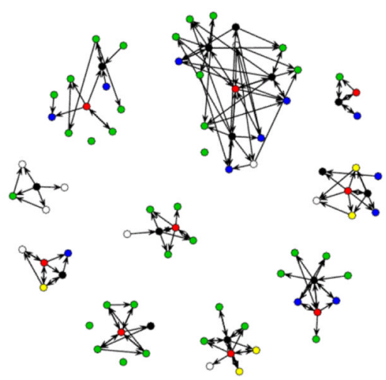
Simulated network 7



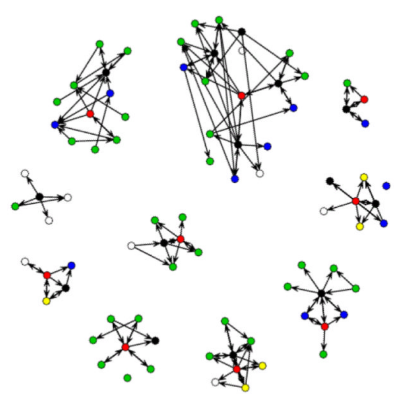
Simulated network 8



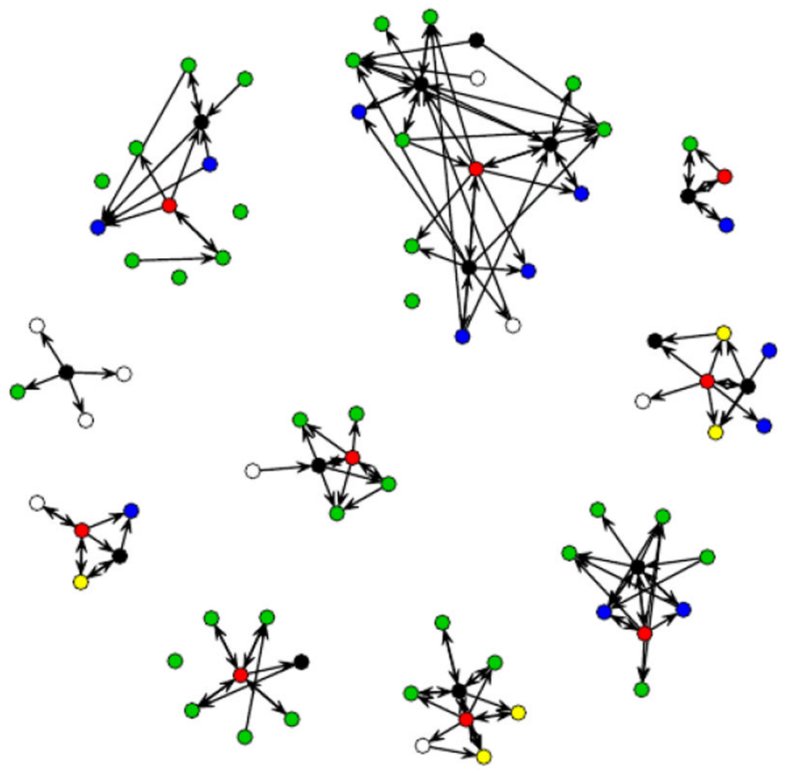
Simulated network 9



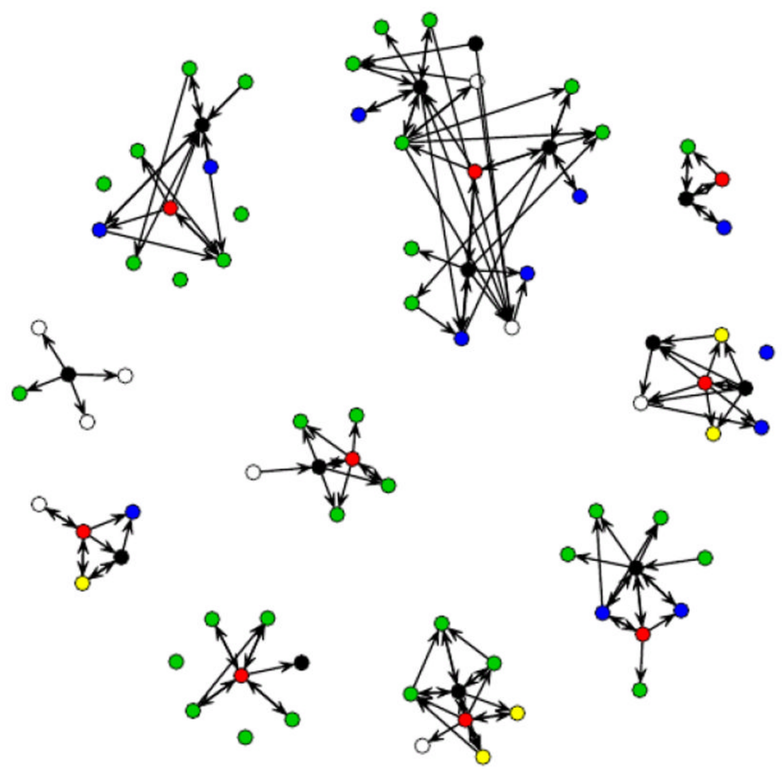
Simulated network 10



