Social Networks in Developing Countries

Yating Chuang[1] and Laura Schechter[2]

[1] UW Madison
[2] UW Madison

Abstract

Social networks function as an important safety net in developing countries which often lack formal financial instruments. They 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 in developing countries using explicit social network data. 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, along the way mentioning some areas we believe to be especially ripe for future study.

xxxxxx 0000. 00:1–23

JEL Code: O1. Thanks to the students of Yale Econ 479, Fall 2014, for helping us review the articles and think through the issues, as well as for bringing up new perspectives.

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 non-digital 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); college GPA and joining a fraternity (Sacerdote 2001); and job search (Ioannides & Loury 2004). Bramoullé, Djebbari & Fortin (2009) and De Giorgi, Pellizzari & Redaelli (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 over-generalizing, 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 so basic and vital because social networks are arguably both more necessary and more frequently used by individuals in developing countries. We will look first at the relatively high necessity and then at the relatively high use of networks in developing countries.

Banerjee & Duflo (2007) use fourteen major household survey datasets 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 datasets, among households living under a dollar a day, only in one instance do more than 50% of the respondents have some form of insurance, in another six instances the share is over 10% but below 50%, and the other 20 numbers are under 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 shows 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. They argue that this makes frequent small transactions more important than rare large transactions, and they argue 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 presents 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 or not 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 to 99% each 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.

While 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 they use social networks since 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 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 poor Bangladeshi households have on average ten interpersonal credit transactions per year, while in India and South Africa the average was six. 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 didn't 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).

We should note that while 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, while Di Falco & Bulte (2013) find that these networks discourage investment in risk-mitigation measures. This suggests that we should be interested both in how social networks work as a conduit for financial transactions, but also how social networks enforce these transactions.

It is even harder to find comparable cross-country information regarding households' use of social networks as sources of information. Specific small-scale studies suggest that this is common. 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 shows that in 2012 in low income countries there were 53 mobile cellular subscriptions per 100 people. (Compare this to 1 fixed telephone line per 100 people in low income countries, or 120 mobile cellular subscriptions per 100 people in the high income countries.)

We review evidence regarding how individuals in developing countries use social networks. As this is a quickly growing field, we narrow our review by focusing on empirical papers using network data from developing countries. There are also many papers which define networks by group-membership 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 those papers which look at social networks as conduits for financial transactions, versus those which 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 as well as in economic experiments. We mention studies which try to distinguish whether these transfers are motivated by altruism or 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 which look more generally at how information spreads in networks. Next, we look at learning about specific agricultural, financial, and health technologies. Finally, there are some transactions where the spread of money and information both seem to be at play and we discuss these in Section 5. 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. There is very little literature looking at how networks in developing countries form. We will 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 it is difficult to study network formation.

Krishnan & Sciubba (2009) is one of the first empirical papers in a developing country setting which studies network architecture and looks at more than just with how many and 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] They 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 if 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 on the network formation process. They find that these networks have characteristics similar to those found in the developed world

[1] Similarly, Schechter & Yuskavage (2011) show that reciprocal sharing networks have different architecture from 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 be significantly underestimating informal transfers.

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

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 suggests networks form in a way which allows cooperation to flourish among groups of cooperators.

None of the above papers look at who forms *new* links with whom and why. Barr, Dekker & Fafchamps (2015), Comola & Mendola (2014) and Comola & Prina (2014) aim to do just that. Comola & Mendola (2014) study how Sinhalese Sri Lankan immigrants to Milan form links with one another. They find that migrants are most likely to interact with other migrants who came from close-by localities back in Sri Lanka. Links are more common between individuals 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 their sample, 18% of the time when two sampled individuals know each other it is from back in Sri Lanka rather than a new link formed after arriving in Italy.

Barr, Dekker & Fafchamps (2015) and Comola & Prina (2014) come the closest to looking at how people form new relationships. Barr, Dekker & Fafchamps (2015) look at which households choose to join community-based organizations (CBOs) 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. In the earlier years, geographic proximity was a strong determinant of membership, but that effect faded over the years.

Comola & Prina (2014) don't look at original network formation, but instead randomly give access to savings accounts to some women in 19 villages in Nepal and look at how this changes the network. They find that women who were offered savings accounts are connected with more individuals one year later and make more transfers (both to individuals with and without a savings account). Comola & Prina (2014) 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 in fact 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 pre-existing links.

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

These papers give preliminary evidence regarding how friendships form in a developing country context and they are wonderful first steps towards learning more about these complex relationships. Given that it is difficult to look at network formation, if one isn't dealing with newly resettled households, 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 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 inter-household transfers which occur by non-electronic means, as well as those occurring vis-a-vis 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 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) was one of the first to provide evidence of this in rural India. He did not find full insurance, as a small share of idiosyncratic income shocks were passed on to consumption. Townsend (1994) implicitly assumed that sharing took place at the level of the network.

