The Network Architecture of Reciprocated Versus Unreciprocated Sharing*

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Abstract

We empirically explore predictions from the theoretical network literature regarding reciprocated (undirected) sharing and unreciprocated (directed) sharing. The predictions that networks of undirected two-way transfers should exhibit high levels of support while networks with one-way flows of transfers should exhibit star-like characteristics are both supported in the data. Because our social network data comes from a sample, rather than a census, we show results both for the original sample data, as well as from the network reconstruction techniques described in Chandrasekhar & Lewis (2011).

1 Introduction

While informal insurance and social networks are important in all societies, networks are particularly critical in rural villages of developing countries. In these areas people know each other well and interact over several generations. Many formal institutions such as health insurance and old age support are lacking. Townsend (1994), Jalan & Ravallion (1999), and Ligon et al. (2002), among others, document the importance of informal risk-sharing within villages. More recently, theorists have begun to model the sharing that takes place within a network, rather than within the village as a unified whole (Bramoullé & Kranton 2007, Bloch et al. 2008, Ambrus et al. 2014). These papers show that sharing may be local since network architecture may inhibit full risk sharing.

As researchers gain access to data sets with more detailed information about transfers between specific households, empirical studies are beginning to show the importance of risk-sharing within these social networks. Rosenzweig (1988), Udry (1994), Fafchamps & Lund (2003) and De Weerdt & Dercon (2006) all give evidence of the prevalence of network-level sharing. These papers tend to find that households participate in more gift-giving and informal lending following the negative income shock of a fellow network member. Given

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this local nature of risk-sharing within networks, it is important to analyze who forms links with whom and the types of relationships formed. The effects of development policies will depend on the operation of social networks and the features that cause individuals to form links.

Past survey-based evidence has, somewhat surprisingly, found that individuals are more likely to be linked when wealth differences between them are greater (De Weerdt 2004, Fafchamps & Gubert 2007). Schechter & Yuskavage (2012) distinguish between links which are reciprocated and links which are unreciprocated and find that, while unreciprocated relationships are more likely to exist when one household is wealthier and more educated than the other, reciprocated links do not depend on wealth differences and instead are more likely to occur between two wealthier households.[1]

Given that Schechter & Yuskavage (2012) show that *the predictors* of reciprocated relationships are different from those of unreciprocated relationships, this paper takes that analysis one step further showing that *the architecture* of reciprocated networks is significantly different from that of unreciprocated networks. The main contribution of this paper is that we are one of the first to empirically test specific predictions of network theory.

The theoretical literature on network formation distinguishes between networks with benefits which flow in one direction and those with benefits which flow in both directions. Jackson et al. (2012) shows that networks with two-way flows should exhibit high levels of support. Bala & Goyal (2000) and Galeotti (2006) show that networks with one-way flows may exhibit a star-like structure. We find exactly these patterns of architecture in our reciprocated and unreciprocated networks respectively. While Falk & Kosfeld (2012) test the predictions of theoretical models of one and two-way flows using experimental data on network formation among anonymous students, this is the first paper that we know of to use data on naturally arising social networks in the real world to test these predictions.

A common problem is that much data on social networks comes from a sample of the network rather than a census. Chandrasekhar & Lewis (2011) have shown that measures of social networks which come from a sample rather than a census may be biased, and this bias can not be signed. But, they also show a network reconstruction technique one can use if one has some information on the network members which did not participate in the sample. We show results using the original sample, the reconstruction technique proposed by Chandrasekhar & Lewis (2011) and a variant of that technique which makes use of more survey information. Our results are robust across the three estimation methods.

The rest of the paper is organized as follows. Section 2 discusses the predictions of

[1]Since our question defining a link asks who the household would go to if they needed to borrow 20 KGs one might worry that, in fact, all sharing is reciprocated but not all of it in the form of cash. This paper shows that network architecture is significantly different in reciprocated and unreciprocated links, making it unlikely that what we classify as unreciprocated links are actually reciprocated by some other unobserved means. In addition, we can look more directly at measures of cash-on-hand. Because we have information on donations to the church and community projects we are able to classify households based on their comparative advantage in cash versus labor. In results available upon request, we do not find any evidence that households with a comparative advantage in cash share in an unreciprocated manner with households with a comparative advantage in labor.

the theoretical literature on directed and undirected networks. Section 3 gives the details regarding the data used in the analysis and explains how we define links. Section 4 lays out the basic estimation strategy and results. Section 5 uses the data to test the theoretical predictions and Section 6 concludes.

2 Network Architecture

The literature on patterns of network formation distinguishes networks in which benefits flow in one direction from those in which they flow in two directions. The literature in economics has tended to focus on networks with two-way flows because many economic interactions exhibit two-way flows of benefits. However, the predictions from the two types of models are quite different (Jackson 2008).

We use two existing models of network formation to make testable predictions about the relationship between the network formed by unreciprocated links and that formed by reciprocated links. By drawing on theories which make general claims about the shape that networks of one-way and two-way flows should take, we can empirically verify if the different links behave as expected.[2]

This approach allows us to see if the distinction between reciprocated and unreciprocated links affects understanding of the network as a whole. If the only difference between reciprocated and unreciprocated links is their correlates, then it may not be important to distinguish between them. But if the two networks have different architectures, then combining the two types of links will at best result in analytical noise and at worst obscure the truth. By comparing architecture for the two types of links, we can therefore explore how important it is to distinguish between different link types.

2.1 Two-Way Flows of Benefits in Undirected Networks

While there are many models of efficient and/or stable undirected networks, we focus on a recent model which seems especially well-suited to our situation. Jackson et al. (2012) construct a model of risk-sharing in which the interaction between two individuals is sufficiently infrequent that the two individuals will not be able to sustain exchange between themselves bilaterally. But if the loss of one relationship may cause them to lose others as well, this bilateral exchange can be sustained. This type of situation fits our data because households claim to have relationships with one another in which monetary transfers could flow in either direction. On the other hand, there are extremely few cases in which monetary flows actually occurred in both directions in a single year. Thus, we hypothesize that bilateral interactions may be infrequent enough to necessitate that the network be used to maintain exchange.

Jackson et al. (2012) show that networks corresponding to robust equilibria have the characteristic that all connected links (sets of neighbors) are "supported". A link is sup-

[2]We look at predictions from models of either only one-way or only two-way flows. This is because there is no model that we know of which combines the two types of links in one model, although the existence of one type of relationship is sure to impact the other in practice.

ported if both nodes in the link share a common neighbor. These equilibria must fulfill two requirements. First, threats to terminate relationships must be renegotiation proof. Second, the networks must be robust against social contagion, meaning that if one link breaks down it will only result in a local loss of exchange, and will not cause the rest of the network to break down. They show that the only network configuration which is possible is that of a 'social quilt' and that in such robust equilibrium networks all links must be "supported". They apply this concept of support to social network data from 75 villages in India and find that support is quite high in such networks.

To be more precise about how to define support, we use the following notation. We will write ij to represent the link between i and j, and $ij \in g$ means that i and j are linked (i.e., are neighbors) in network g. Jackson et al. (2012) begin by defining support for a network g but also expand their definition to include the support of a network g' relative to another network g. (The original case where $g = g'$ is called 'self-support'.) Support is defined as $S(g', g) = \frac{\sum_{ij \in g'} 1_{\{\exists k, ik \in g, kj \in g\}}}{\sum_{ij \in g'} 1}$. This is the proportion of links in network g' whose nodes have common neighbors in network g. So, for example, if $g' = g$ is the reciprocated lending network, it would be the proportion of reciprocated lending links which share a common neighbor with whom both are also linked reciprocally.