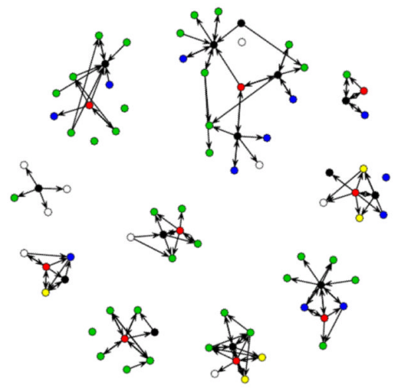
Simulated network 11



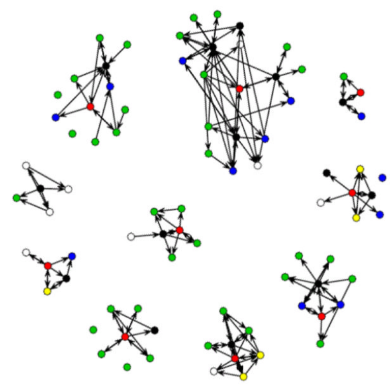
Simulated network 12



Simulated network 13



Simulated network 14



Simulated network 15

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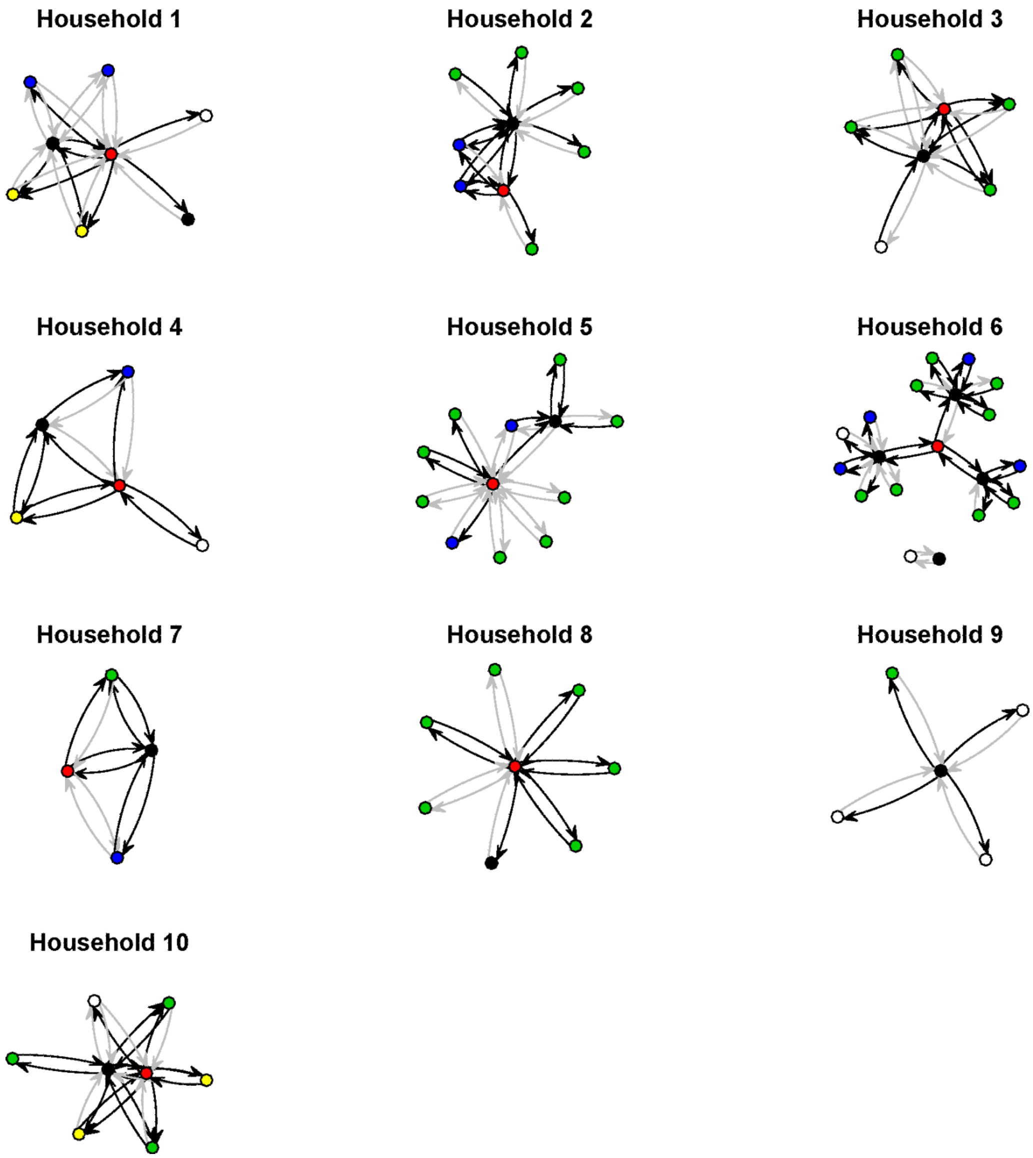