Newer research looks at whether sharing may in fact 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 (who the individual would go to in times of need) in addition to actual partners (who the individual actually went to in the past year). Rather than looking at lending, gifts, and transfers separately, Dercon & De Weerdt (2006) test if all strategies together smooth consumption. They find that food consumption is fully insured against health shocks at the village level but non-food consumption is not. Non-food consumption is partially insured within smaller networks.

Kinnan & Townsend (2012) take this in another direction and look at which networks are most useful for consumption smoothing and which for helping members make investments. They find that financial networks (loans and transfers) are useful for consumption smoothing while kin networks are more useful for financing big investments. Similarly, Angelucci, De Giorgi & Rasul (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 smaller and less closely linked networks, though they exhibit similar investment responses.

Results from Angelucci, De Giorgi & Rasul (2014) suggest that network architecture, and not just who is linked with whom, matters for risk sharing. Karlan et al. (2009) is one of the first papers 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 is used to construct the network and money can flow up to two links away. They show that direct and indirect paths contribute equally to risk sharing, and that each indirect path contributes through its weakest link. Ambrus, Möbius & Szeidl (2014) build on this model to show that the extent of informal insurance depends on network architecture, and specifically a characteristic called expansiveness. Their empirical results show that villages in Peru do 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, Genicot & Ray (2008) and Jackson, Rodriguez-Barraquer & Tan (2012). Both papers prove that efficient risk-sharing networks should exhibit specific architectural features. For example Jackson, Rodriguez-Barraquer & Tan (2012) predict that risk-sharing networks should exhibit a characteristic they call support, and then they show that Indian risk-sharing networks do 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, Chandrasekhar & Elliott (2014), wherein there is full commitment and perfect information, but the relevant friction is costly link formation. Social network data from 75 Indian villages is in accord with the predictions of their model.

All of the previously mentioned papers looked at non-electronic transfers. The advent of mobile money, allowing individuals to easily and cheaply transfer money to one another 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 does not suffer the recall bias and other measurement error from which self-reported interactions suffer.

Although they do not have access to administrative data or individual-to-individual transaction data, Jack, Ray & Suri (2013) and Jack & Suri (2014) show that access to mobile money increases risk-sharing. It decreases consumption variability, increases the physical distances that transfers flow, and increases the prevalence of reciprocal transfers. Blumenstock, Eagle & Fafchamps (2014) do have access to high-frequency administrative data - they literally have billions of observations on phone calls, text messages, and transfers - but their transfer data is for transfers of airtime (used primarily to make phone calls) rather than mobile money.[5] They find that transfers sent after natural disasters appear to be motivated by risk-sharing rather than altruism.[6] These transfers are sent over large physical distances and in response to covariate shocks. They are more likely to be sent to wealthy individuals, 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 looking at how mobile money is used within existing networks, it will be interesting to see how mobile money affects existing networks. Jack, Ray & Suri (2013) show that mobile money leads to an increase in person-to-person reciprocal transactions, but Mbiti &

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

[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. On the other hand, Comola & Fafchamps (2014a) and De Weerdt & Fafchamps (2011) find that transfers are motivated by altruism.

Weil (2014) 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 had traveled home to their rural families to deliver money now 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.

This section so far has focussed on inter-household transfers. Here we briefly mention studies looking at corrupt transfers from politicians to businesses. (We address vote-buying later in this paper.) Faccio (2006) creates a dataset of politically connected firms across almost fifty countries and finds that when a business person 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.

One mechanism through which this increased valuation might occur is shown by Khwaja & Mian (2005). 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 only found in 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.

3.2. Informal Insurance in Economic Experiments

Data on day-to-day financial interactions has great external validity. Administrative data on mobile money monetary flows has 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 of 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, since 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 non-anonymous experiments both with and without partner choice. Such experiments take advantage of subjects' ongoing relationships with one another. When running non-anonymous 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 has been found to be 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 which tease out whether other-regarding preferences may be the motive for some of these transfers. As with the non-experimental literature, most experimental risk-sharing papers focus on limited commitment as the friction preventing full insurance.

Chandrasekhar, Kinnan & Larreguy (2014b) run risk sharing games where they preassign non-anonymous partners and vary the level of commitment. With full commitment, both socially distant 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, Chandrasekhar & Larreguy (2014) show that a third party monitor or enforcer can increase 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. They find that individuals match assortatively on risk preferences, presumably leading to more efficient outcomes.

While limited commitment may be the most common explanation for incomplete risk sharing, Ligon & Schechter (2010) combine anonymous and non-anonymous 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, Kinnan & Larreguy (2014a) vary information asymmetries and whether or not players can choose their partners. They find that hidden income does significantly reduce risk sharing, though 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, social distance is only correlated with efficiency when individuals are allowed to choose their partners, but not when they are assigned by the experimenter.

