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Social Networks in Developing Countries

Yating Chuang and Laura Schechter

Department of Agricultural and Applied Economics, University of Wisconsin, Madison, Wisconsin 53706; email: ychuang5@wisc.edu, lschechter@wisc.edu

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Abstract

Social networks function as an important safety net in developing countries, which often lack formal financial instruments. Such networks are also an important source of information in developing countries with relatively low access to the Internet and literacy rates. We review the empirical literature that uses explicit social network data collected in developing countries. We focus on social networks as conduits for both monetary transfers and information. We also briefly discuss the network-formation literature and comment on data collection strategies, mentioning some areas we believe to be especially ripe for future study.

1. INTRODUCTION

In the past decade, economic research on the impacts of social networks has grown. The advent of digital social networks such as Facebook and Twitter brought renewed interest to nondigital social networks. Economic research on social networks in the developed world has focused on identifying peer effects by which the propensity of an individual to behave a certain way varies with the behavior of others in his network. Examples include studies of peer effects on obesity, smoking, and happiness (Christakis & Fowler 2007, 2009); on college GPA and joining a fraternity (Sacerdote 2001); and on job search (Ioannides & Loury 2004). Bramoullé et al. (2009) and De Giorgi et al. (2010) designed techniques specifically suited to network data to tease out such peer effects. See Sacerdote (2014) for an overview of the literature measuring peer effects, focusing almost exclusively on data collected in the developed world.

At the risk of overgeneralizing, research using developing country data focuses on more basic outcomes such as income levels, vulnerability to economic shocks, and ability to borrow money in times of need; take-up of loans, new agricultural technologies, and new health technologies; and access to jobs. The outcomes of interest are basic and vital because social networks are arguably both more necessary and more frequently used by individuals in developing countries. We look first at the relatively high necessity and then at the relatively high use of networks in developing countries.

Banerjee & Duflo (2007) use 14 major household survey data sets, including nine Living Standards Measurement Study (LSMS) surveys, to look for cross-country regularities. In terms of need for social networks, they find that the poor have little access to any form of insurance. Across the data sets, among households living on under a dollar a day, only in 1 instance do more than 50% of the respondents have some form of insurance; in another 6 instances, the share is greater than 10% but less than 50%, and the share for the other 20 instances is less than 10%. Given that these households face so much uninsured risk, one might imagine that they could use loans to smooth these shocks, but the data also show that less than 5% of the rural poor and less than 10% of the urban poor have a loan from a bank. Similarly low numbers are found for access to savings accounts.

Likewise, Collins et al. (2009) find evidence for the need for social networks. They conducted financial diaries with 300 poor households at two-week intervals for a year. They find that poor households face what they call a triple whammy: Their incomes are low, irregular, and unpredictable. Collins et al. argue that this reality makes frequent, small transactions more important than rare, large transactions and that formal financial instruments, at least as currently designed, are not well placed to help the poor shield themselves from financial risk. Finally, the World Development Indicators (WDI) suggest that, between 2008 and 2012, 67% of employed individuals in lower-middle-income countries were vulnerable (unpaid family workers and own-account workers). In high-income countries, this number was only 11%.

The WDI present other evidence suggesting that individuals in poor countries are especially in need of social networks. In the developed world, if someone wants to decide whether to adopt a new technology, there are a myriad of sources to look to for information. In low-income countries in 2013, only 7% of the population was using the Internet, whereas in high-income countries, that statistic was 78%. In low-income countries over the period 2005–2013, only 68% of men and 54% of women were literate (compared with 99% for both men and women in high-income countries). Thus, individuals living in low-income countries have limited access to information, and many are not literate enough to be able to read the information they do have access to.

Although it is relatively easy to find representative data showing that individuals in developing countries have a great need for social networks, it is harder to find evidence from such representative data sets that these individuals use social networks, because many of the largest household surveys do not contain social network data. Banerjee & Duflo (2007) find that a high share (between 10% and 90%, depending on the country) of households living on under a dollar a day have access to some loan. The proportion of loans from villagers, friends, or relatives is between 25% and 90%. If one adds in savings groups, shopkeepers, and moneylenders, this share approaches 100%.

Collins et al. (2009) find that for Bangladesh, poor households have on average ten interpersonal credit transactions per year, whereas in India and South Africa the average is six for such households. Similarly, Udry (1990) finds that in Nigeria, every household in his sample had, on average, four credit transactions with other individuals in the village in the past year. Only 10% of the households in the village did not participate at least once in village-level borrowing and lending in that year. The financial diaries presented in Collins et al. (2009) show that a large share of the monetary flows are transactions within social networks such as loans, money guarding, and rotating savings and credit associations (ROSCAs).

Although there is evidence that social networks are commonly used by individuals in developing countries, these interactions are not always positive. The financial diaries presented in Collins et al. (2009) provide numerous examples of interpersonal loans not being repaid, ROSCAs disintegrating before all members receive their payout, and money-guarding relationships in which the money guarder uses up the saver's money. Di Falco & Bulte (2011) find evidence that forced sharing in kinship networks reduces investment in sharable liquid assets and decreases income growth, and Di Falco & Bulte (2013) find that these networks discourage investment in risk-mitigation measures. These findings suggest that we should be interested not only in how social networks work as a conduit for financial transactions, but also in how social networks enforce these transactions.

It is even harder to find comparable cross-country evidence regarding households' use of social networks as sources of information. Such evidence can be found only in specific small-scale studies, which suggests that networks are often used for this function. The recent rapid spread of mobile phones (which do not necessarily access the Internet) suggests that individuals now have greater ability to share information over longer distances. The WDI show that in 2012 in low-income countries there were 53 mobile cellular subscriptions per 100 people. (Compare this statistic with 1 fixed telephone line per 100 people in low-income countries and with 120 mobile cellular subscriptions per 100 people in high-income countries.)

We review evidence regarding how individuals in developing countries use social networks. As this field is quickly growing, we narrow our review by focusing on empirical papers using network data from developing countries. Many papers define networks by membership in groups such as ethnicity or caste, but we do not focus on these articles. Munshi (2014) provides a nice review of the literature on such "community networks."