Figure 1. Household networks of economic resource transfers

Note: Colors indicate relationship to the female respondent. Black arrows depict transfers of wealth, gray arrows depict reported non-transfers, and a lack of an arrow between two nodes indicates no transfer data for that pair.

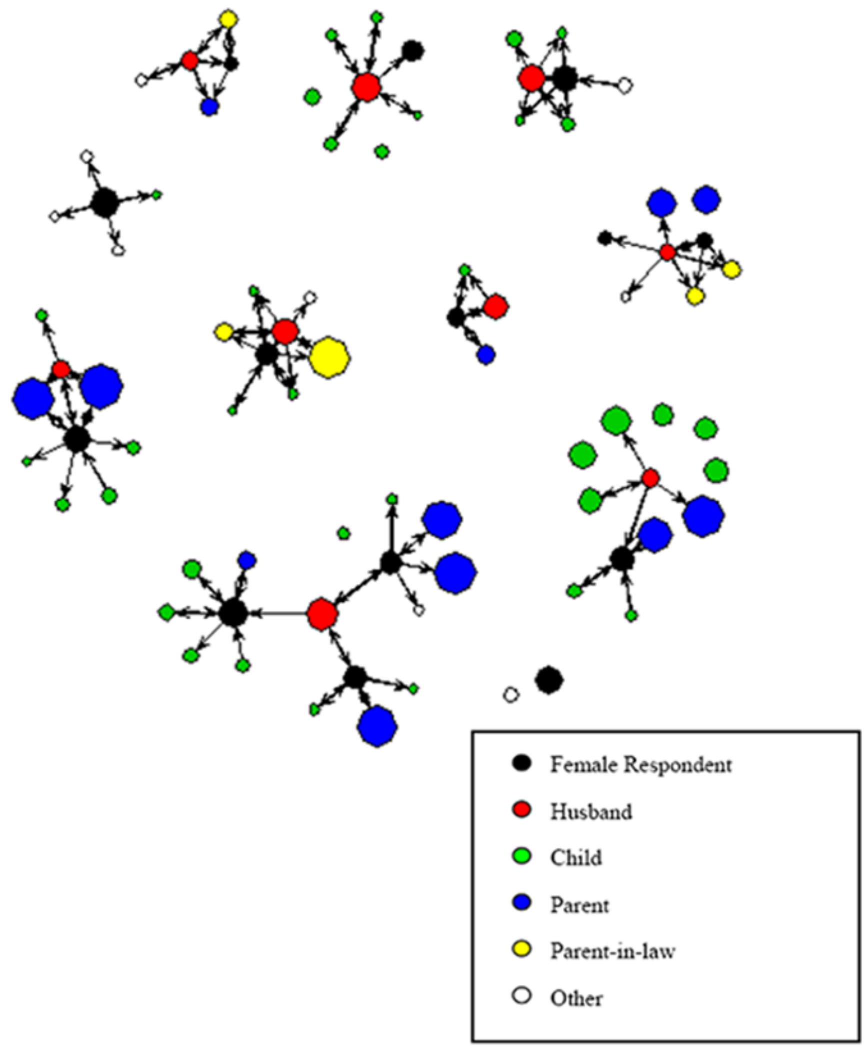

Figure 2. Observed within household networks
Note: Vertex size indicates age of actor.