So far we have worked under the assumption that these transfers are motivated by the desire to increase efficiency and share risk. Some papers play dictator games to test this assumption. They vary whether or not the dictator can choose the recipient (Ligon & Schechter 2012), whether or not the dictator knows the recipient (Binzel & Fehr 2013), whether or not the transaction is anonymized (Binzel & Fehr 2013; Ligon & Schechter 2012), and whether or not the transfer is in cash or in kind (Batista, Silverman & Yang 2014). These papers all find that transfers are motivated both by social preferences and risk-sharing incentives. In anonymous dictator games, where altruism should be the only reason for sharing, D'Exelle & Riedl (2013) find that central people give more, and dictators give more to central people. On the other hand, Ligon & Schechter (2012) find some evidence that better-connected people are more motivated by incentive-based reciprocity as opposed to altruism.

4. Networks as Conduits for Information Flows

The network architecture which is useful in sustaining monetary transfers is potentially quite different from the architecture which is useful to spread 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 they show that better-connected households know more about their village-mates, and 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), called diffusion centrality, which they 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, which is not necessarily the same as, for example, village leaders or people with many friends. This suggests people recognize important characteristics of other individuals in the network, even if they are not directly connected to that individual, and this can be potentially useful to help in the spread of information.

Next we will 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 social networks have on adoption of new agricultural technologies while Munshi (2008) reviews the literature on how networks spread information regarding both agricultural technologies and fertility outcomes.

Foster & Rosenzweig (1995) is one of the first papers to look at learning from others in agricultural technology adoption in the developing world, although they don't have explicit data on social networks. They find that farmers do 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 not on the identities of those individuals. One of the first is Boahene, Snijders & Folmer (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 is because when there are few adopters, knowing more adopters helps with the spread of information, but when there are many adopters there is an incentive for farmers to free-ride. Liverpool-Tasie & Winter-Nelson (2012) also find an inverse-U shaped relationship in adoption of new agricultural technologies in Ethiopia. Matuschke & Qaim (2009) use similar data and find that the share (rather than number) of network members adopting hybrid seeds in India increases the probability of adoption. They do not look for non-linearities. One criticism by Hogset & Barrett (2010) of such work is that these surveys often ask respondents how many people in their network adopt. These 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 or not to adopt Bt cotton in India. She finds that farmers learn most from progressive farmers rather than the non-progressive peer farmers with whom they are linked. Social pressure can significantly deter adoption of genetically modified crops.

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

BenYishay & Mobarak (2014) find that incentives to spread information are important in increasing the flow of information, 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 actually 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, having census data on 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 (farmers knowing one person who adopts are more likely to adopt), complex contagion (farmers knowing two people who adopt are more likely to adopt), or complex geographic contagion (same as complex contagion, but using geographic proximity rather than social network links). They find that all three simulation methods do significantly better than letting the extension agents choose. The geographic method doesn't do quite as well as the methods based on social network links, but given that it is much cheaper and easier to conduct, it may be promising in practice.

Emerick (2014) is less interested in the transmission of information through networks than the transmission of the seeds themselves. 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 limited purchasers to family and close friends of the individuals selling the technology. This suggests that social networks are not a panacea for the spread of productive technologies.

The papers mentioned thusfar look at the impact of networks on the adoption of a new technology. These papers can only indirectly infer learning. Conley & Udry (2010) is one of the only papers to look directly at learning regarding how to use a new technology, specifically how much fertilizer to apply conditional on adopting the new technology. Using data on who talks with whom about agriculture, they find significant evidence of farmers, and especially inexperienced farmers, learning from one another regarding best practices. This seems like a fruitful avenue 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 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 can 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 only know 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 vis-a-vis which neighbors and friends make similar technology choices. Bandiera & Rasul (2006) approach this in a more indirect fashion by focusing on the inverse U-shaped relationship between number of friends adopting and own adoption. They walk through the logic regarding why such a relationship could only be explained 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 quite 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 information flow, rather than the specific influence of neighbors' participation decisions ('endorsement effects').

One nice feature of the work by Banerjee et al. (2013) is that they focus on a specific measure of centrality which their model suggests should be most relevant for the spread of information. Borgatti (2005) emphasizes that different measures of centrality are developed based on different assumptions regarding how the object in question (money, information, etc) flows. He focuses on two dimensions. First, he looks at whether the object in question takes the shortest path or if it is free to wander through the network repeatedly visiting nodes and edges. Second, he looks at whether the object is transferred (e.g., money or tools), duplicated (e.g., word-of-mouth gossip), or parallely duplicated (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, de Janvry & Sadoulet (2014) 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), they 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, Katz & Menzel (1957)), they find that the least central individuals are the most influenced by their social network.[8]

Other work on social networks and financial decisions includes Bursztyn et al. (2014) who

[7] Chuang (2014) suggests another reason that 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.