We broadly divide the literature into papers that look at social networks as conduits for financial transactions and papers that look at social networks as conduits for information. In Section 3, we discuss the former. We look at informal insurance both in the real world and in economic experiments. We mention studies that try to distinguish whether these transfers are motivated by altruism or by reciprocal, repeated transactions. We then look at other ways in which social networks transmit money, including mobile money and corruption.

In Section 4, we look at how social networks transfer information. We first review studies that look more generally at how information spreads in networks. Next, we look at learning about specific agricultural, financial, and health technologies. Finally, in Section 5, we discuss transactions in which the spread of both money and information seems to be at play. These interactions include job search, vote buying, and default in microfinance groups.

We briefly discuss data collection issues related to social networks in Section 6 before concluding in Section 7. The reader may note that most of the studies discussed in the above-mentioned sections take the existing network as given. Very little literature looks at how networks in developing countries form. We begin by briefly addressing this literature in Section 2.

2. NETWORK FORMATION

The theoretical literature on network formation is quite advanced; see Jackson (2009) for a brief overview. Most of the empirical work on network formation uses data from experiments run in the laboratory (Kosfeld 2004). Empirical work outside the lab tends to look at schools and colleges because there one can look at networks as they form. In developing countries, and especially in rural areas therein, families have interacted for generations, and studying network formation in these contexts is difficult.

Krishnan & Sciubba (2009) present one of the first empirical studies in a developing country context to examine network architecture and to look at more than just with how many and with which other households the individual is linked. They construct a labor-sharing network-formation model and derive the characteristics of equilibrium networks. Their model suggests that networks of farmers of equal quality will be symmetric (with each person having the same number of links) and that these groups should exhibit significant clustering. In asymmetric networks, farmer qualities must differ, and there will be less clustering.[1] Krishnan & Sciubba find that these characteristics of the networks are confirmed in Ethiopian data.

Comola & Fafchamps (2014b) also bring a network-formation model to the data to see whether the equilibrium outcomes are in accord with the model predictions. They use discordant reports of links (i.e., when one individual claims to be linked to the second, but the second does not claim to be linked to the first) to test between models of unilateral link formation, bilateral link formation, or a desire to link. They find that the desire-to-link model better fits the data for risk-sharing networks in Tanzania, whereas unilateral link formation with misreporting better fits the data for information-sharing networks in India.[2,3]

Apicella et al. (2012) likewise look at the characteristics of existing networks among Tanzanian hunter-gatherers to provide insights into the network-formation process. They find that these networks have characteristics similar to those found in the developed world, including a skewed degree distribution (with some individuals having many links and some very few) and high levels of clustering. They find evidence of homophily, with high between-group and low within-group variation in the amount donated in a public goods game. This evidence suggests networks form in a way that allows cooperation to flourish among groups of cooperators.

None of the above papers look at either who forms new links with whom or why those new links are formed. Barr et al. (2015), Comola & Mendola (2015), and Comola & Prina (2014) aim to do just that. Comola & Mendola study how Sinhalese Sri Lankan immigrants to Milan form links with one another. They find that immigrants are most likely to interact with other immigrants who came from close-by localities back in Sri Lanka. Links are more common between individuals

[1]Similarly, Schechter & Yuskavage (2011) show that reciprocal sharing networks have architecture different from that of unreciprocal networks, with reciprocal relationships exhibiting higher levels of support.

[2]In a related paper, Comola & Fafchamps (2014a) use discordant data on actual transfers to suggest that the data may significantly underestimate informal transfers.

[3]Fafchamps & Gubert (2007) look at which households are connected with one another in long-standing Philippine communities, and these researchers discuss what those data imply about the functioning of risk sharing.

who arrived at the same time and between individuals who have been there a long time and those newly arrived. Still, most Sinhalese migration is planned in advance and is based on existing ethnic social networks in the host country. Even within Comola & Mendola's sample, 18% of the time when two sampled individuals know each other, they know each other from back in Sri Lanka rather than from forming a new link after arriving in Italy.

Barr et al. (2015) and Comola & Prina (2014) come the closest to looking at how people form new relationships. Barr et al. look at which households choose to join community-based organizations in newly created resettled villages formed by the Zimbabwean government and how these memberships evolve over time. They find that these organizations were created by wealthier households, but poorer households are included over time. Geographic proximity was a strong determinant of membership in earlier years, but that effect faded over the years.

Comola & Prina (2014) do not look at original network formation. Instead, they randomly give access to savings accounts to some women in 19 villages in Nepal and look at how this access changes the network. They find that women who were offered savings accounts are connected with more individuals one year later and make more transfers (to both individuals with and individuals without a savings account). Comola & Prina define a link as existing when one household states that it regularly exchanges gifts and/or loans with another. Thus, it is difficult to determine whether the underlying network has changed or whether the individuals were always linked, but once a woman gains access to a savings account, she becomes more likely to send money through those preexisting links.

One final technique for getting at network formation is to randomly create new links. Fafchamps & Quinn (2012) do this by having entrepreneurs work together in randomly formed groups. They find that these entrepreneurs continue to interact after the experiment is over. Vasilaky & Leonard (2014) work with an NGO that randomly picks pairs of women and encourages them to talk with one another throughout the growing season. The intervention successfully created new links between female farmers. Unfortunately, all women in the social network treatment group received both the social network intervention and cotton training, and thus teasing apart the effects of the network and information interventions on agricultural productivity is impossible.

These papers give preliminary evidence regarding how friendships form in a developing country context, and they are wonderful first steps toward learning more about these complex relationships. Given that looking at network formation outside the context of newly resettled households is difficult, we believe that more longitudinal studies of how networks change over time, especially after some individuals are exposed to randomized interventions, have the potential to be a fruitful area of future research.