Given this model, we predict that the reciprocated networks should exhibit high levels of support because they involve the relatively rare potential for two-way favor-sharing. It is possible that unreciprocated links also require support to convince the lender to lend or the borrower to repay. Support may be less necessary either because these relationships are treated more as typical credit relationships which use other means to enforce repayment, or because the lender is giving for reasons other than risk-sharing (e.g., altruism).

2.2 One-Way Flows of Benefits in Directed Networks

There is much less written in economics on directed networks than there is on undirected networks. Bala & Goyal (2000) construct a model of network formation in a directed network. They examine cases both with and without decay (meaning that the value of an indirect connection goes down with the distance between the two individuals). They show that the star can be both an efficient network structure and a Nash equilibrium in networks with one-way flows and decay.[3] A star network is one in which a central household is connected to all other households, while no other links exist.

Galeotti (2006) adds heterogeneity into the previous model and shows that with heterogeneity and one-way flow of benefits, stars and wheels with local stars can be equilibrium outcomes even without decay. He also finds that a characteristic of these equilibrium networks is that they have high levels of centralization, meaning that there are few nodes with many links, while most nodes maintain few links. Centralization is a global network-level concept which looks at how central the most central individual is compared with all of the other individuals.

[3] With one-way flows without decay, the wheel would be the equilibrium outcome.

There are multiple measures of individual-level centrality and Galeotti (2006) do not discuss which measure one should use. We focus on degree, or the number of direct links a household has. Given that we are looking at bilateral monetary transactions, degree is more relevant than measures such as betweenness or eigenvector centrality which take into account longer paths between individuals.[4]

Banerjee et al. (2013) define a measure of diffusion centrality which allows T iterations of diffusion with probability q at each iteration. If $T = 1$ then their measure is proportional to degree, and as $T \to \infty$ (and if q is high enough) their measure converges to eigenvector centrality. In their setting, which is the diffusion of information regarding microfinance, betweenness and eigenvector centrality had more explanatory power than degree. This makes sense since information may travel long distances (meaning that T may be large). In our setting looking at bilateral transactions (where $T = 1$ in their terminology) degree is more appropriate.[5] Another benefit of focusing on degree is that, given that our data comes from a sample rather than a census, it is much more difficult to estimate betweenness and eigenvector centrality which depend on long chains of links compared with degree and support which focus on one-on-one interactions.

The more disparate the individuals are, the more centralized is the network. Global measures of degree centralization for the network as a whole include the standard deviation of individual degree and Freeman's index which is a normalization of the sum of the difference between the largest individual's degree and all other individuals' levels of degree. For both of these measures, the maximum is reached in a star network in which case one individual lies in the center (and therefore has a degree of $N-1$), while the other individuals are connected to him and only him (and therefore have a degree of 1) (Wasserman & Faust 1994).

Since both Bala & Goyal (2000) and Galeotti (2006) suggest that networks with one-way flows should exhibit a star-like structure, we hypothesize that the unreciprocated networks we are looking at will be star-like and so will have high values of degree centralization. We would also expect that households with high levels of degree will be linked with households with low levels of degree. On the other hand, given the results on support in networks with two-way flows, we do not necessarily expect reciprocated networks to exhibit these characteristics.

One can separate degree into the number of outgoing unreciprocated links (out-degree) and the number of incoming unreciprocated links (in-degree). We predict that out-degree is highly centralized, with a few very central individuals giving to everyone else. On the other hand, we predict that in-degree is much less centralized with many people potentially receiving loans from a few households.

[4]Betweenness for individual i measures the share of shortest paths in the network on which individual i falls. Eigenvector centrality takes into account that if i is linked with highly central individuals, then his own centrality should be higher.

[5]In a previous draft of this paper we explored results using betweenness centrality. The results go in the same general direction, but with less significance.

3 Data

In 1991, the Land Tenure Center at the University of Wisconsin in Madison and the Centro Paraguayo de Estudios Sociológicos in Asunción worked together in the design and implementation of a survey of 300 rural Paraguayan households in fifteen villages in three departments (comparable to states) across the country. The households were stratified by land-holdings and chosen randomly with an over-sampling of households with larger land-holdings. The original survey was followed up by subsequent rounds of data collection in 1994, 1999, 2002, and 2007. All rounds include detailed information on production and income.

In 2007, new households were added to the survey in an effort to interview 30 households in each of the fifteen randomly selected villages. Villages ranged in size from around 30 to 600 households. In one small village only 29 households were surveyed. The 2007 round added many questions measuring social networks.

The process undertaken in each village was the following. We arrived in a village and found a few knowledgeable villagers to collect a list of the names of all of the household heads in the village. These knowledgeable villagers were also asked to point out the approximate 5% richest and 5% poorest households in the village. We then randomly chose new households to be sampled to complete 30 interviews in the village. (This meant choosing between 6 and 24 new households in each village in addition to the original households.)

These villages are mostly comprised of smallholder farmers and do not involve any tribes or castes. There are no village chiefs, large plantation owners, or major money-lenders. Government is at the municipal level which is larger than the village. In our sample, 42% of households lent money in the past year (to anyone inside or outside the village) but only 4% lent to three or more households. Additionally, of the 30% of households which borrowed money in the past year, 62% also lent money.

Although the exact survey question used and the definition of a risk-sharing link differ across existing papers, there are similarities. Fafchamps & Gubert (2007) ask households who they could rely on in case of need or to whom they give help when called upon to do so. Note that this is asked as one question, not two separate questions. Similarly, De Weerdt (2004) asked "Can you give a list of people, who you can personally rely on for help and/or that can rely on you for help in cash, kind or labour". These questions do not allow the researcher to differentiate giving help from receiving help. However, it is possible that the direction in which transfers flow and whether or not they are reciprocated identify different types of relationships within a network.

Our survey asks respondents from which households they would ask to borrow 20 thousand Guaranies (KG's) (approximately \$4) if they had a personal problem, and then asks separately which households would ask to borrow 20 KGs from them if they had a personal problem. In order to make it easier for respondents to understand the question and so that all respondents interpreted it in the same way, we asked about this one very specific interaction. This amount is much smaller than that which formal institutions will lend (and it is the median value of a day's labor in agriculture). The lowest amount lent to a survey respondent by a formal institution is 100 KGs while the median is 2,500 KGs. Many authors have shown that such informal credit is a form of risk-sharing, as lending and repayment often depend on shocks received by both borrower and lender (Platteau & Abraham 1987, Udry 1994, Ligon et al. 2002). Note that although loans, by nature, involve reciprocal transfers, the hypothetical question we use in our analysis only asks about the initial loan transfer, and not the repayment transfer.

Respondents could list as many households as they wanted. They listed anywhere from 0 to 14 to whom they would go (with a median of 2) and anywhere from 0 to 32 (also with a median of 2) who would go to them. There are 1113 total instances of another household being listed as a source from which to request borrowing, and 1086 total instances of another household being listed as a possible requester of lending. When a household stated they would request lending from another household, 48.9% of the time they stated that the relationship was reciprocal and the other household would also request lending from them. Conversely, when a household claimed another household would request to borrow money from them, 50.1% of the time they stated that they would reciprocally also request to borrow from that household.

