Reciprocated Versus Unreciprocated Sharing in Social Networks*

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Abstract

We recognize that some sharing relationships in social networks are reciprocated (undirected), while others are unreciprocated (directed). We find that in unreciprocated relationships transfers are likely to flow from more to less wealthy households, while reciprocated risk-sharing relationships are more likely between wealthier households. We are also one of the first papers to empirically explore predictions from the theoretical network literature. This literature finds that networks of undirected two-way transfers should exhibit high levels of support while networks with one-way flows of benefits should exhibit star-like characteristics. These two predictions hold for the reciprocated and unreciprocated networks respectively.

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. 2010). These papers show that sharing may be local since the 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

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(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 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.

Survey-based evidence, such as De Weerdt (2004) and Fafchamps & Gubert (2007), often finds that individuals are more likely to be linked when wealth differences between them are greater. But, these papers only consider one type of link. A main contribution of this paper is that we distinguish between those links which are reciprocated and those which are unreciprocated. We find that dyad characteristics affect the likelihood of reciprocated and unreciprocated links differently. Both links are more likely to be present when two households are related or live closer to one another. But 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.

Most of our analysis centers around the hypothetical question regarding to whom a household can turn for help in times of need. We also look at actual loans and gifts in the previous year and find similar results. We find evidence 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. This suggests a disadvantage of using data on actual rather than potential transfers.

A second contribution is that we are one of the first papers to test specific predictions of network theory. We show that the architecture of reciprocated networks is significantly different from the architecture of unreciprocated networks. 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. (2010) 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 (2003) 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.

The rest of the paper is organized as follows. In Section 2 we discuss the previous literature regarding sharing in 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 discusses the predictions of the theoretical literature on directed and undirected networks and tests them in our data. Section 6 concludes.

2 Sharing in Networks

Although the exact survey question used and the definition of a risk-sharing link differ across 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, and so the analyses necessarily combine reciprocated and unreciprocated sharing.

The cited papers use the existence of a link as the dependent variable, but each defines a link slightly differently. Fafchamps & Gubert (2007) consider directional links where the directionality is determined by who mentions whom. De Weerdt (2004) defines a non-directional link as existing if either household says it would give help to or receive help from the other.

Fafchamps & Gubert (2007) find that wealth differences and geographic proximity are good predictors of the existence of a link between two individuals. Links are more common between households which are more different in terms of wealth. Poorer households are more likely to mention households that are richer than themselves. De Weerdt (2004) finds that when two households live closer to one another, are related, or are of the same religious affiliation, they are more likely to be linked. Households are also more likely to be linked when household wealth is more dissimilar.

Both of these papers assume one underlying structure for all links within the network. This is largely driven by the wording of the question asked to survey respondents. Fafchamps & Gubert (2007) and De Weerdt (2004) do not ask respondents to differentiate between links for which they expect only to give, links in which they expect only to receive, and links for which they expect to do both. Instead, the basis for link direction is based on which household listed the other on the survey. It is difficult to interpret this type of directionality since we do not know why a household would or would not choose to list another household. 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.

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. 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. This 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. 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. These Paraguayan villages do not involve any tribes or castes. There are no village chiefs and government is at the municipal level which is larger than the village. There are no major moneylenders. 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. There are no large plantation owners.

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.

There are 947 unique households mentioned by respondents as either a potential borrower or a potential lender. Adding in the 188 survey respondents who are not themselves mentioned by someone else (but may have mentioned someone), we have 1135 potential network members. We have survey data on 39.6% of these network members.[1] Since the relevant unit of observation is the dyadic link between households, our sample will consist of all potential links between those households for which we have survey data.

We look at two types of links we call lending links (L-links). In this case $L_{ij} = 1$ 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 in which households expect transfers to flow, regardless of which household mentions that the link exists. We divided these L-links into reciprocated and unreciprocated links. Reciprocated lending links (LR-links) are those for which $L_{ij} = L_{ji} = 1$ while unreciprocated lending links (LU-links) are those for which $L_{ij} = 1$ while $L_{ji} = 0$. Of the 748 links for which $L_{ij} = 1$, 434 links (217 pairs) are reciprocated while 314 are unreciprocated.

4 Empirical Estimation

In this section we model the prediction of the existence of both reciprocated and unreciprocated lending links. From the 449 observations there are 12,992 possible relationships. This is fewer than the 201,152=449*448 we would obtain if we allowed for every possible link between households. Because the 15 villages are not close to one another and so households in a village do not know households in the other villages, we do not include these as potential links.

In all regressions we include the geographic distance between the two households and whether the two households are immediate relatives (that is, parents, children, or siblings but not uncles, cousins, or grandparents). These are characteristics of the relationship between the pair of individuals, not household-level characteristics.

We also make use of some household-level characteristics. For directional (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.[2] 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.[3]

The household characteristics which we include are the maximum years of education in the household, the age of the household head, the number of working age people in the household, the share of income coming from agriculture in the past year, the number of days anybody over 10 years old and not disabled was sick enough to miss school or work in the past year, and the log of wealth (which includes the value of land, animals, and tools owned but not consumer durables, education, or cash-on-hand). We also include village fixed effects. Table 1 shows summary statistics of household characteristics, while Table 2 shows summary statistics of dyad characteristics.

[1] The 449 survey respondents listed 947 unique households. 261 of the households listed were themselves survey respondents. This is similar to the results of Fafchamps & Gubert (2007) who survey 206 respondents reporting 939 unique households, of which 189 were themselves survey respondents.

[2] We also ran our regressions with the squared value of each of these terms. However, the squared terms were almost never significant and did not have qualitative impacts on the other regression coefficients.