3. NETWORKS AS CONDUITS FOR FINANCIAL FLOWS

Social ties can be used to transfer money, and to monitor and enforce such transfers, across a network. In this section, we discuss the literature on informal insurance and risk sharing, looking at real-world interhousehold transfers that occur by nonelectronic means, as well as those occurring by using mobile money. In addition, we look at corrupt transfers to socially connected firms. Finally, we look at transfers made in social networks in controlled economic experiments and at attempts to distinguish informal insurance from altruism. For a review of the literature on risk sharing in networks in developing countries, see Cox & Fafchamps (2008) and Fafchamps (2011).

3.1. Informal Insurance in the Real World

It is well established that individuals living in developing countries provide each other with informal insurance. Townsend (1994) is one of the first to provide such evidence in rural India. He does not find full insurance, as a small share of idiosyncratic income shocks are passed on to consumption. Townsend implicitly assumes that sharing takes place at the level of the village.

Newer research looks at whether sharing may take place within social networks rather than in the village as a whole, potentially explaining the lack of full insurance at the village level. Udry (1994) looks at how friends and family use borrowing and lending networks to insure one another. Fafchamps & Lund (2003) take this work one step further by looking at gifts and transfers in addition to loans and by taking into account potential partners (to whom the individual would go in times of need) in addition to actual partners (to whom the individual actually went in the past year). Rather than looking at lending, gifts, and transfers separately, Dercon & De Weerdt (2006) test whether all strategies together smooth consumption. They find that food consumption is fully insured against health shocks at the village level but that nonfood consumption is not. Nonfood consumption is partially insured within smaller networks.

Kinnan & Townsend (2012) take this line of study in another direction and look at which networks are most useful for consumption smoothing and which are most useful for helping members make investments. They find that financial networks (loans and transfers) are useful for consumption smoothing, whereas kin networks are more useful for financing big investments. Similarly, Angelucci et al. (2014) find that the randomized Progresa conditional cash transfer in Mexico is pooled within kin networks, thus allowing members to both better smooth consumption and make higher-return investments. Larger and more closely linked networks achieve better consumption smoothing than do smaller and less closely linked networks, although they exhibit similar investment responses.

Results from Angelucci et al. (2014) suggest that network architecture, and not just who is linked with whom, matters for risk sharing. Karlan et al. (2009) are one of the first to distinguish between the underlying network and the transfers flowing through that network, as well as one of the first to take indirect links seriously. Data on how much time people spend with one another are used to construct the network, and money can flow up to two links away. Karlan et al. show that direct paths and indirect paths contribute equally to risk sharing and that each indirect path contributes through its weakest link. Ambrus et al. (2014b) build on this model to show that the extent of informal insurance depends on network architecture, and specifically on a characteristic termed expansiveness. Their empirical results show that villages in Peru tend to exhibit sufficient expansiveness, leading to very good but not full insurance.

The model in the previous paragraph assumes that limited commitment is the main impediment to full risk sharing. Other theoretical work making this assumption includes Bloch et al. (2008) and Jackson et al. (2012). Both papers prove that efficient risk-sharing networks should exhibit specific architectural features. For example, Jackson et al. (2012) predict that risk-sharing networks should exhibit a characteristic they term support, and then they show that Indian risk-sharing networks have this characteristic.[4] Support is a variant of network closure, a construct whose importance for fostering cooperation was first emphasized by sociologists such as Coleman (1990) and Burt (2005).

If there is not full insurance, there must be some friction preventing it. The above-mentioned focus on limited commitment (as opposed to information asymmetries) is supported by evidence presented by Udry (1990) that information asymmetries are not of first-order importance in rural areas of developing countries. A different option is presented by Ambrus et al. (2014a), wherein there is full commitment and perfect information, but the relevant friction is costly link

[4]Bramoullé & Kranton (2005) model risk sharing in networks with full commitment and full information.

formation. Social network data from 75 Indian villages are in accord with the predictions of this Ambrus et al. model.

All the previously mentioned papers look at nonelectronic transfers. The advent of mobile money, allowing individuals to easily and cheaply transfer money to one another by using their cell phones, should make such transfers easier. In addition, as researchers gain access to administrative data from mobile phone operators, they will have high-frequency data, which do not suffer the recall bias and other measurement errors from which self-reported interactions suffer.

Although lacking access to administrative data or individual-to-individual transaction data, Jack et al. (2013) and Jack & Suri (2014) show that access to mobile money increases risk sharing. Such access decreases consumption variability, increases the physical distances over which transfers flow, and increases the prevalence of reciprocal transfers. Blumenstock et al. (2014) do have access to high-frequency administrative data—they have billions of observations on phone calls, text messages, and transfers—but their transfer data are for transfers of airtime (used primarily to make phone calls) rather than for monetary transfers.[5] They find that transfers sent after natural disasters appear to be motivated by risk sharing rather than by altruism.[6] These transfers are sent over large physical distances and in response to covariate shocks. The transfers are more likely to be sent to wealthy individuals, to central individuals, and to people from whom the sender has received transfers in the past.

This is just the tip of the iceberg in terms of what can be done with such data. In addition to examinations of how mobile money is used within existing networks, it will be interesting to see how mobile money affects existing networks. Jack et al. (2013) show that mobile money leads to an increase in person-to-person reciprocal transactions, but Mbiti & Weil (2015) show that mobile money leads to a decrease in the use of group-based ROSCAs. Morawczynski & Pickens (2009) cite worries that husbands who in the past traveled home to their rural families to deliver money will in the future send money electronically and visit home less frequently, contributing to the disintegration of marriages. One can only imagine that this new social network–based technology, which has been taking the developing world by storm, is sure to have large impacts, both good and bad, on economic outcomes and social networks themselves. We hope that there will be more research in this area in upcoming years.

The main focus of this section is interhousehold transfers. Here we briefly mention studies looking at corrupt transfers from politicians to businesses. (We address vote buying later in this article.) Faccio (2006) creates a data set of politically connected firms across almost 50 countries and finds that when a businessperson enters politics, the stock price of his company increases significantly. Fisman (2001) looks at the value of political connections to Suharto in Indonesia in the 1990s. He finds that whenever Suharto's health was called into question, the market value of large businesses connected to him dropped significantly.