[8] Shakya, Christakis & Fowler (2014) also find that social influence is strongest for individuals on the edge of the network.

look at investment in a risky investment fund with a minimum investment of $1000 in Brazil. They find that both social learning and social utility play an important role. Learning effects are stronger when flowing from financial sophisticates to the unsophisticated. Social utility has largely been ignored in the rest of the literature discussed in this review. It may be caused by the desire to "keep up with the Joneses" or due to the enjoyment 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 adoption of new technology occurred in sociology. Coleman, Katz & Menzel (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 those with smaller networks. Behrman, Kohler & Watkins (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 are impressive studies which 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 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 where social networks don't have positive impacts on adoption. Miller & Mobarak (2014) conduct a randomized controlled trial looking at how networks impact adoption of cookstoves with health and environmental benefits by rural Bangladeshis. They find that opinion leaders are influential and that social learning can decrease adoption of a new technology if it is not well-suited for the local culture. Negative social learning is found to be 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, Subramanian & Christakis (2014) reviews the articles linking sociocentric networks to health outcomes. One consistent result is that the speed of behavioral change can by increased by targeting more central individuals. Kim et al. (2014) test this by conducting a randomized controlled trial introducing a new health technology in Honduras either

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

to randomly chosen individuals, randomly chosen friends of randomly chosen individuals, or 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 they have rather few villages, but they find suggestive evidence that there is no difference between targeting randomly chosen individuals and individuals with high in-degree. Targeting randomly chosen friends, on the other hand, leads to much higher diffusion of the technology. They 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 it is much easier to collect data on randomly chosen friends of randomly chosen individuals than it is to collect 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 which Mix Financial and Information Flows

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

5.1. Micro-credit

Group liability loans are common practice in micro-credit 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 co-authors 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 take existing group liability lending groups and randomly convert some to individual liability. In the second, they form new groups and randomly make some group and some individual liability. Because they find no difference in the default rates across the groups and thus 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 co-signer. They randomly assign interest rates based on 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.

[10]This is the opposite of the results mentioned earlier by Beaman et al. (2014). They 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.

Finally, Bryan, Karlan & Zinman (2014) looks 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, Karlan & Zinman (2014) randomly give existing borrowers one of two incentives for referring a new borrower. They were either offered a bonus if the referred individual's loan application was approved or a bonus if the referred individual repayed 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 loans 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, Karlan & Zinman (2014) find strong peer enforcement effects, but 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 U.S. 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, this will depress the employment outcomes of cohorts arriving close in time to that given cohort, yet will benefit the cohorts arriving later. These papers focus on the role of networks in sharing information.[11]

Beaman & Magruder (2012) is one of the first papers to use a job referral field experiment. They asked subjects to make referrals either for a fixed bonus or a contingent bonus depending on the referral's performance. They find evidence that, compared to the fixed fee, performance pay leads individuals to refer more coworkers rather than family members.[12] But, only high skilled workers are able to 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 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 them both that the referrer will actually get the maximum finder's fee no matter what. Thus the researchers will only capture information effects. Antoninis (2006)

[11] There is little evidence with explicit network data on how networks impact the initial migration decision, or the remittances sent thereafter. Collecting migration data is quite difficult, as is 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, Karlan & Zinman (2014) find that individuals who get a bonus for referring someone who repays their 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 who they know *better* under individual liability compared to group liability.

suggests that both effects may be important in Egypt. Workers referred by their old colleagues earn more than the average worker, while workers referred by friends or relatives earn less than the average worker.

While job referrals are often found to reduce information asymmetries for firms, Heath (2013) 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. They 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, Keleher & Magruder (2013) find that using job referrals puts qualified female workers at a disadvantage. This is due to 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 (2014) find that individuals who are referred are of low quality and this 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, Labonne & Querubin (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. They also find that in villages where challengers come from more central families, vote-buying is higher. Cruz (2013) and Finan, Larreguy & Schechter (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, Labonne & Querubin 2014) but most papers thusfar 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 turn out to vote, and whether he is likely to be influenced by a vote-buying transfer. On the other hand, middlemen may also make use of social networks as an enforcement mechanism. For example, if it appears that the voter did not vote for the specified politician, the middleman can cut the voter off from both future political transfers as well as 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 their paper is more speculative. Finan, Larreguy & Schechter (2014) divide networks into information-based and transaction-based, and then categorize different measures of centrality as being better for spreading information

[13] After the elections, voter-party network connections have been found to impact outcomes such as jobs (Fafchamps & Labonne 2013) and food aid (Caeyers & Dercon 2012), though we might consider this clientelism rather than vote-buying since it occurs post-election.

versus enforcing transactions. They show that both information-sharing and monitoring and enforcement are significant in predicting the targeting of vote-buying.

6. Data Collection Issues for Social Networks

Data collection strategies and issues for networks have been summarized by Advani & Malde (2014), Marsden (1990), and Morris (2004). Maertens & Barrett (2013) and Perkins, Subramanian & Christakis (2014) are 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 of the other individuals with whom he participates in this type of interaction. Sometimes a limit is placed on how many individuals the respondent may list, but this is usually discouraged as it may lead to empirical difficulties. It may also seldom be necessary since 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 the majority of the studies listed in this review, the questions were asked of a random sample of respondents rather than a complete census. What effect does this have on the information one can infer from the data? The sociological literature on this topic has gone in two different directions. Costenbader & Valente (2003) and Borgatti, Carley & Krackhardt (2006) investigate the effects of random sampling on the structural properties of networks. The latter shows that the accuracy of centrality measures declines smoothly and predictably with the share of non-response. Other papers look at the effect of sampling on parameters in exponential random graph models (ERGMs). One example is Huisman & Steglich (2008) who try multiple methods for dealing with the missing data. They find that the model-based prediction method performs best, although this is not surprising given that the data was generated with such a model in the first place.