[3] Inclusion of these sums and differences makes it impossible to include individual fixed effects.

Our main analysis focuses on the determinants of reciprocated and unreciprocated links. For every directed relationship (i, j), there is either an unreciprocated link from i to j, a reciprocated link from i to j, or no link at all from i to j. This would suggest that we should estimate the correlates of unreciprocated and reciprocated links jointly using the multinomial logit. We use differences $(x_i - x_j)$ to explain the existence of unreciprocated links and the absolute difference $(|x_i - x_j|)$ to explain the existence of reciprocated links. We can not use both absolute and actual differences to simultaneously explain one type of link, but it is possible to use the different explanatory variables to explain different types of links.[4]

One issue is that our network data comes from a sample rather than a census of individuals in the network.[5] Our data comes from 30 random individuals in 14 villages in rural Paraguay and 29 individuals in another village. For the three smallest villages we have data on a higher proportion of the population. In these villages we have data on 29/33 (88%), 30/36 (83%), and 30/46 (65%) of the households.[6] Throughout the paper we show our results both for all 15 villages, as well as for the three smallest villages for which we come closer to having a census of the population. The results may differ across these two samples because the estimates are less precise in the smaller sample, and because network characteristics may differ between larger and smaller villagers. Despite this, we find that our main results hold both in the full sample, and in the restricted set of villages for which we come closer to having a census of the network.

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 using two methods. When looking at the full sample of fifteen villages, we can cluster the standard errors at the village level to allow for arbitrary correlation between observations in the same village. This is not possible when we look at only the three smallest villages. Because of this we also bootstrap confidence intervals for both the full sample and the three smallest villages. In the bootstrap we draw 30 individuals from each village with replacement. We then construct a sample which consists of all the dyads which combine those 30 households (but omitting self-links) and run the regressions on this sample. Our bootstrap sample consists of 1000 such replications.

[4]To implement this, we constrain the coefficients of the differences to be 0 in the reciprocated equation and the coefficients of the absolute differences to be 0 in the unreciprocated equation.

[5]There is some evidence that the parameter estimates in link-formation regressions from such a sampling scheme are not very efficient if the underlying data-generating process is not stochastic (i.e., it does not contain an error term)(Santos & Barrett 2008). If the underlying data-generating process does contain an error term, the parameter estimates perform quite well.

[6]The village size in the remaining 12 villages ranges from 87 to 577 households with an average of 200 and a median of 137.

4.1 Basic Results

We first look at the determinants of the two types of lending links. Table 3 shows the correlates of unreciprocated lending links (LU) and reciprocated lending links (LR) using all 15 and the 3 smallest villages. Like Fafchamps & Gubert (2007), we find that households which live closer to one another or are directly related to one another are more likely to be linked. This may be due to the lowering of informational asymmetries and monitoring costs when households live closer and are related. On the other hand, correlated risks are probably larger when households live closer to one another. But since we look only at networks within villages, we are unlikely to see households diversifying risk over large distances in our data.

We use the share of agricultural income in total income to test whether households which are more or less dependent on agriculture as their main source of income are more or less likely to be linked. Theory would predict that households will want to reduce correlated risk by linking with households which have different earning portfolios. On the other hand, it may be easier for a farmer to monitor another farmer than for a farmer to monitor a brickmaker. We find some evidence that households which depend more on agriculture are more likely to be linked. But we don't find a consistent tendency for diversification with agricultural households linking to non-agricultural households.[7][8] Likewise, Fafchamps & Gubert (2007) find that links are not more likely between households with lower income correlations.

Perhaps most important are our results on wealth. De Weerdt (2004) and Fafchamps & Gubert (2007) find that links are more likely from wealthy to poor households, but we find that is only the case for unreciprocated links. Reciprocated links are more likely between wealthier households. On the other hand, unreciprocated links are more likely between households with large wealth differences. While the coefficient on the sum of wealth remains positive for both types of links, it is significantly higher in the LR regression than in the LU regression.[9] Taken together, this would mean that the typical reciprocated relationship would be between two wealthy households. The typical unreciprocated relationship, though, would consist of a wealthy household making transfers to a poorer household.

Additionally, we find that more educated households are more likely to have unreciprocated relationships being likely to be asked to lend money to less educated households.[10] This suggests that the conflation of different kinds of links can have a strong effect on what is considered an important determinant of the existence of links. Previous results in the survey-based literature finding that households of different wealth and education levels are

[7]We tried separating agricultural income into that which comes from crops and that which comes from animals, but found no significant relationship.

[8]It might also be the case that households who have lived in a village longer have better land and so have higher shares of income from agriculture. We do not know years of residence in the village in the 2007 data used here, but when looking at the 2002 data we find no correlation between the agricultural share and the years of residence in the village.

[9]In the full sample, we can reject the hypothesis that the effect of wealth differences is the same in the LU and LR models at the 1% level and that the effect of wealth sums is the same in the LU and LR models at the 5% level.

[10]In the full sample, we can reject the hypothesis that the effect of education differences is the same in the LU and LR models at the 5% level.

more likely to be linked may be concentrating on unreciprocated relationships. The bigger the difference in wealth levels between the two households, the more likely they are to have an unreciprocated risk-sharing relationship.

Direct links between households may not provide a full picture of the sharing network that exists within a community. Karlan et al. (2009) show that direct and indirect links have similar effects on the borrowing of residents of Peruvian shantytowns. Thus, the amount of credit available through a network may depend on the nature not just of a household's immediate links but on the overall network architecture. The mechanics of such risk-sharing networks are discussed in Leider et al. (2009) and Ambrus et al. (2010).