Khwaja & Mian (2005) show one mechanism through which this increased valuation might occur. They show that, in Pakistan, politically connected firms have access to more credit and are more likely to default on that credit. This effect is found only for loans given by government-owned banks. Johnson & Mitton (2003) show another potential mechanism: the fact that politically connected firms have greater access to government subsidies.

[5]Björkegren (2014) uses detailed data on five billion cell phone calls in Rwanda to model the spread of cell phones as a function of social networks.

[6]Schechter & Yuskavage (2012) look at reciprocated and unreciprocated sharing networks more generally (not after natural disasters) and similarly find evidence that both are forms of risk sharing rather than altruism. In contrast, Comola & Fafchamps (2014a) and De Weerdt & Fafchamps (2011) find that transfers are motivated by altruism.

3.2. Informal Insurance in Economic Experiments

Data on day-to-day financial interactions have great external validity. Administrative data on mobile money monetary flows have the added benefit that the timing and size of flows have less measurement error. Economic experiments in which individuals are given money and can choose what to do with it within the confines of the game give researchers more control over the environment, allowing them to tease out different motivations for giving.

Traditionally, experimental economists gave university students money to play games in labs with other randomly chosen anonymous university students. Since their early days, experiments have moved out of the lab and into the field. And because most real-world situations in which people share resources with one another are not anonymous, and often involve the ability to choose with whom one wants to interact, experimentalists have begun to run nonanonymous experiments both with and without partner choice. Such experiments take advantage of subjects' ongoing relationships with one another. When running nonanonymous experiments, researchers do not assume that they control the punishments and rewards occurring outside the frame of the experiment. In fact, these experiments exploit the fact that the economic experiment is just one interaction within the social network in a repeated game, which often goes on for decades. The choice of partner made by players in such games is correlated with real-world networks (Attanasio et al. 2012, Barr & Genicot 2008, Ligon & Schechter 2012).

We first look at experiments focused on risk-sharing transfers embedded in networks. We subsequently look at papers that tease out whether other-regarding preferences may be the motive for some of these transfers. As with the nonexperimental literature, most experimental risk-sharing papers focus on limited commitment as the friction preventing full insurance.

Chandrasekhar et al. (2015) run risk-sharing games in which they preassign nonanonymous partners and vary the level of commitment. With full commitment, both socially distant pairs and socially close pairs reach equally efficient outcomes. Close pairs perform equally well with and without commitment, whereas the efficiency of distant pairs decreases substantially when there is limited commitment. Breza et al. (2014) show that a third-party monitor or enforcer can increase the efficiency levels reached by socially distant pairs. In a different setup, Attanasio et al. (2012) run risk-sharing games without commitment and allow individuals to choose their partners. These researchers find that individuals match assortatively on risk preferences, presumably leading to more efficient outcomes.

Although limited commitment may be the most common explanation for incomplete risk sharing, Ligon & Schechter (2010) combine anonymous and nonanonymous games both with and without partner choice to distinguish between different models of risk sharing. Players' strategies in the games suggest that there is both asymmetric information and limited commitment. Chandrasekhar et al. (2014) vary information asymmetries and whether players can choose their partners. They find that hidden income significantly reduces risk sharing, although the impact is only half the size when individuals can choose with whom they would like to play. Unlike later results found by some of the same authors (Chandrasekhar et al. 2015), social distance is correlated with efficiency when individuals are allowed to choose their partners, but not when the experimenter assigns partners.

So far we are working under the assumption that these transfers are motivated by the desire to increase efficiency and to share risk. Some papers play dictator games to test this assumption. They vary whether the dictator can choose the recipient (Ligon & Schechter 2012), whether the dictator knows the recipient (Binzel & Fehr 2013), whether the transaction is anonymized (Binzel & Fehr 2013, Ligon & Schechter 2012), and whether the transfer is in cash or in kind (Batista et al. 2014). All these papers find that transfers are motivated by both social preferences and risk-sharing incentives. In anonymous dictator games, in which altruism should be the only reason for sharing, D'Exelle & Riedl (2013) find that central people give more and that dictators give more to central people. In contrast, Ligon & Schechter (2012) find some evidence that better-connected people are more motivated by incentive-based reciprocity than by altruism.

4. NETWORKS AS CONDUITS FOR INFORMATION FLOWS

The network architecture that is useful for sustaining monetary transfers is potentially quite different from the architecture that is useful for spreading information, the next topic of discussion. Within development economics, most of the empirical literature looks at the spread of information regarding new agricultural, financial, and health technologies. It does not tend to focus on strategic information transmission. By that, we mean that researchers do not usually consider strategic reasons for individuals to withhold information or spread false information. This is an interesting area for future research.

Before looking at information flows and technology adoption, we first briefly discuss papers looking at information flows more broadly. Alatas et al. (2014) look at information sharing in 631 Indonesian villages. At the individual level, Alatas et al. show that better-connected households know more about their village mates and that individuals know more about others with whom they are more closely linked. At the network level, networks with higher first eigenvalues are better at aggregating information.

Banerjee et al. (2014) conduct related work. They work with a new measure of centrality first constructed by Banerjee et al. (2013), termed diffusion centrality, which Banerjee et al. (2014) posit is important for spreading information. In India, individuals who are more diffusion central are better at spreading information. Of course, it may be difficult for policy makers wishing to target central individuals to collect the network data necessary to calculate diffusion centrality. So Banerjee et al. (2014) also ask villagers which person in their village is best suited to initiate the spread of information. They find that villagers nominate the most diffusion central individuals, who are not necessarily the same as, for example, village leaders or people with many friends. This finding suggests that a person recognizes important characteristics of other individuals in the network, even if he is not directly connected to that individual.

Next we discuss how networks aid in (or deter) the adoption of productive agricultural technologies, new financial instruments, and health-enhancing products.

4.1. Networks Spreading Information Regarding Agricultural Technologies

Maertens & Barrett (2013) review the literature looking at the impacts that social networks have on the adoption of new agricultural technologies. Munshi (2008) reviews the literature on how networks spread information regarding both agricultural technologies and fertility outcomes.