The village leaders gave us 2514 names of individuals in the villages. Of those, 947 unique households are mentioned by respondents as either a potential borrower or a potential lender. There are an additional 188 survey respondents who are not themselves mentioned by someone else (but may have mentioned someone).

Our analysis in this paper centers around the hypothetical question regarding to whom a household can turn for help in times of need. In Schechter & Yuskavage (2012) we also looked at actual loans and gifts in the previous year and found similar results for the predictors of links, although that paper did not look at the architecture of links. A disadvantage of using the actual transfers is that households have potentially reciprocated relationships with one another as defined by the hypothetical questions, but that in any given year transfers may not actually flow in both directions since it is relatively unlikely that *both* households will be in need of help in the same year. This suggests a disadvantage of using data on actual rather than potential transfers.

4 Empirical Estimation

In this section we model the prediction of the existence of both reciprocated and unreciprocated lending links. Each unique pair of households is an observation. By this we mean that the dyad (i, j) counts as an observation, but the dyad (j, i) does not. From the 449 observations there are 6,496 pairs of households which may possibly be linked. This is fewer than the $100, 576 = (449 * 448)/2$ we would obtain if we allowed for every possible link between households. This is because the 15 villages are not close to one another so we do not allow for cross-village relationships.

Each dyad (ij) can be in one of four states: reciprocated lending between i and j, unreciprocated lending from i to j, unreciprocated lending from j to i, and no transfers between i and j. We define lending links (L-links) where $L_{ij} = 1$ if household i says that household j would ask to borrow from it, *or* household j says it would ask to borrow from i. The direction of this link is determined by the direction of the flow of transfers, regardless of which household mentions that the link exists. Reciprocated links (LR-links) are those for which $L_{ij} = L_{ji} = 1$. Unreciprocated links (LU-links) are those for which $L_{ij} = 1$ while $L_{ji} = 0$ or $L_{ij} = 0$ while $L_{ji} = 1$. 217 pairs have reciprocated relationships while 314 have unreciprocated relationships.

We would like to predict the probability of being linked in each type of link. Given that each dyad can be in one of four states, the alternative specific conditional logit is appropriate for estimation. This allows for the inclusion of dyad-level variables (such as geographic distance) interacted with alternative dummies (such as being in a reciprocated relationship). Each dyad (i, j) has four choices $k \in \{0, 1, 2, 3\}$ where 0 represents no relationship, 1 represents a pure lending relationship, 2 represents a reciprocated relationship, and 3 represents a pure borrowing relationship. The model specifies that the probability of dyad (i, j) being in relationship $k \neq 0$ can be represented as follows:

$$p_{ijk} = \frac{\exp(\gamma_k' \nu_k + \alpha_k'(\nu_k X_{ij}))}{1 + \sum_{l=1}^{3} \exp(\gamma_k' \nu_k + \alpha_k'(\nu_k X_{ij}))}$$

where ν_k are alternative (relationship type) fixed effects, X_{ij} are dyad characteristics.

In the regressions we can control for dyad-level characteristics such as the dyad's measure of support, the geographic distance between the two households, and whether members of the two households are immediate relatives (that is, parents, children, or siblings). For these variables we must impose the constraint that $\alpha_1 = \alpha_3$. In other words, the impact of distance must be the same on incoming unreciprocated links and outgoing unreciprocated links. This constraint must also be imposed for village fixed effects and the constant.[6]

We also make use of some household-level characteristics such as the household's degree. For unreciprocated links we include the sum $(x_i + x_j)$ and the difference $(x_i - x_j)$ of each of the household characteristics as explanatory variables. For the reciprocated links, symmetry implies that the absolute value of the difference $(|x_i - x_j|)$ must be used rather than the difference itself. To implement this, we impose the constraint that $\alpha_1 = \alpha_3 = 0$ for the absolute difference variables and $\alpha_2 = 0$ for the difference variables. We also constrain $\alpha_1 = -\alpha_3$ for the difference variables. Intuitively, $x_i - x_j$ should have the opposite impact on i lending to j as $x_i - x_j$ has on j lending to i.

The standard errors of the regressions must take into account that dyadic observations are not independent due to individual-specific factors common to all observations involving that household. We correct both for the non-independence of dyads sharing a common member and for the non-independence of all observations within the same village. We cluster the standard errors at the village level to allow for arbitrary correlation between observations in the same village. But, because there are only 15 villages this may not be appropriate. We have not done so yet, but we are looking into implementing other options such as the wild bootstrap recommended by Cameron et al. (2008) for future versions of this paper.

Table 1 shows summary statistics of household characteristics, Table 2 shows summary statistics of dyad characteristics in the sample, and Table 3 shows summary statistics of

[6]Remember that our analysis does not include both dyad (i, j) and dyad (j, i); it only includes the former.

dyad characteristics in the census. Figure 1 shows histograms of the number of links each household in the sample has (their degree).

4.1 Simulation of Network Measures

One issue is that our network data comes from a sample rather than a census of households in the network. Chandrasekhar & Lewis (2011) show that regressions predicting link formation where the explanatory variables do not include network variables can be consistently estimated with a sample if the sample was selected randomly. But, if one includes network variables such as degree and support as explanatory variables, this is no longer the case. There can be attenuation of estimates, but also expansion of estimates and even sign-switching.

Because our main interest is related to the impact of degree and support on network formation, we use the network reconstruction technique outlined in Chandrasekhar & Lewis (2011). First, we estimate link probabilities within the sample using only characteristics we have for all households in the census. Then we can use this to predict links for the out-of-sample households. We keep the original links between the in-sample households, rather than using the predictions for those links. Then, using the predicted links we can calculate network measures such as degree and support for all members of the sample. We both predict the links and calculate measures of degree and support 4000 times. Then we take the average of the measures of degree and support and use those as explanatory variables in our regressions.

We have a useful list of characteristics for households in the census due to the fact that we know the names of all household heads in the village. From that, we can create dyad-level variables for all households such as an indicator for when the two household heads have the same last name; indicators for dyads with two female-headed households, two male-headed households, or one of each; and indicators for two households of Paraguayan heritage, two of Brazilian heritage, or one of each. We also asked village leaders to name the very richest and the very poorest households in each village. Approximately 5% of households fall in each category. From that we can create dyad-level indicators for two rich households, one rich with one who is neither rich nor poor (call that 'medium'), etc.

The results from the alternative-specific conditional logit regression used for prediction can be found in Table 4. As discussed above, for the reciprocated link categorization, the coefficients on variables such as rich/poor and poor/rich are constrained to be the same. This can be seen in the table. For the unreciprocated link categorizations, the coefficient on a variable such as rich/poor for outgoing links is constrained to be the negative of the coefficient on the opposing variable poor/rich for incoming links. Also, the coefficient on same last name is constrained to be the same for both incoming and outgoing links. The imposition of these constraints can not be seen in the table since we present the results for out-going links.

The results in Table 4 are not surprising. Unreciprocated links are extremely unlikely from the poor to the rich, or from Paraguayans to Brazilians. The rich are much more likely to have unreciprocated links to the poor and to the 'medium'. Reciprocated links are less likely between households of different wealth level, different gender, and different ethnicity. Having the same last name increases the likelihood of both types of link.