A situation in which i has a one-way link to j, and j has a one-way link to k, allowing i access to the resources of k, would be analogous to our unreciprocated link in the bilateral setup. If k in addition linked to i, or if the links between i, j, and k were all reciprocated rather than one-way, k could also expect to have access to the resources of household i. This would then meet our requirements for a reciprocated link. We can generalize bilateral links to rings and chains of any size.

As a robustness check, we look at the determinants of unreciprocated lending chains and reciprocated lending rings. We find that most of the determinants of indirect relationships are the same as the determinants of the direct relationships. Specifically and most importantly, the results on wealth differences and wealth sums do not change.

The costs of sending transfers from one individual to another indirectly vis-a-vis multiple people may be high, and may create incentives for defecting (Bloch et al. 2008). Karlan et al. (2009) assume that transfers can only travel through up to two links. That said, if creating links is also costly, indirect relationships may be a cost-effective way of transferring money without forming new bilateral relationships. Since we find that our original results do not change when including these indirect links, our results are not an artifact of our decision to focus on direct links. The main findings of this paper continue to hold for links and rings of all sizes.

Remembering that 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. If both households have cash, they exchange cash. If one household has cash and the other does not, then the other would reciprocate in kind (e.g., in labor). So, what we are calling unreciprocated links might actually be reciprocated links in which one side gives money and the other side gives labor.

Section 5 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, our basic results show that wealthy households give without reciprocation to less wealthy households. Since wealth is the value of land, animals, and tools owned, it is not necessarily closely related to cash-on-hand.

But, we can also give some more direct evidence regarding this issue. Because we have information on donations to the church and to community projects (schools, roads, electricity, etc) we are able to classify households based on their comparative advantage in cash versus labor. We know the value of the donations they made in cash as well as the number of days of labor they contributed, and by valuing labor at the median daily wage we can directly compare the two amounts. Assuming that households primarily choose to make donations in the manner of their comparative advantage, we classify them based on whether they made the same or more donations in labor, more donations in cash, or no donations at all.

Using this information we can explore what types of households are most likely to be linked in reciprocated and unreciprocated relationships. We classify directed dyads into one of nine categories (two household which don't donate sharing with each other, a household which donates more cash sharing with a household which donates more labor, etc). 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. We have also tried creating a variable which is the share of total donations made in the form of cash (which is missing for all non-donators). If we include its sum and difference in regressions we again do not find evidence that unreciprocated links are more likely from the cash-advantaged to the labor-advantaged. In combination with our results that the underlying architecture of reciprocated links is different from the underlying architecture of unreciprocated links, this suggests that the two really do represent different types of relationships.

4.2 Comparison of Hypothetical and Actual Links

The analysis thus far has defined a link as existing when one household states that, in times of need, it would ask to borrow money from another household or the other household would ask to borrow from it (a hypothetical link). We also have data on which households the respondents actually borrowed from or lent to in the past year, in addition to transfers of agricultural produce and gifts of money to cover health expenses in the past year.[11]

Ideally we would look only at actual loan data. The gifts in our data may be transfers to help out a household in need, but they may also be gifts to thank or repay a household which helped them out in the past. Unfortunately, for the regressions involving actual transactions, we must combine giving and lending because there are very few pure lending relationships which happen to be reciprocated within the past 12 months. Across the 15 villages, there are only 30 instances in which two households lent each other money in the same year. There are 90 other instances in which one household lent cash to another in an unreciprocated manner. In other words, it is extremely unlikely that both i lends to j and j lends to i in a 12 month period.[12] This is true even though there are quite a few relationships which are reciprocal according to the answer to the hypothetical question. Looking at data on actual loans would not make it obvious whether or not the relationship was reciprocated. We now

[11]The hypothetical questions were asked at the beginning of the interview, while the actual lending questions were asked towards the end of a two to three hour interview.

[12]We ran logit regressions on the determinants of unreciprocated pure lending LU-Links and find that, in general, the results are stronger than when considering giving and lending together. But, we can not compare unreciprocated and reciprocated actual pure lending links since there are not enough reciprocated links.

verify that the hypothetical links have economic meaning for daily transactions.

A bit more than half of all gifts and loans in the past year come from households that a household says they would go to or would go to them if they needed help. This may be because the hypothetical data is prospective while the actual data is retrospective. There are 120 links involving loans in the past year and 430 links involving either loans or gifts in the past year. But, the hypothetical data shows 736 links which are listed as someone to whom they could go to for help or who would go to them for help. This number is so much higher because although the households would have asked each other to borrow money, it might not have been necessary to do so in the past year. We argue that this shows the value of collecting data on hypothetical links, given the short period over which one can credibly collect data on actual transfer flows.

The above discussion does not distinguish between reciprocated and unreciprocated relationships. A bit more than half of the gifts and loans which were reciprocated in the past year come from somebody with whom the household states having a hypothetical reciprocated relationship. Of the unreciprocated gifts and loans, a bit less than a quarter come from a household with whom they state having a hypothetical reciprocated relationship, and a bit less than a quarter come from a household with whom they state having a hypothetical unreciprocated relationship. It may be the case that households have potentially reciprocal relationships with one another as mentioned by whom they *would* go to for help, but that in any given year that relationship may not actually be reciprocated. Thus, seemingly unreciprocated transfers in one year may be part of reciprocated relationships. Thus, relying only on actual transfers when performing empirical work will cause us both to underestimate the number of relationships, and also to misclassify many reciprocated relationships as unreciprocated.