Foster & Rosenzweig (1995) are one of the first to look at learning from others in agricultural technology adoption in the developing world, although they do not have explicit data on social networks. They find that farmers learn from one another and that farmers also free ride, waiting for other farmers to experiment and learn before adopting. Munshi (2004) uses a similar technique but distinguishes between rice and wheat. He finds more social learning for wheat, which can be explained by the fact that rice is much more sensitive to plot characteristics than is wheat.

A subsequent group of papers on this topic uses data on the number or share of adopters that a farmer knows, but does not use data on the identities of those individuals. Among the first to use this approach are Boahene et al. (1999), who find that Ghanaian farmers who know more adopters of hybrid cocoa are themselves more likely to adopt. More recently, Bandiera & Rasul (2006) find an inverse-U-shaped relationship between the number of friends and family adopting and the probability a farmer adopts sunflowers in Mozambique. They hypothesize that this relationship occurs because when there are few adopters, knowing more adopters helps with the spread of information, but when there are many adopters, farmers have an incentive to free ride. Liverpool-Tasie & Winter-Nelson (2012) also find an inverse-U-shaped relationship in the adoption of new agricultural technologies in Ethiopia. Matuschke & Qaim (2009) use similar data and find that the share (rather than the number) of network members adopting hybrid seeds in India increases the probability of adoption. These researchers do not look for nonlinearities. One criticism by Hogset & Barrett (2010) of such work is that these surveys often ask respondents how many people in their network adopt. Such responses may not be accurate, and individuals may project their own behavior onto their peers. When Hogset & Barrett (2010) use respondents' proxy reports, they find significant peer effects, but when they instead use the peer's self-reports, they no longer find significant peer effects on adoption.

Newer papers on this topic fully map out social networks, rather than relying on data on the number of friends adopting. Maertens (2014) looks specifically at from whom farmers learn when deciding whether to adopt Bt cotton in India. She finds that farmers learn most from progressive farmers rather than from the nonprogressive peer farmers with whom they are linked. Social pressure can significantly deter the adoption of genetically modified crops.

Some papers use randomized controlled trials to get at this issue. Magnan et al. (2014) create random variation in the adoption of laser land leveling in India by using auctions. They find that farmers with more friends who adopt are more likely to adopt themselves and that this is true only for those farmers whose networks include someone who benefited from the technology. This impact seems to come through observing the leveled fields rather than through conversations with network members. Carter et al. (2014) create variation in the adoption of fertilizer by randomly giving out vouchers. Having more friends who received vouchers (*a*) has no effect on the respondent's fertilizer use in the year that the vouchers were given, (*b*) affects maize fertilizer use in the year after the vouchers were given, and (*c*) affects fertilizer use on all crops in the second year postvoucher—a pattern suggesting learning.

BenYishay & Mobarak (2014) find that incentives to spread information are important in increasing information flows and that recipients of information are more likely to be persuaded when the information comes from someone facing similar agricultural conditions. Without incentives, progressive farmers are the only ones to spread information. But with incentives, peer farmers also spread information and do so more effectively.

Most of the papers mentioned thus far look at how many of a person's contacts adopt or which of a person's contacts adopt. Beaman et al. (2014) look at the network structure as a whole by examining a census of 200 Malawian villages. They try two different ways of choosing injection points to help spread a new technology: Let agricultural extension agents choose, or simulate linear threshold technology adoption models and choose injection points to maximize predicted adoption. There are three simulation methods: simple contagion (in which farmers knowing one person who adopts are more likely to adopt), complex contagion (in which farmers knowing two people who adopt are more likely to adopt), and complex geographic contagion (which is the same as complex contagion, but with a focus on geographic proximity rather than on social network links). Beaman et al. find that all three simulation methods do significantly better than letting the extension agents choose. The geographic method does not do quite as well as the methods based on social network links, but given that the former method is much cheaper and easier to conduct, it may be promising in practice.

Emerick (2014) is less interested in the transmission of information regarding new technologies through networks and is more interested in the transmission of the technology itself. He finds that relying on social networks to spread new technologies through the sale of seeds leads to large inefficiencies in seed allocation. Relying on social networks to spread technologies limits purchasers to family and close friends of the individuals selling the technology. This finding suggests that social networks are not a panacea for the spread of productive technologies.

The papers mentioned thus far look at the impact of networks on the adoption of a new technology. These papers can only indirectly infer learning. Conley & Udry (2010) present one of the only papers to look directly at learning regarding how to use a new technology, namely how much fertilizer to apply conditional on adopting the new technology. Using data on who talks with whom about agriculture, Conley & Udry find significant evidence that farmers, especially inexperienced farmers, learn from one another regarding best practices. This area seems fruitful for future research.

A concern in many of these papers is distinguishing learning from other reasons that friends' and neighbors' behaviors might be correlated, such as mimicry, correlated weather shocks, correlated unobserved characteristics, and social pressure. Different papers approach this issue in different ways. For example, Conley & Udry (2010) separate out learning from correlated shocks by using network data on both who goes to whom for agricultural advice and geographic location. They separate out learning from mimicry by showing that farmers adjust input toward surprisingly successful input levels but away from surprisingly unsuccessful levels. Maertens (2014) uses data on farmers' knowledge regarding both progressive farmers and randomly chosen farmers. She also uses data on whether farmers know only which crop the person plants or whether they additionally know the inputs used and yield obtained. In this way, she can distinguish between the different mechanisms by which neighbors and friends make similar technology choices. Bandiera & Rasul (2006) approach this issue in a more indirect fashion by focusing on the inverse-U-shaped relationship between the number of friends adopting and own adoption. These researchers walk through the logic of why such a relationship could be explained only by learning.