Meanwhile, within economics, Chandrasekhar & Lewis (2011) wrote an influential working paper showing that if one collects network data from a sample of individuals, uses that data to measure network characteristics such as degree or clustering, and then includes those measures in regressions, there will be non-classical measurement error and the direction of the bias can not be signed. They do develop a graphical reconstruction strategy which 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. It seems reconstruction works best for local network measures such as degree compared to more global measures such as eigenvector centrality. Many of the papers we have looked at in this review have social network data from a census (Beaman et al. 2014; Blumenstock, Eagle & Fafchamps 2014; Comola & Prina 2014; D'Exelle & Riedl 2013; Kim et al. 2014; Ngatia 2011), while 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 involves asking a sample of individuals about their links, and then surveying the individuals they list, and possibly continuing on to survey the individuals listed by the second set of respondents etc. Another option is surveying a random sample, but asking them not only about their links, but also about the relationship between the people with whom they are linked. The number of questions grows exponentially large quite quickly, and it is unclear whether informants can reliably report details regarding others' interactions. Ebbes, Huang & Rangaswamy (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 get access to a census of the network, or at least where 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 Sao Paolo. It also means 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 instead spur on even more advances.

7. Conclusion

We reviewed the state of empirical research using social network data in developing countries. We focussed 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 reviewed took 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. This data is 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 of the current research does not consider strategic information sharing and hiding, another area which 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, the majority of research we have reviewed looks at individuals' degree and with whom they are linked directly. Moving forward, researchers could focus more on measures of network architecture which specifically fit the interaction being modeled. And, researchers could make more efforts to tease out the different mechanisms for network effects, specifically separating out their information sharing function from their function monitoring and enforcing monetary transfers.

LITERATURE CITED

Advani A, Malde B. 2014. Empirical methods for networks data: Social effects, network formation and measurement error. Unpublished Manuscript

Alatas V, Banerjee A, Chandrasekhar AG, Hanna R, Olken BA. 2014. Network structure and the aggregation of information: Theory and evidence from Indonesia. Unpublished Manuscript

Ambrus A, Chandrasekhar AG, Elliott M. 2014. Social investments, informal risk sharing, and inequality Unpublished Manuscript

Ambrus A, Möbius M, Szeidl A. 2014. Consumption risk-sharing in social networks. *American Economic Review* 104:149–182

Angelucci M, De Giorgi G, Rasul I. 2014. Resource pooling within family networks: Insurance and investment. Unpublished Manuscript

Antoninis M. 2006. The wage effects from the use of personal contacts as hiring channels. *Journal of Economic Behavior and Organization* 59:133–146

Apicella CL, Marlowe FW, Fowler JH, Christakis NA. 2012. Social networks and cooperation in hunter-gatherers. *Nature* 481:497–501

Attanasio O, Barr A, Cardenas JC, Genicot G, Meghir C. 2012. Risk pooling, risk preferences, and social networks. *American Economic Journal: Applied Economics* 4:134–167

Bandiera O, Rasul I. 2006. Social networks and technology adoption in northern Mozambique. *Economic Journal* 116:869–902

Banerjee A, Chandrasekhar AG, Duflo E, Jackson MO. 2013. The diffusion of microfinance. *Science* 341

Banerjee A, Chandrasekhar AG, Duflo E, Jackson MO. 2014. Gossip: Identifying central individuals in a social network. Unpublished Manuscript

Banerjee AV, Duflo E. 2007. The economic lives of the poor. *Journal of Economic Perspectives* 21:141–168

Barr A, Dekker M, Fafchamps M. 2015. The formation of community-based organizations: An analysis of a quasi-experiment in Zimbabwe. *World Development* Forthcoming

Barr A, Genicot G. 2008. Risk sharing, commitment, and information: An experimental analysis. *Journal of the European Economic Association* 6:1151–1185

Batista C, Silverman D, Yang D. 2014. Directed giving: Evidence from an inter-household transfer experiment. Unpublished Manuscript

Beaman L, BenYishay A, Magruder J, Mobarak AM. 2014. Can network theory based targeting increase technology adoption? Unpublished Manuscript

Beaman L, Keleher N, Magruder J. 2013. Do job networks disadvantage women? Evidence from a recruitment experiment in Malawi. Unpublished Manuscript

Beaman L, Magruder J. 2012. Who gets the job referral? Evidence from a social networks experiment. *American Economic Review* 102:3574–3593

Beaman LA. 2012. Social networks and the dynamics of labour market outcomes: Evidence from refugees resettled in the US. *Review of Economic Studies* 79:128–161