We use the results from this regression of sample households to predict links on which we do not have data. We have two different ways of predicting these links. The first, which we call the "Normal Simulation," is the method laid out by Chandrasekhar & Lewis (2011). In this case all links which are not between two households in the main survey are simulated.

We additionally conduct a second simulation which we call the "Robust Simulation." This method uses information which respondents gave regarding out-of-sample households, as well as from a shorter survey on a non-random sample of households. These households are those households which were not in our original sample and who were chosen by our main sample respondents to be recipients in a dictator game. In both the shorter survey and the general survey, respondents were asked about borrowing and lending for all households in the village, whether or not that household was in our sample. Thus, we do already have quite a bit of information regarding dyads involving one household who responded to a survey and another who did not.

In the "Robust Simulation," for those dyads where one household responded to the general survey and one responded to the shorter survey, or where both households responded to the shorter survey, we use the information from the surveys rather than simulating predicted links. For those dyads where one household responded to either survey while the other did not we at least know what the one in-sample household stated about their relationship and we take that into account. If the in-sample household states the relationship is reciprocal, we consider it to be reciprocal. If the in-sample household states the relationship is unreciprocated in either direction, we know that the true relationship is either unreciprocated or reciprocated (but that there is definitely a link of some sort). Thus, we predict the link using the relative probabilities for the two possible link types (either unreciprocated in a specific direction or reciprocated). If the in-sample household does not claim to have a relationship with the out-of-sample household, we predict the relationship as we do with two out-of-sample households, allowing all four link types.

We conduct both simulations because the "Normal Simulation" throws away some information but does not add any bias. The "Robust Simulation" method keeps all the information we already have but it may lead to some biases being introduced in the prediction. Figures 2 and 3 show histograms of the number of links each household in the sample has (their degree) after the normal and robust simulations.

5 Results

Given the theoretical models discussed in Section 2, we will look at support and degree in reciprocated and unreciprocated relationships. We can look at both global measures of network architecture (i.e., measures for which there is one observation per village) and local measures of network architecture (i.e., measures for which there is one observation per individual or per dyad).

The results above suggest that reciprocated networks should exhibit high global levels of support. They also suggest that, at the local level, most reciprocated links should exhibit support. For unreciprocated networks, the theory predicts that they should exhibit high global levels of degree centralization. It also suggests that, at the local level, households with high degree should be linked with those with low levels of degree. We predict that unreciprocated out-degree should be more centralized than unreciprocated in-degree. People with high out-degree will give to people with low out-degree, and people with low in-degree will give to people with high in-degree. These are the predictions that we will take to the data.

5.1 Support

We will first compare global measures of support for reciprocated and unreciprocated networks. We consider three networks: the network of reciprocated hypothetical sharing links, the network of unreciprocated hypothetical sharing links, and the network of all hypothetical sharing links (both reciprocated and unreciprocated). Remember that support is the proportion of links in network g' whose nodes have common neighbors in network g. We allow reciprocated links to either be supported by other reciprocated links (which may be the most obvious type of support), but also explore the case in which reciprocated links are supported by any sharing link. In the latter case, support would be the proportion of reciprocated lending links which share common neighbors who are linked in any manner. It is less obvious how this latter type of support would work in practice, since it might not be useful punishment to threaten to cut an unreciprocated link if a partner reneges on a promise in a reciprocated link.

If g' is the network of unreciprocated links and g is the network of all links, then it is simple to calculate the support of unreciprocated links. One just looks at the share of dyads which are linked unreciprocally which have any type of friend in common. It is not so clear how to determine which dyads have a friend in common when measuring self-support and $g' = g$ is the network of unreciprocated links. One could consider an unreciprocated link to be supported if that dyad has any neighbor in common, no matter whether the neighbor is lending or receiving or both. Or one could only look at different directions of links. For example, one might decide to only consider the link from i to j to be supported if there is some k so that i lends to k who lends to j. As do Jackson et al. (2012) in their empirical application, in order to measure support we ignore the directionality of links in the unreciprocated network and assume a link ij exists if i lends to j or j lends to i. In the social network literature this is called symmetrizing the network (Costenbader & Valente 2003).[7]

We do this because measures of support would not be comparable across the reciprocated and unreciprocated networks if one measure were directed and the other were not. Given that we predict reciprocated relationships to exhibit more support than unreciprocated links, we do not want to unfairly mechanically decrease unreciprocated support. Thus, when measuring self-support we consider an unreciprocated dyad to be supported unreciprocally

[7]The reciprocated network is symmetric by construction.

when they are both linked in an unreciprocal manner (in either direction) with the same household.

Table 5 shows the average measures of support over 14 villages. We first take the average measure of support among all sample households in the village, and then show the average across the 14 villages. We drop one village which has no reciprocated links within the sample since we cannot measure support for that village. The results are for the sample, the normal simulation, and the robust simulation.

Because we only collected data from a sample of individuals rather than a census, we do not know the level of support for the network as a whole. Thus, our un-simulated measures of support will be biased downwards (Jackson et al. 2012). The simulated measures can only be higher than the un-simulated ones. If a dyad is supported by an in-sample household, then it will continue to be supported when additionally considering potential links with out-of-sample households. But, if a dyad is not supported by an in-sample household, it may still be supported by an out-of-sample household in the simulation. In Table 5 we see that 55% of reciprocally linked dyads have an in-sample friend in common in all the networks. Once conducting the normal simulation this goes up to 67% and with the robust simulation this increases even more to 79%.

The fact that simulated measures of support are higher than sample measures of degree is purely mechanical. The fact that support in the robust simulation is higher than in the normal simulation is due to the fact that the prediction regression only takes into account dyad-level characteristics. Since we can only control for variables such as whether both households are female-headed, but not for variables such as whether they have a friend in common, the prediction equation misses out on some of the clustering inherent in the true underlying networks. The robust simulation takes into account more true relationships and thus finds higher levels of support.

We conduct two different one-sided tests to see whether support is higher in reciprocated networks than it is in unreciprocated networks. We conduct a t-test of the mean of support in the villages, and we conduct a binomial test looking at the number of villages for which reciprocated support is higher than unreciprocated support. Although the power of our tests is quite low given how few observations we have, we see suggestive evidence that reciprocated networks have higher levels of support than unreciprocated networks. We also see that this result is strongest for the case of self-support (where reciprocated links support reciprocated links and unreciprocated links support unreciprocated links). This is true both in the original data on only in-sample households, as well as in the data which simulates links with out-of-sample households.

We next look at the results of alternative specific conditional logit regressions including the measures of unreciprocated and reciprocated support as explanatory variables. Locally, support is a characteristic of a dyad (either the two households share a neighbor, or they don't). So, we can test to see if reciprocated links are more likely to be supported than other dyads.

It is important to remember that there is nothing causal about the relationships explored in these regressions. We are only trying to determine whether unreciprocated networks have different network architecture than reciprocated networks.[8] We do not control for explanatory variables such as wealth and education because we are interested in focusing purely on network architecture, not looking at network architecture conditional on, e.g., wealth. [THEIR ADDITION DIDN'T CHANGE THINGS PREVIOUSLY, BUT SHOULD TRY AGAIN AND PUT IN FOOTNOTE.]