We run regressions checking if the predictors of stated links (both reciprocated and unreciprocated) are the same as the predictors of actual links by running regressions with the same regressors as before. The dependent variable describes what type of actual transfers took place between the two households during the previous year. These regressions are found in Table 4. The first and fourth columns look at the determinants of giving and lending relationships which were unreciprocated in the past year, while the second and fifth look at the determinants of giving and lending relationships which were reciprocated in the past year. The third and sixth columns look at the determinants of all directional relationships in the past year, whether or not they were reciprocated.

The main thing to notice here is that the results regarding wealth which we found using hypothetical links continue to hold when considering actual links. Unreciprocated actual transfers are more likely to flow from wealthier to poorer households, while reciprocated actual transfers are more likely to flow between two wealthy households.[13] This encourages our belief that the hypothetical data does represent true sharing relationships, with the additional bonus that the hypothetical data captures more relationships and especially many more reciprocated relationships, due to the fact that so few actual relationships are

[13]The qualitative results in which the dependent variable is the value of the transfers rather than a binary variable indicating whether or not a transfer took place are quite similar.

reciprocated over the course of one year.

5 Network Architecture

We have shown that the determinants of link formation differ between those links classified as reciprocated and those classified as unreciprocated. However, this may not be conclusive in arguing that reciprocated and unreciprocated links form according to different mechanisms. We classified links based on whether households said they would ask to borrow or lend to each other in times of need, but this may misclassify some links. Households may assist each other non-monetarily, in which case the links we classify as unreciprocated may in reality be reciprocated. In addition, there may be more typical misclassifications based on mistakes made by the respondents or surveyors. As we mentioned in the previous section, we do not find that households with a comparative advantage in giving cash are more likely to be linked in an unreciprocated manner with those with a comparative advantage in giving labor, but we would like more definitive evidence that the two link-types are truly different.

In order to strengthen our argument that reciprocated and unreciprocated links differ, we consider the network architecture of each type of relationship. 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. In the prior section, we merely looked for differences in the correlates of the two types of links. But, 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.[14]

In addition to testing the robustness of our results, this approach also 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.

[14]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.

5.1 Theory

5.1.1 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. (2010) 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, as shown in the previous section, 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. (2010) show that networks corresponding to robust equilibria have the characteristic that all connected links (sets of neighbors) are "supported". A link is supported 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 favor 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. (2010) 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, if the passive member of the link is providing a non-measurable or intangible good in return. On the other hand, our results that unreciprocated links do not seem to be more common from households with a comparative advantage in cash to households with a comparative advantage in labor reject one of the main potential unobserved transfers that could be taking place.

Because of this, and because the model makes no predictions about directed-link networks, we do not make any predictions about the level of support in the unreciprocated networks. It is also unclear how to measure support in a directed network. One could consider an unreciprocated link to be supported if that dyad has a neighbor in common, no matter whether the neighbor is lending or receiving or both. Or, one could consider 'reverse support' which looks like a ring in which i lends to j who lends to k who lends back to i. Or, one could consider 'direct support' (i lends directly to j, and i also lends to k who lends to j). Without theory to give us guidance, we remain agnostic as to what type of support, if any, unreciprocated networks should exhibit.

5.1.2 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.[15] 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 centrality, meaning that there are few nodes with many links, while most nodes maintain few links.

There are multiple measures of centrality. Wasserman & Faust (1994)[pp. 215-219] cite evidence that betweenness centrality is a better measure of centrality than degree and that it is less sensitive to measurement error, and so we focus on betweenness. A node which lies on the shortest path between many other nodes has high betweenness. A betweenness index for individual i measures the share of shortest paths in the network on which individual i falls. To be more precise, first, for all dyads which do not involve i, one finds all of the shortest paths between the two nodes. Then, for each of these dyads, one calculates the share of shortest paths which involve individual i. Finally, one sums this fraction over all dyads. One then divides by the number of dyads which do not involve i as a normalization. Thus, the minimum of betweenness is 0 and its maximum is 1.

Global measures of betweenness for the network as a whole include the standard deviation of individual betweenness and Freeman's index which is a normalization of the sum of the difference between the largest individual's betweenness and all other individuals' levels of betweenness. For both of these measures, the maximum is reached in a star network in which case one individual lies on the shortest path between all other individuals (and therefore has a betweenness of one), while the other individuals lie on no shortest paths (and therefore have a betweenness of zero)(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

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

we are looking at will be star-like and so will have high values of betweenness centrality. We would also expect that households with high levels of betweenness will be linked with households with low levels of betweenness. On the other hand, given the results on support in networks with two-way flows, we do not expect reciprocated networks to exhibit these characteristics.

5.2 Empirics

Given the theoretical models discussed above, we will look at support and betweenness 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 betweenness. It also suggests that, at the local level, households with high levels of betweenness should be linked with those with low levels of betweenness. These are the predictions that we will take to the data.

5.2.1 Support

We would first like to compare global measures of support for reciprocated and unreciprocated networks. As before, we let the directionality of the transfers define the difference between the reciprocated and unreciprocated networks. But, as do Jackson et al. (2010) 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).[16] We do this both because, as we mentioned earlier, it is not obvious how one would estimate support in a directed network, but also because measures of support would not be comparable across the reciprocated and unreciprocated networks if one measure was directed and the other was not. In other words, if we did not symmetrize the network, and we showed that support was higher in reciprocated networks than unreciprocated networks, we wouldn't know if this was due to a true difference in network architecture, or if it was due to a difference in the measurement of support in undirected compared to directed networks.[17]

We will 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

[16] The reciprocated network is symmetric by construction.

[17] Also, as do Jackson et al. (2010), we ignore stated links with out-of-sample households.

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.[18]

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 measures of support will be biased downwards (Jackson et al. 2010). On the other hand, since both reciprocated and unreciprocated links suffer from this problem, we can still compare the relative support measures. As with our previous results, we show the results for all villages as well as the three smallest villages with fewer missing households.