4.2. Networks Spreading Information Regarding Financial Technologies

Individuals in developing countries often have very little experience with formal financial instruments such as loans, savings accounts, and insurance. As the offerings for such populations become more common and varied, learning through social networks has been found to be important.[7]

Banerjee et al. (2013) look at how social networks impact the adoption of microfinance loans. The microfinance institution gave information on microfinance to village leaders. In villages in which these injection points were more central, a higher share of the village ended up taking out a loan. Social networks aid in the flow of information, but the authors do not find evidence of "endorsement effects" (the direct influence of one person's participation decision on that of his neighbor).

One nice feature of the work by Banerjee et al. (2013) is that they focus on a specific measure of centrality that their model suggests should be most relevant for the spread of information. Borgatti (2005) emphasizes that different measures of centrality are developed on the basis of different assumptions regarding how the object in question (e.g., money or information) flows. He focuses on two dimensions. First, he looks at whether the object in question takes the shortest path or whether it is free to wander through the network by repeatedly visiting nodes and edges. Second, he

[7]Chuang (2014) suggests another reason why the adoption of financial technologies may be correlated within networks: Social networks encourage the purchase of temptation goods such as alcohol and gambling and decrease savings.

looks at whether the object is transferred (e.g., money or tools), duplicated (e.g., word-of-mouth gossip), or duplicated in parallel (e.g., email broadcasts or group meetings). Being more discerning about which centrality measures to use in which situations is a useful direction in which the field could go.

In related research, Cai et al. (2015) conduct a randomized controlled trial on the adoption of agricultural weather insurance. They give information about the new insurance product to a random subset of farmers and find that the more friends a farmer has who received information, the more likely he is to adopt. As with Banerjee et al. (2013), Cai et al. find that this effect is due to the diffusion of information rather than endorsement effects. In contrast to some of the previous research (e.g., Coleman et al. 1957), Cai et al. find that the least central individuals are the most influenced by their social network.[8]

Other work on social networks and financial decisions includes that of Bursztyn et al. (2014), who look at investment in a risky investment fund with a minimum investment of $1,000 in Brazil. They find that both social learning and social utility play an important role. Learning effects are stronger when learning flows from financial sophisticates to the unsophisticated. Social utility has largely been ignored in the remaining literature discussed in this review. It may be caused by the desire to "keep up with the Joneses" or by the enjoyment that individuals get from following a stock and tracking returns together with their friends.

4.3. Networks Spreading Information Regarding Health Technologies

We next look at the impact of social networks on the adoption of health products. Some of the earliest work looking at the impact of social networks on the adoption of new technology occurred in sociology. Coleman et al. (1957) look at doctors' prescriptions of a new drug and find that when opinion leaders adopt, doctors in their network are more likely to adopt. They also find that doctors with larger social networks adopt new drugs earlier than do doctors with smaller networks. Behrman et al. (2002) find that social networks influence the adoption of contraceptives in Kenya and that this impact is due to learning rather than social pressure. These impressive studies were arguably ahead of their time. Later work has added randomization.

Oster & Thornton (2012) randomly give menstrual cups to Nepalese adolescents and find strong social network effects on trying the cup and using it successfully. They also find suggestive evidence that the impact is through learning. Similarly, Godlonton & Thornton (2012) find that randomly giving incentives to some Malawian individuals to pick up their HIV test results increases the probability that the individuals who live close to them geographically will also pick up their results. Ngatia (2011) looks at the original decision to get tested for HIV (as opposed to the above-mentioned decision of whether to pick up one's results), giving individuals financial incentives of differing sizes to get tested. She finds that if an individual is connected to more people who got tested while receiving a low financial incentive, the individual is less likely to get tested himself due to stigma. A person who gets tested with low financial incentives is admitting that he has engaged in risky behavior, and his friends are subject to guilt by association.[9] One can mitigate the effects of stigma by raising the financial incentives high enough.

There are other examples in which social networks do not have positive impacts on adoption. Miller & Mobarak (2015) conduct a randomized controlled trial looking at how networks impact

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[8]Shakya et al. (2015) also find that social influence is strongest for individuals on the edge of the network.

[9]This finding is similar to the results in Maertens (2014) that social pressure decreases the adoption of genetically modified crops.

the adoption of cookstoves with health and environmental benefits by rural Bangladeshis. They find that opinion leaders are influential and that social learning can decrease the adoption of a new technology if it is not well suited for the local culture. Negative social learning is especially important for technologies whose attributes are less readily apparent. Kremer & Miguel (2007) show the importance of negative social learning for deworming drugs. Parents with more direct and indirect social contacts whose children received deworming drugs were less likely to have their own children take the medicine.

Perkins et al. (2015) review the articles linking sociocentric networks to health outcomes. One consistent result is that the speed of behavioral change can be increased by targeting more central individuals. Kim et al. (2014) test this idea by conducting a randomized controlled trial introducing a new health technology in Honduras either to randomly chosen individuals, to randomly chosen friends of randomly chosen individuals, or to those with the highest in-degree (the number of times a person was mentioned by somebody else). The intervention is at the village level, and Kim et al. include rather few villages, but they find suggestive evidence that there is no difference between targeting randomly chosen individuals and targeting individuals with high in-degree. Targeting randomly chosen friends, in contrast, leads to much higher diffusion of the technology. Kim et al. hypothesize that targeting based on in-degree may lead to "redundant clustering among targets resulting in an 'echo chamber of influence' that fails to reach more dispersed or peripheral parts of the network."[10] Given that collecting data on randomly chosen friends of randomly chosen individuals is much easier than collecting data on the entire network, these results are encouraging for leading to cost-effective means of best getting new technologies out to populations.

5. NETWORKS THAT MIX FINANCIAL AND INFORMATION FLOWS

In the previous two sections, we discuss how social networks can serve either to enforce monetary transfers or to transmit information. Next we review situations, including group liability loans, job searches, and vote buying, in which social networks combine these two functions. For a review of the role of networks in access to jobs and credit in developing countries, see Munshi (2011).