Table 6 shows the results of these regressions. We find that support of all types makes links of any type more probable. Reciprocal or unreciprocal support have similar impacts on the probability of an unreciprocated link. On the other hand, the impact of reciprocal support on reciprocated links is much higher than the impact of any other type of support on any other type of relationship. The differential impact of reciprocal support on reciprocal links is especially true once we take into account family relationships and geographic distance (since households may be more likely to be linked purely because they are close in space or in the family tree). We find that reciprocated support has the most predictive power over reciprocated links compared to any other combination of support and link types. This confirms the prediction of Jackson et al. (2012) that two-way favor-sharing links ought to have high levels of support. This is true in the original sample data, as well as the data simulating out-of-sample links.

In these regressions we only include measures of reciprocal support, unreciprocal support, and family support (with the variable measuring if the two households are immediate family). We have also experimented with measuring support provided by other networks. Other providers of support we look at include exchanging actual gifts or loans in the past year. We find that including the additional regressor of support from reciprocated actual transfers and support from unreciprocated actual transfers does not affect our main results. Furthermore, controlling for family relations and distance between households renders most of these other support measure insignificant. Therefore, we believe our hypothetical links to be a reasonable and robust measure of support.

5.2 Degree

Next we test the prediction that unreciprocated networks should exhibit a star-like quality, with high levels of degree centralization. We look at degree ignoring directionality, as well as in-degree and out-degree. We look at two global measures of degree centralization: the standard deviation of individual degree and Freeman's degree index (the normalized sum of the difference between the maximum degree and all other degrees).

In the sample, the degree is the number of links with in-sample households. In the simulations, it is the number of known links with in-sample households, plus predicted links with out-of-sample households. In all cases the standard deviation and the sum in the Freeman index are taken over only those households in the sample. For Freeman's degree index, the measure is normalized so that its potential range is from 0 to 1. Let N be the total number of households in the village and n be the number of households in the village

[8] As before we consider a link to have unreciprocated support if that dyad has an unreciprocated neighbor in common, no matter whether the neighbor is lending or receiving.

in the sample. For the sample, we divide by $(n-1)*(n-2)$ whereas for the simulations we divide by $(N-1)*(n-2)$ since those are the respective maximum sum of degree differences which would occur in a star.

Table 7 shows the average measures of degree centralization over all 15 villages (with one observation per village). Table 7 shows some weak evidence at the village level that unreciprocated networks are more centralized than reciprocated networks. It shows stronger evidence that outgoing unreciprocated links are more centralized than incoming unreciprocated links. This suggests the star-like architecture, with very few individuals having many outgoing links and many people having fewer or none. The distribution of incoming links is much less varied. With that in mind, we next consider local measures of degree in dyad-level regressions.

Whereas support is a characteristic of a dyad, degree is a characteristic of a node. Therefore, we can run regressions to see if pairs of households with higher sums or differences of degree are more or less likely to be linked.[9] The coefficients in these regressions are likely to exhibit a specific type of bias. The correlation between the sum of degree for a reciprocated link and the existence of a reciprocated link will be positive by construction. If two households are linked, they are more likely to have a higher degree and thus the sum of their degree is likely to be higher. This is true for unreciprocated degree and unreciprocated links as well.

In a similar manner, this mechanical relationship is also likely to bias the coefficient on differences of reciprocal degree towards zero in the reciprocal regression. Households which aren't linked reciprocally to anyone have a degree of zero and the difference of their degree and that of other households will be higher. Similarly, the coefficient on difference of unreciprocal in-degree in the unreciprocal link regression will be biased downwards. Households which don't have unreciprocated incoming links from anyone have an in-degree of zero. They are less likely to be linked and the difference of their degree and that of other households will be higher. With these caveats in mind, it is still interesting to look at the relationship between degree and the existence of a link. As before, we make no causal claims based on the results of these regressions.

Table 8 runs these regressions using all 15 villages. The results show that, as we expected mechanically, the sum of unreciprocated in- and out-degree is highly correlated with the existence of an unreciprocated link while the sum of reciprocated degree is highly correlated with the existence of a reciprocated link.

The results on the differences of degree are more interesting. We had predicted that *LU*-links would be more common from a household with high out-degree to a household with low out-degree. This would mean we expect a positive coefficient on the difference of out-degree in the *LU*-link regressions, which is what we find. Unreciprocated links are more common from people with large out-degree to people with low out-degree (seen for example in the Unrecip-out difference coefficient in the *LU*-link column) while unreciprocated links are more

[9]This is similar to a technique used by Krishnan & Sciubba (2009). They classify individuals as being part of symmetric versus asymmetric networks (based on number of links) and within asymmetric networks as being either a spoke or a hub. They find that symmetric networks exhibit high levels of clustering. Other than that they do not find major differences in household characteristics across the three categories.

common from people with small in-degree to people with high in-degree (seen for example in the Unrecip-in difference coefficient in the LU-link column). On the other hand, reciprocated links are more common between individuals with similar numbers of reciprocated links (seen for example in the Recip difference coefficient in the LR-link column).

In sum, we see evidence that reciprocated sharing networks exhibit high levels of support. We see weaker evidence that unreciprocated sharing networks exhibit high levels of overall degree centralization. Out-degree centralization is much higher than in-degree centralization in the unreciprocated networks. At the local level, unreciprocated networks involve well-connected people sharing with less well-connected people, while this is not a characteristic of the reciprocated networks. Overall, the data confirms the different theoretical predictions for networks with one-way and two-way flows of benefits.

6 Conclusion

We look at lending relationships within social networks and distinguish between unreciprocated relationships in which loans go only from one household to the other, and reciprocated relationships in which loans can go in both directions. We find differences in network architecture across reciprocated and unreciprocated networks.

The theory for networks with one-way flows of transfers predicts quite different outcomes than the theory for networks with two-way flows of transfers. A main prediction of the theory that we test is that reciprocated (two-way flow) networks should exhibit high levels of support whereas unreciprocated (one-way flow) networks should exhibit star-like architecture. We find that these differences suggested by the theory are supported by the data.

Since the two types of links do have differing architectures, differing in ways predicted by theory, this shows that the classification of link types is not an arbitrary distinction but rather a necessary step in understanding how and why relationships form. Looking in depth at network architecture, and taking predictions from the theory to the data, is a fruitful area for future research.