Table 5 shows the average measures of support over 14 villages (taking the average of one observation per village) as well as the average measure of support over the three smallest villages for which we are closer to having a full census of the population. We must drop one village which has no reciprocated links within the sample since we cannot measure support for that village.

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 means 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. (Note that with only three villages, it is impossible to get a significant result on the binomial test.) 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 results is strongest for the case of self-support (where reciprocated links support reciprocated links and unreciprocated links support unreciprocated links).

We next look at the results of multinomial 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.[19] We do not control for explanatory variables such as wealth and education as we did in previous regressions (although the results are not sensitive to their inclusion). This is because we are interested in focusing purely on network architecture, not looking at network architecture conditional on, e.g., wealth.

Table 6 shows the results of these regressions. We find that both types of links are

[18] We also look at support provided by other networks such as the family.

[19] As before we consider a link to have unreciprocated supported if that dyad has an unreciprocated neighbor in common, no matter whether the neighbor is lending or receiving. We have experimented with incorporating directionality using measures of 'reverse support' or 'direct support' but the effects of direct and reverse unreciprocated support on the existence of unreciprocated links are statistically indistinguishable. So, for the analysis here we symmetrize the unreciprocated links.

well-supported. Unreciprocated links tend to be equally well-supported by reciprocated and unreciprocated links. On the other hand, reciprocated links are much better supported by reciprocated links than they are by unreciprocated links. And, this 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. (2010) that two-way favor-sharing links ought to have high levels of support.

We have also experimented with measuring support provided by other networks. Other providers of support we look at include being immediate family and exchanging actual gifts or loans in the past year. So, for example, we test whether two households are more likely to have an LR-link if they also happen to share a household with an immediate family member in common. We find that including the three additional regressors of support from family members, 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.

5.2.2 Betweenness

Next we test the prediction that unreciprocated networks should exhibit a star-like quality, with high levels of betweenness centrality. As with measuring support, we symmetrize the network and ignore the directionality of links for easier comparability of the magnitudes of betweenness centrality in the reciprocated and unreciprocated networks.[20] Unfortunately, because betweenness depends on the architecture of the entire network, whereas support only depends on the direct ties of the surveyed individuals, betweenness is measured less accurately with data from a sample than from a census (Costenbader & Valente 2003).

There are measures of betweenness which take into account the directionality of the links. We purposely do not use these measures. We are exploring whether unreciprocated networks look like stars in which the center lends to the spokes. In the symmetrized network the center of such a star would have high symmetrized betweenness since it is located between all of the spokes. But, in a directed network the center would not have high directed betweenness. Since he gives to the spokes but they do not give back to him, he would not be located between the spokes on a directed path.

We look at two global measures of betweenness: the standard deviation of individual betweenness and Freeman's betweenness index. Table 7 shows the average measures of betweenness centrality over all 15 villages (with one observation per village) as well as the average measure of betweenness centrality over the three smallest villages for which we are closer to having a full census of the population. Although, as before, the level of power is low in this global analysis, we see suggestive evidence that unreciprocated networks have

[20]Also, as with support, we construct the networks using only those households which are in the sample.

higher levels of betweenness centrality than reciprocated networks. The global evidence that betweenness is higher in unreciprocated networks is much less strong than the global evidence that support is higher in reciprocated networks. With that in mind, we next consider local measures of betweenness.

Whereas support is a characteristic of a dyad, betweenness is a characteristic of a node. Therefore, we can run regressions to see if pairs of households with higher sums or differences of betweenness are more or less likely to be linked.[21] The coefficients in these regressions are likely to exhibit a specific type of bias. The correlation between the sum of betweenness for a reciprocated (unreciprocated) link and the existence of a reciprocated (unreciprocated) link will be positive by construction. If two households are linked, they are more likely to be on the shortest path between any two other households and thus the sum of their betweenness is likely to be higher. In a similar manner, this mechanical relationship is also likely to bias the coefficient on differences of betweenness towards zero. Households which aren't linked to anyone have the minimum level of betweenness, zero. With these caveats in mind, it is still interesting to look at the relationship between betweenness 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 and using just the smallest three villages. The results show that, as we expected mechanically, the sum of unreciprocated betweenness is highly correlated with the existence of an unreciprocated link while the sum of reciprocated betweenness is highly correlated with the existence of a reciprocated link.

The results on the differences of betweenness are more interesting. We had predicted that LU-links would be more common from a household with high betweenness to a household with low betweenness. This would mean we expect a positive coefficient on the difference of betweenness in the LU-link regressions. We have no such expectation for the LR-link regressions. Unfortunately, as mentioned above, the coefficients on differences in unreciprocated betweenness will be biased down in the unreciprocated estimation equation by construction. Even with this downward bias, we find that the coefficient on betweenness differences are positive and significant in the LU-link regressions. The coefficients on betweenness differences are never significant in the LR-link regressions.

We do also find that in the LU-link regressions, the difference of reciprocated betweenness is a higher predictor than the difference of unreciprocated betweenness. This result must be taken with a grain of salt, since the coefficient on the difference of unreciprocated betweenness in the LU-link regression is biased downwards, while the coefficient on reciprocated betweenness in that regression faces no such bias. But, if it were a true result, it would mean that households which are highly central in the reciprocated networks are likely to be sharing in an unreciprocated manner with those households which are not highly central in the reciprocated networks.

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

[21] This is similar to a technique used by Krishnan & Sciubba (2008). 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.

betweenness globally. At the local level, we find that 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 that the determinants of these two types of relationship are quite different. One-directional loans are more likely to involve flows from wealthier households to less wealthy households while reciprocated relationships are more likely to occur between two wealthier households.