Table 1

Mean (SD) or categorical proportions

	Village	Rumphi
Age (years)	34 (17)	40 (20)
Household size	9 (4)	8 (3)
Sex (% Female)	59%	53%
Employed in past 6 months	85%	77%
Health Status:		
Excellent	19%	30%
Very Good	61%	40%
Good	13%	25%
Poor	7%	5%
Health relative to others of same age and sex		
Much Better	25%	33%
Better	56%	36%
Same	13%	26%
Worse	6%	4%
Been ill in past 12 months	25%	28%
Education Level		
No school	3%	3%
Some Elementary	59%	60%
Some High School	20%	20%
Some post-secondary	0%	2%
Still in Elementary	13%	9%
Still in High School	5%	5%
Marital Status		
Married	66%	69%
Separated or divorced	4%	5%
Widowed	5%	7%
Never Married	26%	20%
Relationship to Female Respondent		
Self	17%	19%
Spouse	10%	14%
Parent	14%	14%
Parent-in-law	6%	13%
Child	42%	33%
Other	10%	6%
Mobility		
Moved here in last two years	23%	42%
Moved here 2+ years ago	41%	9%
Born here	36%	49%

Table 2

Estimates (standard errors) of model parameters

	Model 1		Model 2		Model 3		Model 4	
Giver completed some high school	0.1 (0.54)		0.04 (0.32)		0.05 (0.34)		0.08 (0.29)	
Receiver ill in past 6 months	-0.29 (0.54)		-0.41 (0.32)		-0.16 (0.27)		-0.32 (0.33)	
Receiver aged 26-39	-1.54 (0.63)	*	-1.3 (0.43)	**	-0.94 (0.38)	*	-1.34 (0.38)	***
Receiver aged 40-59	-0.65 (0.63)		-0.51 (0.36)		-0.65 (0.3)	*	-0.86 (0.36)	*
Receiver over 60 years old	2.62 (1.02)	*	2.95 (0.5)	***	1.55 (0.48)	**	2.39 (0.53)	***
Male to male	-2.74 (1.12)	*	-2.87 (0.63)	***	-0.15 (0.84)		0.62 (1.14)	
Female to male	-4.83 (1.21)	***	-4.87 (0.67)	***	-2.05 (0.78)**	**	-1.34 (1.23)	
Male to female	-3.81 (1.16)	**	-3.88 (0.62)	***	-1.28 (0.75)	.	-0.5 (1.15)	
Female to female	-3.3 (1.15)	**	-3.23 (0.59)	***	-0.85 (0.75)		0.22 (1.24)	
Giver age 26-39	1.09 (0.63)	.	1.08 (0.41)	**	0.88 (0.42)	*	0.79 (0.38)	*
Giver age 40-59	0.63 (0.64)		0.67 (0.35)	.	0.38 (0.38)		0.27 (0.35)	
Giver age 60+	1.67 (0.93)	.	2.04 (0.54)	***	1.27 (0.51)	*	1.46 (0.52)	**
Small (<6) households	1.11 (0.67)	.	0.85 (0.55)		1.19 (0.54)	*	1.34 (0.49)	**
Large (>18) households	0.18 (0.56)		-0.17 (0.35)		-0.64 (0.4)		-0.32 (0.52)	
Giver is working	1.03 (0.74)		0.9 (0.45)	*	1.26 (0.46)	**	0.44 (0.41)	
Receiver regular compound member	1.29 (0.54)	*	1.53 (0.34)	***	0.75 (0.27)	**	1.36 (0.32)	***
Giver regular compound member	1.75 (0.47)	***	1.91 (0.31)	***	1.61 (0.32)	***	1.13 (0.32)	***
Giver is spouse of receiver	2.51 (0.83)	**	2.7 (0.69)	***	1.91 (0.73)	**	2.33 (0.71)	**
Giver is child of receiver	0.94 (0.58)		1.06 (0.38)	**	0.6 (0.38)		0.87 (0.4)	*
Giver is parent of receiver	1.97 (0.61)	**	2.01 (0.39)	***	1.52 (0.42)	***	1.47 (0.39)	***
Mutuality Term	-0.37 (0.5)		-0.5 (0.45)		-0.31 (0.44)		-0.38 (0.43)	
Cyclic triple term			-0.13 (0.12)					
Gwidegree term					-2.83 (0.99)	**		
Gwodegree term							-3.19 (1.12)	**

Note: Model 1 fits the network of economic resource transfers from individual and dyadic effects only. Models 2-4 include network effects of cyclic giving (ctriple), heterogeneity in receiving patterns (gwidegree) and heterogeneity in giving patterns (gwodegree)