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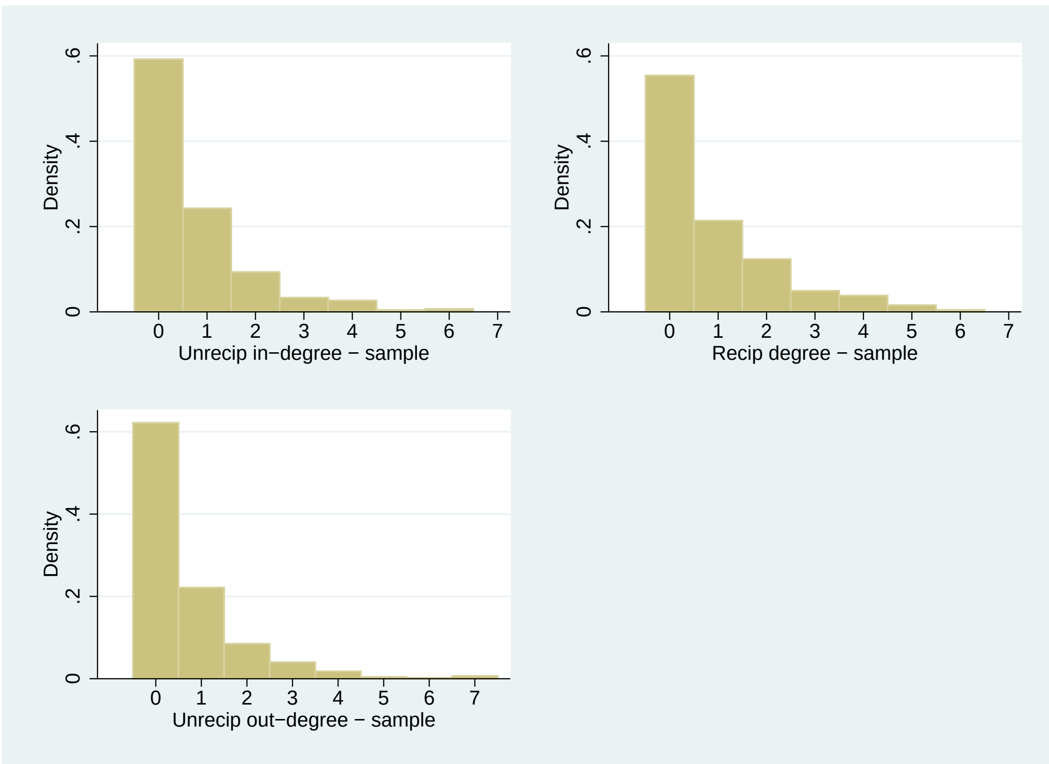

Figure 1: Degree Distribution in Sample

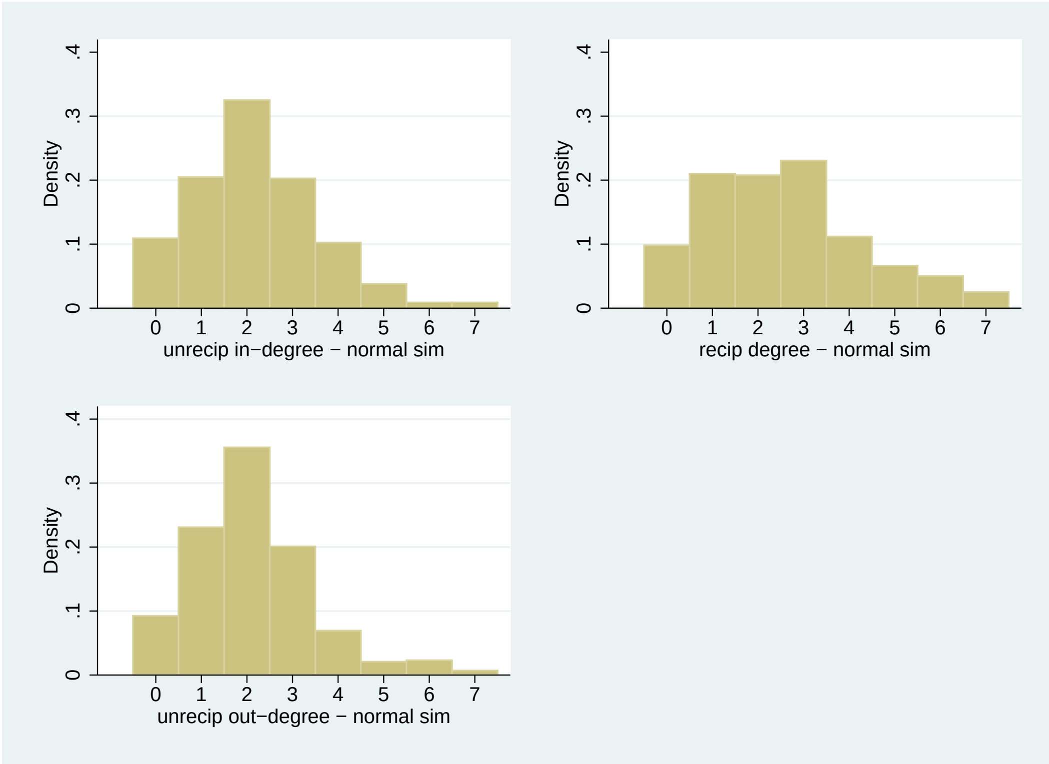

Figure 2: Degree Distribution in Normal Simulation

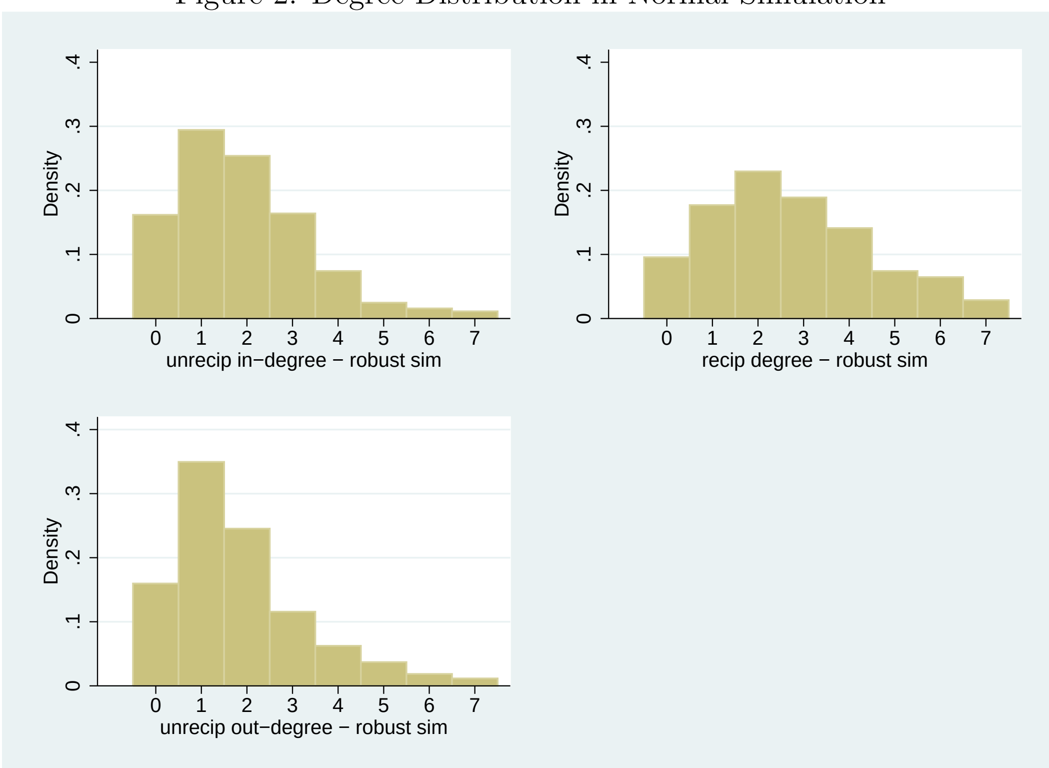

Figure 3: Degree Distribution in Robust Simulation

Table 1: Household level summary statistics

Variable	Mean	Std. Dev.	Min.	Max.
Household wealth (in $)	33,356	138,833	0	2,104,162
Log household wealth (in KGs)	10.21	1.91	0	16.23
Recip degree - sample	0.97	1.55	0	11
Unrecip in-degree - sample	0.70	1.1	0	6
Unrecip out-degree - sample	0.70	1.23	0	8
Recip degree - normal simulation	2.75	2	0	11.29
Unrecip in-degree - normal simulation	2.2	1.33	0.08	6.88
Unrecip out-degree - normal simulation	2.35	1.89	0.08	13.85
Recip degree - robust simulation	3.33	2.93	0	31.28
Unrecip in-degree - robust simulation	1.99	1.56	0.02	9.02
Unrecip out-degree - robust simulation	2.2	2.25	0	16.42
N		449		