We might worry that hypothetical relationships do not reflect reality, so as a robustness check we look at actual giving and lending. In this case we again find similar results. This implies that the hypothetical question is meaningful for real-life transactions. A disadvantage of using the actual data is that potential reciprocated risk-sharing relationships may appear to be unreciprocated or a potential relationship may not appear to be a relationship at all if only one or neither of the households experienced a negative shock in the past 12 months. Researchers interested in looking at risk-sharing relationships should consider including questions regarding potential lending relationships on their survey instruments in addition to actual lending relationships.

Finally, we look at 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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Table 1: Household statistics

Variable	Mean	Standard Deviation
Household Wealth (in $)	32,655	138,246
Log Household Wealth	8.54	1.89
Years of Education	8.26	3.72
Age of Household Head	53.73	14.53
Agriculture Share	0.62	0.28
Adult Members	2.32	1.16
Days Sick	23.30	45.04
Households	445	
Villages	15	

Wealth is calculated in USD using the exchange rate of 5.3 KGs to 1 USD.

Table 2: Link statistics

	Difference of		Abs Difference of		Sum of	
Variable	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Household Wealth (in $)	0	186,791	48,154	180,477	66,821	205,443
Log Household Wealth	0	2.37	1.77	1.58	17.09	3.00
Years of Education	0	5.10	3.96	3.22	16.53	5.42
Age of Household Head	0	20.04	16.01	12.05	107.48	20.98
Agriculture Share	0	0.38	0.30	0.23	1.23	0.40
Adult Members	0	1.61	1.19	1.09	4.65	1.68
Days Sick	0	63.80	36.20	52.53	46.51	63.36
Variable	Mean	Std. Dev.				
Immediate Family	0.03	0.17				
Distance in Km	1.91	1.57				
Households	445					
Villages	15					
Possible Links	12762					
Standard Links	653					
Reciprocated Links	312					
Unreciprocated Pairs of Links	212					

Wealth is calculated in USD using the exchange rate of 5.3 KGs to 1 USD.

Table 3: Basic Regressions

Variable	All villages *LU*-Link	All villages *LR*-Link	3 smallest villages *LU*-Link	3 smallest villages *LR*-Link
Immediate Family	1.669	2.081	1.224	1.475
	(0.99, 2.37)***	(1.34, 3.15)***	(-0.01, 2.22)*	(0.42, 3.12)**
	[0.276]***	[0.310]***		
Distance in Km	-1.395	-2.333	-0.985	-2.598
	(-1.96, -1.01)***	(-3.58, -1.75)***	(-2.14, -0.38)***	(-4.56, -1.68)***
	[0.180]***	[0.204]***		
Difference of				
Log Household Wealth	0.306	-0.161	0.363	-0.191
	(0.19, 0.45)***	(-0.53, 0.12)	(0.18, 0.60)***	(-0.81, 0.35)
	[0.023]***	[0.109]		
Years of Education	0.054	-0.013	0.032	-0.019
	(0.00, 0.11)**	(-0.13, 0.08)	(-0.05, 0.11)	(-0.20, 0.13)
	[0.016]***	[0.022]		
Age of Household Head	-0.010	-0.005	-0.014	0.017
	(-0.02, 0.00)*	(-0.03, 0.02)	(-0.03, 0.00)	(-0.03, 0.07)
	[0.003]***	[0.010]		
Agriculture Share	0.094	0.113	0.296	0.964
	(-0.58, 0.84)	(-1.54, 1.80)	(-0.68, 1.37)	(-1.55, 3.71)
	[0.290]	[0.646]		
Adult Members	-0.026	-0.005	-0.009	-0.102
	(-0.16, 0.13)	(-0.32, 0.31)	(-0.25, 0.22)	(-0.66, 0.39)
	[0.036]	[0.010]		
Days Sick	0.002	0.004	-0.000	0.003
	(-0.00, 0.01)	(-0.01, 0.02)	(-0.01, 0.01)	(-0.02, 0.03)
	[0.001]	[0.003]		
Sum of				
Log Household Wealth	0.139	0.320	0.099	0.411
	(0.01, 0.28)**	(0.15, 0.55)***	(-0.10, 0.38)	(0.10, 0.95)**
	[0.041]***	[0.050]***		
Years of Education	0.004	0.034	0.008	0.016
	(-0.05, 0.06)	(-0.04, 0.11)	(-0.07, 0.08)	(-0.12, 0.15)
	[0.015]	[0.018]*		
Age of Household Head	-0.004	-0.006	0.002	-0.002
	(-0.02, 0.01)	(-0.03, 0.01)	(-0.02, 0.02)	(-0.04, 0.04)
	[0.004]	[0.008]		
Agriculture Share	0.405	0.660	0.558	0.523
	(-0.35, 1.22)	(-0.45, 2.12)	(-0.45, 1.67)	(-1.25, 3.13)
	[0.253]	[0.301]**		
Adult Members	0.056	0.188	0.095	0.345
	(-0.10, 0.21)	(-0.06, 0.45)	(-0.13, 0.35)	(-0.09, 0.82)*
	[0.039]	[0.095]**		
Days Sick	0.000	-0.004	-0.002	-0.006
	(-0.00, 0.00)	(-0.02, 0.01)	(-0.01, 0.00)	(-0.03, 0.01)
	[0.001]	[0.004]		
Households	445	445	89	89
Villages	15	15	3	3
Possible Links	12762	12762	2552	2552
Actual Links	312	424	143	220