Behrman JR, Kohler HP, Watkins SC. 2002. Social networks and changes in contraceptive use over time: Evidence from a longitudinal study in rural Kenya. *Demography* 39:713–738

BenYishay A, Mobarak AM. 2014. Social learning and communication. Unpublished Manuscript

Binzel C, Fehr D. 2013. Giving and sorting among friends: Evidence from a lab-in-the-field experiment. *Economics Letters* 121:214–217

Björkegren D. 2014. The adoption of network goods: Evidence from the spread of mobile phones in Rwanda Unpublished Manuscript

Bloch F, Genicot G, Ray D. 2008. Informal insurance in social networks. *Journal of Economic Theory* 143:36–58

Blumenstock J, Eagle N, Fafchamps M. 2014. Risk sharing and mobile phones: Evidence in the aftermath of natural disasters. Unpublished Manuscript

Boahene K, Snijders TAB, Folmer H. 1999. An integrated socioeconomic analysis of innovation

adoption: The case of hybrid cocoa in Ghana. *Journal of Policy Modeling* 21:167–184
Borgatti SP. 2005. Centrality and network flow. *Social Networks* 27:55–71
Borgatti SP, Carley KM, Krackhardt D. 2006. On the robustness of centrality measures under conditions of imperfect data. *Social Networks* 28:124–136
Bramoullé Y, Djebbari H, Fortin B. 2009. Identification of peer effects through social networks. *Journal of Econometrics* 150:41–55
Bramoullé Y, Kranton R. 2005. Risk-sharing networks. *Journal of Economic Behavior and Organization* 64:275–294
Breza E, Chandrasekhar A, Larreguy H. 2014. Social structure and institutional design: Evidence from a lab experiment in the field. Unpublished Manuscript
Bryan GT, Karlan D, Zinman J. 2014. Referrals: Peer screening and enforcement in a consumer credit field experiment. *American Economic Journal: Microeconomics* Forthcoming
Bursztyn L, Ederer F, Ferman B, Yuchtman N. 2014. Understanding mechanisms underlying peer effects: Evidence from a field experiment on financial decisions. *Econometrica* 82:1273–1301
Burt RS. 2005. Brokerage and closure: An introduction to social capital. Oxford University Press
Caeyers B, Dercon S. 2012. Political connections and social networks in targeted transfer programs: Evidence from rural Ethiopia. *Economic Development and Cultural Change* 60:639–675
Cai J, de Janvry A, Sadoulet E. 2014. Social networks and the decision to insure. *American Economic Journal: Applied Economics* Forthcoming
Calvo E, Murillo MV. 2013. When parties meet voters: Assessing political linkages through partisan networks and distributive expectations in Argentina and Chile. *Comparative Political Studies* 46:851–882
Carter MR, Laajaj R, Yang D. 2014. Subsidies and the persistence of technology adoption: Field experimental evidence from Mozambique. Unpublished Manuscript
Chandrasekhar A, Kinnan C, Larreguy H. 2014a. Information, networks and informal insurance: Evidence from a lab experiment in the field. Unpublished Manuscript
Chandrasekhar A, Kinnan C, Larreguy H. 2014b. Social networks as contract enforcement: Evidence from a lab experiment in the field. Unpublished Manuscript
Chandrasekhar A, Lewis R. 2011. Econometrics of sampled networks. Unpublished Manuscript
Christakis NA, Fowler JH. 2007. The spread of obesity in a large social network over 32 years. *New England Journal of Medicine* 357:370–379
Christakis NA, Fowler JH. 2009. Connected: The surprising power of our social networks. New York: Little Brown and Company
Chuang Y. 2014. Self control or social control?: Peer effects on temptation consumption. Unpublished Manuscript
Coleman J, Katz E, Menzel H. 1957. The diffusion of an innovation among physicians. *Sociometry* 20:253–270
Coleman JS. 1990. Foundations of social theory. Harvard University Press
Collins D, Morduch J, Rutherford S, Ruthven O. 2009. Portfolios of the poor: How the world's poor live on $2 a day. Princeton: Princeton University Press
Comola M, Fafchamps M. 2014a. Estimating mis-reporting in dyadic data: Are transfers mutually beneficial? Unpublished Manuscript
Comola M, Fafchamps M. 2014b. Testing unilateral and bilateral link formation. *Economic Journal* 124:954–976
Comola M, Mendola M. 2014. The formation of migrant networks. *The Scandinavian Journal of Economics* Forthcoming
Comola M, Prina S. 2014. Do interventions change the network? A dynamic peer effect model accounting for network changes. Unpublished Manuscript
Conley T, Udry C. 2010. Learning about a new technology: Pineapple in Ghana. *American Economic Review* 100:35–69
Costenbader E, Valente TW. 2003. The stability of centrality measures when networks are sampled.