Table 2: Link statistics

	Difference of		Abs Difference of		Sum of	
Variable	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Log household wealth	0	2.37	1.77	1.58	20.42	3.00
Recip degree - sample	0	1.85	1.10	1.49	1.92	2.47
Unrecip in-degree - sample	0	1.38	0.86	1.08	1.39	1.71
Unrecip out-degree - sample	0	1.60	0.91	1.31	1.39	1.88
Recip degree - normal sim	0	2.22	1.51	1.62	5.49	3.32
Unrecip in-degree - normal sim	0	1.59	1.09	1.16	4.40	2.13
Unrecip out-degree - normal sim	0	2.44	1.49	1.93	4.70	2.88
Recip degree - robust sim	0	3.87	2.55	2.91	6.66	4.39
Unrecip in-degree - robust sim	0	2.03	1.48	1.39	3.98	2.35
Unrecip out-degree - robust sim	0	3.07	1.96	2.36	4.40	3.28

Variable	Mean	Std. Dev.
Immediate family	0.03	0.17
Distance in Km	1.91	1.56
Recip support - sample	0.07	0.25
Unrecip support - sample	0.10	0.30
Overall support - sample	0.21	0.41
Recip support - normal sim	0.11	0.25
Unrecip support - normal sim	0.20	0.28
Overall support - normal sim	0.39	0.34
Recip support - robust sim	0.13	0.28
Unrecip support - robust sim	0.18	0.31
Overall support - robust sim	0.40	0.38
Observations	12992	

This table has 12,992 observations rather than 6,496 because it includes both dyad (i, j) and dyad (j, i) for ease in understanding of the "Difference of" variables. This does not affect the means or standard deviations of any of the other variables.

Table 3: Dyad level summary statistics for simulation

	Census		Sample	
Variable	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**
Same last name	0.025	0.156	0.041	0.198
Male to male	0.692	0.462	0.758	0.429
Male to female	0.139	0.345	0.111	0.314
Female to male	0.139	0.345	0.111	0.314
Female to female	0.031	0.172	0.02	0.142
Paraguayan to Paraguayan	0.904	0.295	0.899	0.301
Paraguayan to Non-Paraguayan	0.037	0.189	0.022	0.148
Non-Paraguayan to Paraguayan	0.037	0.189	0.022	0.148
Non-Paraguayan to Non-Paraguayan	0.022	0.147	0.056	0.229
Rich to rich	0.002	0.045	0.006	0.075
Rich to middle	0.039	0.192	0.067	0.25
Middle to rich	0.039	0.192	0.067	0.25
Rich to poor	0.003	0.054	0.005	0.072
Poor to rich	0.003	0.054	0.005	0.072
Middle to middle	0.804	0.397	0.755	0.43
Middle to poor	0.054	0.225	0.046	0.21
Poor to middle	0.054	0.225	0.046	0.21
Poor to poor	0.004	0.064	0.002	0.045
N	196,022		12,922	

This table has 196,022 and 12,992 observations rather than 98,011 and 6,496 because it includes both dyad (i, j) and dyad (j, i) .

Table 4: Prediction regressions

Variable	*LU*-Link	s.e.	*LR*-Link	s.e.
Same Last Name	1.081***	(0.235)	1.835***	(0.422)
Rich/Rich	0.502	(0.663)	1.138	(0.848)
Rich/Medium	1.169***	(0.179)	0.635***	(0.151)
Medium/Rich	-0.436	(0.309)	0.635***	(0.151)
Rich/Poor	1.730***	(0.326)	-15.365***	(0.417)
Poor/Rich	-15.415***	(0.372)	-15.365***	(0.417)
Medium/Poor	0.548**	(0.252)	-0.776*	(0.428)
Poor/Medium	-0.845**	(0.355)	-0.776*	(0.428)
Poor/Poor	1.507*	(0.774)	1.199	(1.342)
Female/Female	-0.441	(0.505)	-1.287	(0.905)
Female/Male	-0.555**	(0.263)	-0.674*	(0.401)
Male/Female	0.028	(0.179)	-0.674*	(0.401)
Parag/Parag	0.069	(0.411)	0.139	(1.251)
Parag/Non-Parag	-15.628***	(1.052)	-1.793*	(1.000)
Non-Parag/Parag	0.353	(0.486)	-1.793*	(1.000)
Households	449		449	
Villages	15		15	
Possible Links	6496		6496	
Actual Links	314		217	

LU-Links are unreciprocated lending links, and *LR*-Links are reciprocated lending links. *LU*-Link and *LR*-Link are estimated jointly using multinomial logit. Village fixed effects are included in the estimation but not shown. Regressions clustered at the village level. *,**, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 5: Support in Reciprocated and Unreciprocated Networks

Network g'	g	Support	Network g'	g	Support	t-test	# Times bigger
			Sample				
Recip	Recip	0.392	Unrecip	Unrecip	0.220	2.279**	10*
		(0.296)			(0.205)		
Recip	All	0.550	Unrecip	All	0.389	2.192**	9
		(0.347)			(0.357)		
			Normal Simulation				
Recip	Recip	0.431	Unrecip	Unrecip	0.305	1.701*	10*
		(0.281)			(0.215)		
Recip	All	0.670	Unrecip	All	0.537	2.552**	10*
		(0.278)			(0.314)		
			Robust Simulation				
Recip	Recip	0.556	Unrecip	Unrecip	0.396	3.223***	12**
		(0.208)			(0.045)		
Recip	All	0.791	Unrecip	All	0.699	1.977**	9
		(0.153)			(0.199)		

The last column is the number of villages for which $S(\text{Recip}, g) > S(\text{Unrecip}, g)$ out of 14 villages. Standard deviations in parenthesis. *,**, and *** indicate significance at the 10%, 5%, and 1% levels, respectively for a one-sided test. Normal simulation means that all links which are not between two households in the long survey are simulated. Robust simulation takes into account survey information on relationships between households in the long and short surveys, as well as between one surveyed household and one non-surveyed household.