LU-Links are unreciprocated lending links, and *LR*-Links are reciprocated lending links. *LU*-Link and *LR*-Link are 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. Bootstrapped 95% confidence intervals in parentheses and clustered standard errors in brackets. *,**, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 4: Actual Giving and Lending

	All villages			3 smallest villages		
Variable	*LU*-Link	*LR*-Link	Any Link	*LU*-Link	*LR*-Link	Any Link
Immediate Family	1.698	2.693	2.008	0.996	2.191	1.431
	(1.12, 2.31)***	(1.91, 4.36)***	(1.46, 2.68)***	(0.16, 1.86)**	(0.87, 5.69)**	(0.71, 2.43)***
	[0.312]***	[0.333]***	[0.273]***			
Distance in Km	-1.322	-2.106	-1.478	-1.235	-2.868	-1.647
	(-2.00, -0.89)***	(-4.20, -1.15)***	(-2.13, -1.05)***	(-2.51, -0.52)***	(-8.47, -1.26)***	(-2.86, -0.91)***
	[0.184]***	[0.377]***	[0.162]***			
Difference of						
Log Household Wealth	0.176	0.084	0.141	0.256	0.140	0.182
	(0.04, 0.33)***	(-0.36, 0.53)	(0.03, 0.27)***	(0.06, 0.53)**	(-0.60, 0.94)	(0.04, 0.37)**
	[0.060]***	[0.099]	[0.044]***			
Years of Education	0.015	0.030	0.012	0.023	0.093	0.013
	(-0.04, 0.07)	(-0.16, 0.22)	(-0.03, 0.05)	(-0.07, 0.12)	(-0.18, 0.52)	(-0.05, 0.08)
	[0.010]	[0.040]	[0.008]			
Age of Household Head	-0.011	-0.003	-0.009	-0.018	0.015	-0.013
	(-0.02, 0.00)	(-0.05, 0.04)	(-0.02, 0.00)*	(-0.04, 0.00)*	(-0.04, 0.10)	(-0.03, 0.00)*
	[0.003]***	[0.011]	[0.002]***			
Agriculture Share	0.298	1.420	0.218	0.414	2.815	0.215
	(-0.46, 1.07)	(-0.81, 4.57)	(-0.35, 0.83)	(-0.64, 1.58)	(-0.59, 10.49)*	(-0.48, 1.11)
	[0.284]	[0.811]*	[0.211]			
Adult Members	0.037	0.066	0.028	0.006	-0.040	0.014
	(-0.14, 0.20)	(-0.37, 0.58)	(-0.10, 0.16)	(-0.30, 0.24)	(-0.92, 1.01)	(-0.20, 0.20)
	[0.074]	[0.058]	[0.054]			
Days Sick	-0.000	0.010	-0.000	-0.002	0.021	-0.001
	(-0.00, 0.00)	(-0.01, 0.05)	(-0.00, 0.00)	(-0.01, 0.00)	(-0.01, 0.21)	(-0.01, 0.00)
	[0.001]	[0.007]	[0.001]			
Sum of						
Log Household Wealth	0.053	0.274	0.097	0.064	0.517	0.177
	(-0.07, 0.19)	(-0.00, 0.69)*	(-0.02, 0.22)	(-0.18, 0.32)	(0.16, 1.86)**	(-0.02, 0.41)*
	[0.032]*	[0.083]***	[0.042]**			
Years of Education	-0.009	-0.062	-0.019	0.014	-0.084	-0.001
	(-0.07, 0.05)	(-0.25, 0.07)	(-0.08, 0.03)	(-0.09, 0.09)	(-0.47, 0.07)	(-0.09, 0.08)
	[0.021]	[0.039]	[0.022]			
Age of Household Head	0.005	-0.012	0.001	0.010	-0.016	0.001
	(-0.01, 0.02)	(-0.05, 0.02)	(-0.01, 0.01)	(-0.01, 0.03)	(-0.09, 0.04)	(-0.02, 0.02)
	[0.004]	[0.006]*	[0.004]			
Agriculture Share	0.576	0.406	0.453	0.930	0.710	0.573
	(-0.16, 1.34)	(-1.39, 2.74)	(-0.28, 1.15)	(-0.29, 2.20)	(-2.76, 6.15)	(-0.71, 1.76)
	[0.264]**	[0.442]	[0.228]**			
Adult Members	0.084	0.205	0.100	0.105	0.341	0.102
	(-0.07, 0.24)	(-0.21, 0.69)	(-0.05, 0.26)	(-0.14, 0.39)	(-0.24, 1.58)	(-0.13, 0.38)
	[0.035]**	[0.148]	[0.044]**			
Days Sick	0.000	-0.008	0.000	0.002	-0.018	0.001
	(-0.00, 0.00)	(-0.05, 0.01)	(-0.00, 0.00)	(-0.00, 0.01)	(-0.21, 0.01)	(-0.00, 0.01)
	[0.001]	[0.007]	[0.001]			
Households	445	445	445	89	89	89
Villages	15	15	15	3	3	3
Possible Links	12762	12762	12762	2552	2552	2552
Actual Links	292	138	430	131	84	215

'Any Link' regression is estimated using logit, *LU*-Link and *LR*-Link are 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. Bootstrapped 95% confidence intervals in parentheses and clustered standard errors in brackets. *,**, 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
14 villages							
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)		
3 smallest villages							
Recip	Recip	0.693	Unrecip	Unrecip	0.451	3.363^{**}	3
		(0.054)			(0.150)		
Recip	All	0.920	Unrecip	All	0.857	1.457	2
		(0.076)			(0.131)		

The last column is the number of villages for which $S(\text{Recip}, g) > S(\text{Unrecip}, g)$ out of 14 or 3 villages. Standard deviations in parenthesis. *,**, and *** indicate significance at the 10%, 5%, and 1% levels, respectively for a one-sided test.