Social Networks 25:283–307
Cox D, Fafchamps M. 2008. In *Handbook of Development Economics*, eds. TP Schultz, J Strauss, vol. 4, chap. 58. Oxford: Elsevier
Cruz C. 2013. Social networks and the targeting of illegal electoral strategies. Unpublished Manuscript
Cruz C, Labonne J, Querubin P. 2014. Politician family networks and electoral outcomes: Evidence from the Philippines. Unpublished Manuscript
De Giorgi G, Pellizzari M, Redaelli S. 2010. Identification of social interactions through partially overlapping peer groups. *American Economic Journal: Applied Economics* 2:241–275
De Weerdt J, Fafchamps M. 2011. Social identity and the formation of health insurance networks. *Journal of Development Studies* 47:1152–1177
Dercon S, De Weerdt J. 2006. Risk-sharing networks and insurance against illness. *Journal of Development Economics* 81:337–356
D'Exelle B, Riedl A. 2013. Social embeddedness and resource sharing. Unpublished Manuscript
Di Falco S, Bulte E. 2011. A dark side of social capital? Kinship, consumption, and savings. *Journal of Development Studies* 47:1128–1151
Di Falco S, Bulte E. 2013. The impact of kinship networks on the adoption of risk-mitigating strategies in Ethiopia. *World Development* 43:100–110
Ebbes P, Huang Z, Rangaswamy A. 2013. Subgraph sampling methods for social networks: The good, the bad, and the ugly. Unpublished Manuscript
Emerick K. 2014. The efficiency of trading in social networks: Experimental measures from India. Unpublished Manuscript
Faccio M. 2006. Politically connected firms. *American Economic Review* 96:369–386
Fafchamps M. 2011. In *Handbook of Social Economics*, eds. J Benhabib, A Bisin, MO Jackson, vol. 1B, chap. 24. New York: Elsevier
Fafchamps M, Gubert F. 2007. Risk sharing and network formation. *American Economic Review* 97:75–79
Fafchamps M, Labonne J. 2013. Do politicians' relatives get better jobs? Evidence from municipal elections in the Philippines. Unpublished Manuscript
Fafchamps M, Lund S. 2003. Risk-sharing networks in rural Philippines. *Journal of Development Economics* 71:261–287
Fafchamps M, Moradi A. 2014. Referral and job performance: Evidence from the Ghana colonial army. *Economic Development and Cultural Change* Forthcoming
Fafchamps M, Quinn S. 2012. Networks and manufacturing firms in Africa: Initial results from a randomised experiment. Unpublished Manuscript
Finan F, Larreguy H, Schechter L. 2014. Vote buying and networks: Information, enforcement or both? Unpublished Manuscript
Fisman R. 2001. Estimating the value of political connections. *American Economic Review* 91:1095–1102
Foster A, Rosenzweig MR. 1995. Learning by doing and learning from others: Human capital and technical change in agriculture. *Journal of Political Economy* 103:1176–1209
Giné X, Karlan DS. 2014. Group versus individual liability: Short and long term evidence from Philippine microcredit lending groups. *Journal of Development Economics* 107:65–83
Godlonton S, Thornton R. 2012. Peer effects in learning HIV results. *Journal of Development Economics* 97:118–129
Heath R. 2013. Why do firms hire using referrals?: Evidence from Bangladeshi garmet factories. Unpublished Manuscript
Hogset H, Barrett CB. 2010. Social learning, social influence, and projection bias: A caution on inferences based on proxy reporting of peer behavior. *Economic Development and Cultural Change* 58:563–589
Huisman M, Steglich C. 2008. Treatment of non-response in longitudinal network studies. *Social*

Networks 30:297–308

Ioannides YM, Loury LD. 2004. Job information networks, neighborhood effects, and inequality. *Journal of Economic Literature* 42:1056–1093

Jack W, Ray A, Suri T. 2013. Transaction networks: Evidence from mobile money in Kenya. *American Economic Review* 103:356–361

Jack W, Suri T. 2014. Risk sharing and transaction costs: Evidence from Kenya's mobile money revolution. *American Economic Review* 104:183–223

Jackson MO. 2009. Networks and economic behavior. *Annual Review of Economics* 1:489–511

Jackson MO, Rodriguez-Barraquer T, Tan X. 2012. Social capital and social quilts: Network patterns of favor exchange. *American Economic Review* 102:1857–1897

Johnson S, Mitton T. 2003. Cronyism and capital controls: Evidence from Malaysia. *Journal of Financial Economics* 67:351–382

Karlan D, Möbius M, Rosenblat T, Szeidl A. 2009. Trust and social collateral. *Quarterly Journal of Economics* 124:1307–1361

Karlan D, Möbius MM, Rosenblat TS, Szeidl A. 2010. Measuring trust in Peruvian shantytowns. Unpublished manuscript

Karlan DS. 2007. Social connections and group banking. *Economic Journal* 117:52–84

Khwaja AI, Mian A. 2005. Do lenders favor politically connected firms? Rent provision in an emerging finanacial market. *Quarterly Journal of Economics* 120:1371–1411