5.1. Microcredit

Group liability loans are common practice in microcredit institutions. Group liability takes advantage of the information-sharing function of networks to overcome adverse selection through ex ante peer screening, and it takes advantage of the network's ability to monitor and enforce transactions to decrease moral hazard through ex post peer monitoring. Karlan and coauthors have worked to disentangle these two functions. Karlan (2007) exploits FINCA's quasi-random group selection process in Peru to rule out selection and focus on peer enforcement. He finds that groups that are more connected socially and more similar culturally perform better, suggesting that enforcement is effective.

More recent work relies on randomized experiments. Giné & Karlan (2014) run two experiments in the Philippines. In the first, they randomly convert some existing liability lending groups to individual liability. In the second, they form new groups and randomly make some group

[10]This finding is the opposite of the results of Beaman et al. (2014) mentioned above. Beaman et al. find that diffusion is complex, meaning that people do need to hear about the technology from more than one individual before adopting. Of course, every technology is different, and future research may explore when simple contagion is appropriate and when complex contagion is appropriate.

liability and some individual liability. Because they find no difference in the default rates across the groups and thus find no economic impacts of either monitoring or selection, they cannot tease apart the two mechanisms.

Karlan et al. (2010) look in Peru at loans given to individuals with a cosigner. They randomly assign interest rates on the basis of the borrower's social distance to his cosigner. After the loans have been approved, some cosigners are randomly absolved of responsibility in case the borrower defaults. The authors find suggestive evidence that selection effects are strong when cosigners are not friends but that enforcement effects are strong when cosigners are friends.

Finally, Bryan et al. (2015) look at individual liability loans in South Africa. They look at monitoring as well as two different forms of information about borrower type: ability to repay and susceptibility to social pressure. In the first stage, Bryan et al. randomly give existing borrowers one of two incentives for referring a new borrower. Borrowers were offered a bonus either if the referred individual's loan application was approved or if the referred individual repaid his loan. In the second stage, half of the original clients with the loan repayment incentive were surprised by being given their bonus if their referral's loan was approved (regardless of repayment). Half of the original clients with the loan approval incentive were given an additional bonus for the referral's loan repayment. Bryan et al. find strong peer enforcement effects but find no peer selection effects of either type. There is evidence that the lack of peer selection effects is not for want of trying but rather is due to the fact that the original clients do not have useful information regarding the individuals they refer. Such two-stage randomizations have the potential to be implemented in many other contexts to help researchers separate out the different functions of social networks.

5.2. Job Search Networks

Social networks are a source of job referrals for individuals looking for jobs. Munshi (2003) and Beaman (2012) look at the impact of social networks on migrants' ability to find jobs. Munshi (2003) finds that larger networks facilitate better employment outcomes for Mexican migrants in the United States. Beaman (2012) also finds migrants' network size to have a significant impact on labor market outcomes. But unlike Munshi (2003), Beaman (2012) finds that if a given cohort is larger, the employment outcomes of cohorts arriving close in time to that given cohort are depressed, and employment outcomes of the cohorts arriving later improve relative to that given cohort. These papers focus on the role of networks in sharing information.[11]

Beaman & Magruder (2012) are one of the first to use a job referral field experiment. They asked subjects to make referrals for either a fixed bonus or a bonus that varies with the referral's performance. They find evidence that, compared with the fixed-fee scenario, performance pay leads individuals to refer more coworkers than family members.[12] However, only high-skilled workers can correctly identify high-performing workers.

There are two reasons that individuals hired through performance-based referral contracts might perform better than those hired through a fixed-pay referral program. The referrer might refer higher-quality workers due to their incentives (making use of the information embedded in

[11]There is little evidence making use of explicit network data on the impact of networks on the initial migration decision or on the remittances sent thereafter. Collecting migration data is quite difficult, and collecting network data is quite difficult; combining the two is even more so. But this could be a fruitful area for future research.

[12]Likewise, in their credit experiment, Bryan et al. (2015) find that individuals who get a bonus for referring someone who repays his loan are less likely to refer a relative than those who get a bonus for referring someone who is approved for the loan. Relatedly, Giné & Karlan (2014) find that microfinance groups bring in new borrowers whom they know better under individual liability than under group liability.

networks), or the referred workers might put in more effort (making use of the network's enforcement capabilities). Beaman & Magruder (2012) focus purely on information flows by changing the rules of the experiment after the referred participant arrives, telling both the referrer and the referred individual that the referrer will get the maximum finder's fee no matter what. Thus, the researchers will capture only information effects. Antoninis (2006) suggests that both effects may be important in Egypt. Workers referred by their old colleagues earn more than the average worker, whereas workers referred by friends or relatives earn less than the average worker.

Although job referrals often reduce information asymmetries for firms, Heath (2015) examines how employers take advantage of the enforcement capabilities of social networks. She looks at garment workers in Bangladesh and finds firms use referrals to reduce moral hazard, rather than to reduce search costs. Firms can punish both the referrers and the referred individuals if the referred individual produces low levels of output.

Job referrals may generate biased information. For example, Beaman et al. (2013) find that using job referrals puts qualified female workers at a disadvantage. This disadvantage stems from both the information function of networks (men have less information regarding women) and the enforcement function of networks (men gain more social benefit from recommending other men). Examining data from army personnel records for the British Colonial Army in Ghana, Fafchamps & Moradi (2015) find that individuals who are referred are of low quality, which seems to be due to the incentives given to the referrers.

5.3. Vote Buying in Networks

Vote buying is a common occurrence across the developing world. Candidates for office, or their middlemen, give money or gifts to voters before an election in exchange for their vote.[13] Strong networks are necessary to maintain this institution. Cruz et al. (2014) find that candidates for political office in the Philippines are more central than the average individual. Among candidates, more central candidates are more likely to win. Cruz et al. also find that in villages where challengers come from more central families, vote buying is higher. Cruz (2013) and Finan et al. (2014) show that more central individuals are more likely to accept vote-buying transfers in the Philippines and are more likely to be offered vote-buying transfers in Paraguay, respectively.