Table 6: Support Regressions

	All villages				3 smallest villages			
Variable	LU-Link	LR-Link	LU-Link	LR-Link	LU-Link	LR-Link	LU-Link	LR-Link
Immed Family			1.546	2.086			1.095	1.355
			(0.85, 2.14)***	(1.23, 2.97)***			(-0.04, 1.88)*	(0.26, 2.62)**
			[0.274]***	[0.351]***				
Distance			-1.221	-1.798			-0.726	-1.784
			(-1.74, -0.84)***	(-2.82, -1.26)***			(-1.77, -0.10)**	(-3.38, -0.91)***
			[0.164]***	[0.239]***				
Support								
Unrecip	0.982	0.740	0.586	0.376	0.722	0.473	0.548	0.189
	(0.32, 1.46)***	(0.10, 1.43)**	(-0.01, 1.04)*	(-0.33, 1.12)	(-0.00, 1.35)*	(-0.21, 1.31)	(-0.15, 1.14)	(-0.64, 1.12)
	[0.216]***	[0.233]***	[0.143]***	[0.237]				
Recip	0.814	2.561	0.454	2.007	0.732	2.184	0.500	1.728
	(0.16, 1.40)**	(1.75, 3.31)***	(-0.24, 1.02)	(1.12, 2.77)***	(0.03, 1.36)**	(1.26, 3.21)***	(-0.26, 1.17)	(0.71, 2.77)***
	[0.091]***	[0.257]***	[0.168]***	[0.285]***				
Households	449	449	449	449	89	89	89	89
Villages	15	15	15	15	3	3	3	3
Possible Links	12992	12992	12992	12992	2552	2552	2552	2552
Actual Links	314	434	314	434	143	220	143	220

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. Bootstrapped 95% confidence intervals in parentheses and clustered standard errors in brackets. *,**, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 7: Betweenness Centrality in Reciprocated and Unreciprocated Networks

Standard deviation				t-test	# Times bigger
All villages					
Recip	0.021	Unrecip	0.032	-1.397*	3**
	(0.031)		(0.036)		
3 smallest villages					
Recip	0.078	Unrecip	0.072	0.756	2
	(0.006)		(0.010)		
Freeman's index				**t-test**	**# Times bigger**
All villages					
Recip	0.0027	Unrecip	0.0039	-1.438*	3**
	(0.0039)		(0.0043)		
3 smallest villages					
Recip	0.0096	Unrecip	0.0083	0.785	2
	(0.0020)		(0.0009)		

The last column is the number of villages for which Reciprocated Betweenness > Unreciprocated Betweenness out of 15 or 3 villages. Standard deviations in parenthesis. *,**, and *** indicate significance at the 10%, 5%, and 1% levels, respectively for a one-sided test.

Table 8: Betweenness Regressions

	All villages				3 smallest villages			
Variable	*LU*-Link	*LR*-Link	*LU*-Link	*LR*-Link	*LU*-Link	*LR*-Link	*LU*-Link	*LR*-Link
Immed Family			1.794	2.473			1.254	1.835
			(1.10, 2.44)***	(1.67, 3.38)***			(0.09, 2.23)**	(0.84, 3.08)***
			[0.283]***	[0.347]***				
Distance			-1.325	-2.091			-0.914	-2.306
			(-1.89, -0.91)***	(-3.28, -1.44)***			(-2.07, -0.22)**	(-4.29, -1.26)***
			[0.173]***	[0.279]***				
Difference of Betweenness								
Unrecip	1.227	0.053	1.323	0.876	0.724	0.082	0.736	1.272
	(-0.85, 2.85)	(-5.85, 6.00)	(-0.95, 3.16)	(-5.80, 7.91)	(-2.39, 3.04)	(-7.87, 8.54)	(-2.52, 3.15)	(-7.40, 11.51)
	[0.603]**	[1.447]	[0.648]**	[1.915]				
Recip	4.266	-1.812	4.523	-1.344	3.570	-0.432	3.699	-0.126
	(1.04, 9.18)**	(-11.82, 4.37)	(1.15, 10.12)**	(-11.88, 4.79)	(0.21, 8.36)**	(-9.19, 5.88)	(0.207, 8.87)**	(-8.96, 6.46)
	[1.356]***	[1.923]	[1.558]***	[1.910]				
Sum of Betweenness								
Unrecip	7.670	2.612	7.836	2.819	7.041	1.987	7.128	2.149
	(6.15, 10.41)***	(-1.76, 6.36)	(6.12, 10.88)***	(-2.44, 7.12)	(4.96, 10.03)***	(-4.22, 6.73)	(5.30, 10.67)***	(-4.84, 7.47)
	[0.897]***	[0.339]***	[0.947]***	[0.498]***				
Recip	0.178	11.249	-0.049	11.816	-0.056	9.058	-0.320	9.461
	(-4.54, 3.12)	(6.61, 20.93)***	(-5.15, 3.12)	(7.40, 22.21)***	(-4.60, 2.98)	(4.81, 16.61)***	(-5.11, 2.84)	(5.33, 17.74)***
	[1.657]	[2.506]***	[2.033]	[2.813]***				
Households	449	449	449	449	89	89	89	89
Villages	15	15	15	15	3	3	3	3
Possible Links	12992	12992	12992	12992	2552	2552	2552	2552
Actual Links	314	434	314	434	143	220	143	220

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. Bootstrapped 95% confidence intervals in parentheses and clustered standard errors in brackets. *,**, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.