Kim DA, Hwong AR, Stafford D, Hughes DA, O'Malley AJ, et al. 2014. A randomised controlled trial of social network targeting to maximise population behaviour change. Unpublished Manuscript

Kinnan C, Townsend R. 2012. Kinship and financial networks, formal financial access, and risk reduction. *American Economic Review* 102:289–293

Kosfeld M. 2004. Economic networks in the laboratory: A survey. *Review of Network Economics* 3

Kremer M, Miguel E. 2007. The illusion of sustainability. *Quarterly Journal of Economics* 122:1007–1065

Krishnan P, Sciubba E. 2009. Links and architecture in village networks. *Economic Journal* 119:917–949

Ligon E, Schechter L. 2010. Structural experimentation to distinguish between models of risk sharing with frictions. Unpublished Manuscript

Ligon E, Schechter L. 2012. Motives for sharing in social networks. *Journal of Development Economics* 99:13–26

Liverpool-Tasie LSO, Winter-Nelson A. 2012. Social learning and farm technology in Ethiopia: Impacts by technology, network type, and poverty status. *Journal of Development Studies* 48:1505–1521

Maertens A. 2014. Who cares what others think (or do)? Social learning and social pressures in cotton farming in India. Unpublished Manuscript

Maertens A, Barrett CB. 2013. Measuring social networks' effects on agricultural technology adoption. *American Journal of Agricultural Economics* 95:353–359

Magnan N, Spielman DJ, Lybbert TJ, Gulati K. 2014. Leveling with friends: Social networks and Indian farmers' demand for a resource conserving technology. Unpublished Manuscript

Marsden PV. 1990. Network data and measurement. *Annual Review of Sociology* 16:435–463

Matuschke I, Qaim M. 2009. The impact of social networks on hybrid seed adoption in India. *Agricultural Economics* 40:493–505

Mbiti I, Weil D. 2014. In *NBER Volume on African Economic Successes*, eds. S Edwards, S Johnson, D Weil. University of Chicago Press

Miller G, Mobarak AM. 2014. Learning about new technologies through social networks: Nontraditional stoves in rural Bangladesh. *Marketing Science* Forthcoming

Morawczynski O, Pickens M. 2009. Poor people using mobile financial services: Observations on customer usage and impact from M-PESA. Tech. rep., CGAP: World Bank

Morris M. 2004. In *Network Epidemiology: A Handbook of Survey Design and Data Collection*, ed.

M Morris, chap. 1. Oxford: Oxford University Press

Munshi K. 2003. Networks in the modern economy: Mexican migrants in the US labor market. *Quarterly Journal of Economics* 118:549–599

Munshi K. 2004. Social learning in a heterogeneous population: Technology diffusion in the Indian Green Revolution. *Journal of Development Economics* 73:185–213

Munshi K. 2008. In *Handbook of Development Economics*, eds. TP Schultz, J Strauss, vol. 4, chap. 48. Oxford: Elsevier

Munshi K. 2011. In *Handbook of Social Economics*, eds. J Benhabib, A Bisin, MO Jackson, vol. 1B, chap. 23. New York: Elsevier

Munshi K. 2014. Community networks and the process of development. *Journal of Economic Perspectives* 28:49–76

Ngatia M. 2011. Social interactions and individual reproductive decisions. Unpublished Manuscript

Oster E, Thornton R. 2012. Determinants of peer effects in menstrual cup take-up. *Journal of the European Economic Association* 10:1263–1293

Perkins JM, Subramanian SV, Christakis NA. 2014. Social networks and health: A systematic review of sociocentric network studies in low- and middle-income countries. *Social Science & Medicine* Forthcoming

Sacerdote B. 2001. Peer effects with random assignment: Results for Dartmouth roommates. *Quarterly Journal of Economics* 116:681–704

Sacerdote B. 2014. Experimental and quasi-experimental analysis of peer effects: Two steps forward? *Annual Review of Economics* 6:253–272

Schaffer J, Baker A. 2014. Clientelism as persuasion-buying: Evidence from Latin America. Unpublished Manuscript

Schechter L, Yuskavage A. 2011. Reciprocated versus unreciprocated sharing in social networks. Unpublished Manuscript

Schechter L, Yuskavage A. 2012. Inequality, reciprocity, and credit in social networks. *American Journal of Agricultural Economics* 94:402–410

Shakya HB, Christakis NA, Fowler JH. 2014. Social network predictors of latrine ownership. *Social Science & Medicine* Forthcoming

Townsend R. 1994. Risk and insurance in village India. *Econometrica* 62:539–591

Udry C. 1990. Credit markets in northern Nigeria: Credit as insurance in a rural economy. *World Bank Economic Review* 4:251–269

Udry C. 1994. Risk and insurance in a rural credit market: An empirical investigation in northern Nigeria. *Review of Economic Studies* 61:495–526

Vasilaky K, Leonard KL. 2014. As good as the networks they keep?: Improving farmers' social networks via randomized information exchange in rural Uganda. Unpublished Manuscript