Table 6: Support Regressions

	Sample		Normal Simulation		Robust Simulation	
Variable	*LU*-Link	*LR*-Link	*LU*-Link	*LR*-Link	*LU*-Link	*LR*-Link
Support						
Unrecip	1.055	0.836	1.219	0.955	1.473	0.843
	[0.232]***	[0.234]***	[0.286]***	[0.286]***	[0.243]***	[0.229]***
Recip	0.894	2.623	0.945	2.838	1.192	2.995
	[0.106]***	[0.257]***	[0.111]***	[0.307]***	[0.177]***	[0.300]***
	Sample		Normal Simulation		Robust Simulation	
Variable	*LU*-Link	*LR*-Link	*LU*-Link	*LR*-Link	*LU*-Link	*LR*-Link
Immed Family	1.902	2.448	1.894	2.421	1.885	2.412
	[0.363]***	[0.402]***	[0.363]***	[0.399]***	[0.380]***	[0.396]***
Distance	-1.299	-1.917	-1.301	-1.916	-1.216	-1.822
	[0.182]***	[0.252]***	[0.183]***	[0.252]***	[0.167]***	[0.240]***
Support						
Unrecip	0.667	0.478	0.802	0.580	1.061	0.450
	[0.171]***	[0.224]**	[0.210]***	[0.280]**	[0.173]***	[0.229]**
Recip	0.507	2.051	0.546	2.218	0.728	2.307
	[0.185]***	[0.290]***	[0.189]***	[0.328]***	[0.166]***	[0.295]***
Households	449	449	449	449	449	449
Villages	15	15	15	15	15	15
Possible Links	6496	6496	6496	6496	6496	6496
Actual Links	314	217	314	217	314	217

LU-Links are unreciprocated lending links, and *LR*-Links are reciprocated lending links. Regressions estimated jointly using multinomial logit. Village fixed effects are included in the estimation but not shown. Clustered standard errors in brackets. *,**, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. Normal simulation means that all links which are not between two households in the long survey are simulated. Robust simulation takes into account survey information on relationships between households in the long and short surveys, as well as between one surveyed household and one non-surveyed household.

Table 7: Degree Centralization in Reciprocated and Unreciprocated Networks

Standard Deviation				t-test	# Times bigger
Sample					
Unrecip	1.284	Recip	1.109	1.516*	12**
	(0.641)		(0.737)		
Unrecip-Out	1.006	Unrecip-In	0.864	2.711***	10
	(0.531)		(0.471)		
Normal Simulation					
Unrecip	2.359	Recip	1.910	1.874**	12**
	(0.612)		(0.726)		
Unrecip-Out	2.014	Unrecip-In	1.594	4.043***	14***
	(0.684)		(0.403)		
Robust Simulation					
Unrecip	2.783	Recip	2.780	0.012	7
	(0.861)		(0.966)		
Unrecip-Out	2.244	Unrecip-In	1.651	4.032***	13***
	(0.788)		(0.466)		
Freeman's index				t-test	# Times bigger
Sample					
Unrecip	0.136	Recip	0.118	0.893	8
	(0.076)		(0.089)		
Unrecip-Out	0.127	Unrecip-In	0.078	3.354***	11*
	(0.076)		(0.044)		
Normal Simulation					
Unrecip	0.071	Recip	0.072	-0.245	10
	(0.061)		(0.081)		
Unrecip-Out	0.070	Unrecip-In	0.046	4.650***	13***
	(0.056)		(0.040)		
Robust Simulation					
Unrecip	0.083	Recip	0.104	-2.010	4
	(0.061)		(0.089)		
Unrecip-Out	0.077	Unrecip-In	0.049	3.937***	14***
	(0.054)		(0.041)		

The last column is the number of villages for which Reciprocated Degree Centralization < Unreciprocated Degree Centralization, or Unreciprocated In-Degree Centralization < Unreciprocated Out-Degree Centralization out of 15 villages. Standard deviations in parenthesis. *,**, and *** indicate significance at the 10%, 5%, and 1% levels, respectively for a one-sided test. Normal simulation means that all links which are not between two households in the long survey are simulated. Robust simulation takes into account survey information on relationships between households in the long and short surveys, as well as between one surveyed household and one non-surveyed household.

Table 8: Degree Regressions

	Sample		Normal Simulation		Robust Simulation	
Variable	LU-Link	LR-Link	LU-Link	LR-Link	LU-Link	LR-Link
Difference of Degree						
Unrecip-out	0.306	0.032	0.199	0.070	0.169	0.006
	[0.035]***	[0.071]	[0.020]***	[0.087]	[0.022]***	[0.091]
Unrecip-in	-0.359	-0.220	-0.272	-0.176	-0.236	-0.100
	[0.065]***	[0.092]**	[0.038]***	[0.081]**	[0.028]***	[0.071]
Recip	0.029	-0.412	-0.000	-0.296	0.031	-0.211
	[0.014]**	[0.157]***	[0.022]	[0.110]***	[0.031]	[0.060]***
Sum of Degree						
Unrecip-out	0.347	0.029	0.259	-0.055	0.191	-0.032
	[0.043]***	[0.061]	[0.028]***	[0.082]	[0.033]***	[0.051]
Unrecip-in	0.512	0.149	0.472	0.159	0.297	-0.020
	[0.082]***	[0.041]***	[0.076]***	[0.051]***	[0.041]***	[0.052]
Recip	0.079	0.788	0.029	0.646	-0.034	0.367
	[0.016]***	[0.173]***	[0.022]	[0.111]***	[0.039]	[0.048]***
	Sample		Normal Simulation		Robust Simulation	
Variable	LU-Link	LR-Link	LU-Link	LR-Link	LU-Link	LR-Link
Immed Family	2.298	2.973	2.231	2.896	2.221	2.765
	[0.382]***	[0.365]***	[0.377]***	[0.379]***	[0.401]***	[0.402]***
Distance	-1.457	-2.517	-1.482	-2.626	-1.497	-2.573
	[0.235]***	[0.294]***	[0.206]***	[0.273]***	[0.219]***	[0.317]***
Difference of Degree						
Unrecip-out	0.307	0.073	0.202	0.036	0.172	0.035
	[0.039]***	[0.101]	[0.023]***	[0.081]	[0.022]***	[0.115]
Unrecip-in	-0.362	-0.240	-0.285	-0.182	-0.255	-0.005
	[0.062]***	[0.080]***	[0.039]***	[0.080]**	[0.031]***	[0.060]
Recip	0.031	-0.371	-0.004	-0.291	0.024	-0.255
	[0.025]	[0.161]**	[0.026]	[0.119]**	[0.033]	[0.066]***
Sum of Degree						
Unrecip-out	0.380	0.072	0.296	0.006	0.218	-0.052
	[0.047]***	[0.066]	[0.033]***	[0.072]	[0.031]***	[0.055]
Unrecip-in	0.506	0.162	0.476	0.168	0.283	-0.092
	[0.085]***	[0.037]***	[0.081]***	[0.043]***	[0.038]***	[0.068]
Recip	0.081	0.863	0.043	0.745	-0.033	0.438
	[0.028]***	[0.173]***	[0.024]*	[0.112]***	[0.044]	[0.049]***
Households	449	449	449	449	449	449
Villages	15	15	15	15	15	15
Possible Links	6496	6496	6496	6496	6496	6496
Actual Links	314	217	314	217	314	217

LU-Links are unreciprocated lending links, and LR-Links are reciprocated lending links. Regressions estimated jointly using multinomial logit. 'Absolute Difference' is used instead of 'Difference' for the LR-Link regressions. Village fixed effects are included in the estimation but not shown. Clustered standard errors in brackets. *,**, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. Normal simulation means that all links which are not between two households in the long survey are simulated. Robust simulation takes into account survey information on relationships between households in the long and short surveys, as well as between one surveyed household and one non-surveyed household.