Some papers study the impact of voter-party networks on vote buying (Calvo & Murillo 2013, Cruz et al. 2014), but most papers thus far look at voter-voter or voter-middleman networks. Middlemen may rely on social networks for information regarding which party a voter favors, whether he is likely to vote, and whether he is likely to be influenced by a vote-buying transfer. However, middlemen may also make use of social networks as an enforcement mechanism. For example, if the voter apparently did not vote for the specified politician, the middleman can cut the voter off from both future political transfers and more general risk-sharing transfers. A third possibility is that social networks are used to persuade voters (Schaffer & Baker 2014). For example, middlemen may give transfers to central people who will help spread the word about the advantages of voting for their candidate.

Two papers try to distinguish between the information and enforcement functions of networks. Cruz (2013) suggests that central individuals are targeted because they are easier to monitor and enforce, but this piece of the paper is more speculative. Finan et al. (2014) divide networks into

[13]After elections, voter-party network connections impact outcomes such as jobs (Fafchamps & Labonne 2013) and food aid (Caeyers & Dercon 2012), although we might consider this phenomenon as clientelism rather than as vote buying because it occurs postelection.

information based and transaction based and then categorize different measures of centrality as being better for spreading information versus enforcing transactions. Finan et al. show that both information sharing and monitoring/enforcement are significant in predicting the targeting of vote buying.

6. DATA COLLECTION ISSUES FOR SOCIAL NETWORKS

Advani & Malde (2014), Marsden (1990), and Morris (2004) summarize data collection strategies and issues for networks. Maertens & Barrett (2013) and Perkins et al. (2015) provide useful primers regarding how to collect social network data in developing countries. The most common strategy is to ask a randomly chosen individual to think of a certain interaction (e.g., borrowing money) and list all individuals with whom he participates in this type of interaction. Sometimes a limit is placed on how many individuals the respondent can list, but limits are usually discouraged, as they may lead to empirical difficulties. Limits may also seldom be necessary because respondents tend to get tired and self-limit. Another option is to ask individuals about their relationship with a set of randomly chosen individuals (Conley & Udry 2010).

In most studies listed in this review, the questions were asked of a random sample of respondents rather than a complete census. What effect does this approach have on the information one can infer from the data? The sociological literature on this topic goes in two different directions. Costenbader & Valente (2003) and Borgatti et al. (2006) investigate the effects of random sampling on the structural properties of networks. The latter show that the accuracy of centrality measures declines smoothly and predictably with the share of nonresponse. Other papers look at the effect of sampling on parameters in exponential random graph models. One example is the paper of Huisman & Steglich (2008), who try multiple methods for dealing with the missing data. Huisman & Steglich find that the model-based prediction method performs best, although this finding is not surprising given that the data were generated with such a model in the first place.

Meanwhile, within economics, the influential working paper of Chandrasekhar & Lewis (2011) shows that if one collects network data from a sample of individuals, uses those data to measure network characteristics such as degree or clustering, and then includes those measures in regressions, there will be nonclassical measurement error, and the direction of the bias cannot be signed. Chandrasekhar & Lewis develop a graphical reconstruction strategy that can help alleviate the problem. But this graphical reconstruction requires at least some information on all households in the network. For example, one may know the caste, wall material, roof material, and household head gender for all households in the village, and this information can be used to reconstruct the network for out-of-sample households. Reconstruction seems to work better for local network measures such as degree than for more global measures such as eigenvector centrality. Many of the papers we examine in this review have social network data from a census (Beaman et al. 2014, Blumenstock et al. 2014, Comola & Prina 2014, D'Exelle & Riedl 2013, Kim et al. 2014, Ngatia 2011), although a few use some network reconstruction technique (Maertens 2014, Schechter & Yuskavage 2011).

One alternative to random sampling is snowball sampling and its variant, respondent-driven sampling. This approach involves asking a sample of individuals about their links, then surveying the individuals they list, possibly surveying the individuals listed by the second set of respondents, and so on. Another option is surveying a random sample but asking the surveyed individuals not only about their links, but also about the relationship between the people with whom the surveyed individuals are linked. The number of questions grows exponentially large quite quickly, and whether informants can reliably report details regarding others' interactions is unclear. Ebbes et al. (2013) look at nine different sampling methods and how well they can recover different network statistics. Depending on sample size and whether one is interested in local or global network measures, different methods perform better or worse.

We believe it remains to be seen where this strand of literature will lead and what recommendations will stick. On the one hand, we are sympathetic to the worries that use of a sample rather than a census can lead researchers to draw incorrect implications. On the other hand, if research is limited to situations in which one can access a census of the network, or at least situations in which one can collect some information about every single observation, social network research will be severely limited. It will be nearly impossible to do research involving large urban networks, for example, social networks in São Paulo. Such constraints also imply that it will be more difficult for individuals without the funding to collect census data on multiple networks to do research in this area. One can hope that these early results do not have a chilling effect on future research and will instead spur on even more advances.

7. CONCLUSION

We review the state of empirical research using social network data in developing countries. We focus on two main functions of the network: conduits for information and conduits for financial transfers. Here we reiterate those areas in which we believe there are still many unanswered questions.

Much of the research we review takes the existing network as given. There is very little research on network formation. It may be especially valuable to look at either how randomized interventions change the network or how randomized changes in the network impact economic outcomes.

It is common for researchers to use self-reports of the underlying network and transactions. These data are rife with measurement error. The use of administrative data from cell phone providers on phone calls, text messages, and mobile money transfers will open many doors to study how this new technology is used to share risk and information, as well as how it impacts existing social networks for good and for bad. There is also little research looking at migration and remittance decisions using explicit network data. Mobile money and wire transfer data might be especially useful for studying migrants.

Most current research does not consider strategic information sharing and hiding, another area that could be fruitful for study. Also, most research on learning and information flows focuses on binary adoption decisions. Research regarding how individuals learn the correct quantity of inputs to apply could be quite interesting.

As of now, most of the research we review above looks at the degree of individuals and with whom they are linked directly. Moving forward, researchers could focus more on measures of network architecture that specifically fit the interaction being modeled. Moreover, researchers could make more efforts to tease out the different mechanisms for network effects, specifically separating out networks' information-sharing function from their functions of monitoring and enforcing monetary transfers.

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