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Diffusion of agricultural information within social networks: Evidence on gender inequalities from Mali

Lori Beaman [a], Andrew Dillon [b,*]

[a] Northwestern University, USA
[b] Michigan State University, USA

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ABSTRACT

Social networks are an important mechanism for diffusing information when institutions are missing, but there may be distributional consequences from targeting only central nodes in a network. After implementing a social network census, one of three village-level treatments determined which treated nodes in the village received information about composting: random assignment, nodes with the highest degree, or nodes with high betweenness. We then look at how information diffuses through the network. We find information diffusion declines with social distance, suggesting frictions in the diffusion of information. Aggregate knowledge about the technology did not differ across targeting strategies, but targeting nodes using betweenness measures in village-level networks excludes less-connected nodes from new information. Women farmers are less likely to receive information when betweenness centrality is used in targeting, suggesting there are important gender differences, not only in the relationship between social distance and diffusion, but also in the social learning process.

1. Introduction

Technological innovation has a central role in promoting productivity growth and changes in rural welfare, though the returns to new technologies are often not apparent upon their introduction in rural settings. The diffusion of information about technologies informs farmers' beliefs about the returns and gives them the practical knowledge to implement different technologies they may adopt. Mobius et al. (2015) identify two components of social learning: diffusion of information, and aggregation of information into an individual's correct knowledge or beliefs. Diffusion and aggregation mechanisms are critical precursors to the technology adoption decision.

Many empirical studies have focused on the adoption decision (Beaman et al., 2015; BenYishay and Mobarak, 2015; Duflo et al., 2008; Jack, 2013; Suri, 2011); however, in the face of substantial heterogeneity in returns to agricultural technologies, it may be hard to know if information has properly diffused based on adoption alone, particularly if adoption rates are initially low. This paper uses an experimental design to illuminate the role of social networks in diffusing information in the context of a rural technology adoption promotion program in Mali. Since men and women farm separate plots of land in Mali, they are both agricultural decision-makers and both need to receive the information. In this setting, we can highlight a potential downside of using networks to cheaply disseminate information: those who are less socially connected, women in particular, may be disadvantaged in receiving valuable new information.

In DeGroot (1974)'s seminal model of information transmission and subsequent extensions, beliefs are formed by a farmer's priors and an updating process. Extensions of the DeGroot model characterize updating as either Bayesian, weighted by the number of social interactions, or weighted by the influence of the person with whom the individual interacts (DeMarzo et al., 2003; Jackson, 2008).[1] These theoretical models emphasize that a farmer's information set changes in response to new information depending on farmer and social network characteristics. Farmers learning from each other's experimentation with inputs is well documented (Bandiera and Rasul, 2006; Conley and Udry, 2004; Foster and Rosenzweig, 1995; Griliches, 1957; Munshi, 2004).[2] However, fewer empirical studies document how networks actually function to disseminate information, with notable exceptions including Chandrasekhar et al. (2015) and Mobius et al. (2015).

* Corresponding author.
E-mail address: dillona6@msu.edu (A. Dillon).

[1] Alternative forms of updating may weight interactions with opinion leaders according to a social weighting eigenvector (Jackson, 2008), permit weighting only interactions among those with similar beliefs (Krause, 2000), or permit one's own beliefs to be weighted over time (Friedkin and Johnsen, 1990).

[2] By contrast, Duflo et al. (2011) found little evidence of peer effects in fertilizer adoption among maize farmers in Western Kenya.

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If network structures exhibit a tendency for central nodes within the network to be of only one gender, then the diffusion of information through social networks may reinforce existing gender informational inequality. Information inequality by gender may be due to differences in social distance to central nodes or because information between central nodes and men's and women's networks is transmitted with different frictions. The diffusion process may also vary in important ways depending on whether the good is rival or non-rival. Examples of rival and non-rival good diffusion exist in the technology adoption literature. First, direct experimentation with an agricultural input (for example, improved seed, fertilizer techniques) might result in diffusion since network members may observe the use of the rival good (for example, Milgram, 1967, Conley and Udry, 2004 or Bandiera and Rasul, 2006). Second, non-rival good diffusion is well documented in cases where there are no supply constraints of a good (in the case of microcredit, Banerjee et al., 2013 and for vitamin distribution in Kim et al., 2015) or knowledge can be shared easily among network members (Miller and Mobarak, 2015; Mobius et al., 2015; Beaman et al., 2018).

In our experiment, we provide a short training on composting to four farmers in each study village and provide those farmers with informational placards about composting.[3] The trained farmers (treated nodes) are then asked to distribute the placards to individuals outside of their own household, similar to Milgram's small world experiment (Milgram, 1967). This provides an observable, physical measure of information spread that we can trace back to the original treated node using a code embedded on the placards, allowing us to track the path of diffusion in the village. This provides an estimate of the effect of social network structure on rival good diffusion. We re-visited all households within the study villages after a month to observe which farmers received placards (diffusion of a rival good) and administer a test on farmers' composting knowledge (aggregation and diffusion of a non-rival good).

We randomly assigned 52 villages to three different treatment arms in order to determine how targeting farmers by degree or betweenness – two measures of node influence – affects diffusion and aggregation of composting information within the village. We exploit social network data covering over 80% of households in all 52 villages to calculate each node's position in the network. In 15 villages, farmers with high degree were chosen as treated nodes; in 14 villages,[4] households with high betweenness were chosen as treated nodes; and in 23 villages farmers were randomly chosen to be treated nodes. While there are several measures of influential nodes within the social network literature which could influence the composting diffusion process, this paper focuses on two measures: degree (the total number of links in an individual's network) and betweenness centrality (the share of shortest paths from all pairs of nodes in the network that connect to the node).[5] We focus on betweenness centrality as the interdisciplinary literature on networks has emphasized the importance of betweenness centrality for the flow of information in particular within a network. For example, Granovetter (1973) highlights the importance of structural bridges, and betweenness is a centrality measure close to the concept of bridging (Valente and Fujimoto, 2010).

The empirical analysis proceeds in two parts. First, we look at how the informational placard and composting knowledge spreads through the network. Having a direct link to a treated node significantly increases the chances of receiving a placard, while indirect links (friends of friends of the treated nodes) are significantly less likely to receive a placard. Women are overall much less likely to receive a placard compared to men, but being in close social proximity to the treated node increases the probability of getting a placard. We observe a similar pattern in knowledge of composting. This analysis flexibly controls for how well connected a node is in the network – through a series of fixed effects of the number of links of different social distances a respondent has – and therefore should not merely reflect pre-existing informational differences across nodes located at different positions within a network. This demonstrates that there are frictions in the flow of information about agricultural techniques in rural villages. These frictions are, in part, due to differences in men's and women's social distance to the treated nodes, but is not fully explained by social distance alone.

The second part of the analysis investigates whether targeting influential nodes within the social network affects overall knowledge dissemination, and whether there are distributional consequences to social network-based targeting, with a focus on women as compared to men. While we do not find any significant differences in average knowledge in random, degree-targeted, or betweenness-targeted villages,[6] differences by gender are prominent. Women in villages which were targeted according to betweenness had significantly lower knowledge than women in the degree and random treatment groups. Targeting nodes within the network based on betweenness led to lower knowledge about a new agricultural technology among women – thus demonstrating how social network targeting could reinforce existing gender inequality.

The paper is organized as follows. We begin the analysis in section 2 by describing the social network structure of our sample villages to motivate the empirical analysis. In section 3, the agricultural context, experimental design, and balancing tests for the field experiment are presented. The econometric strategy is described in detail in section 4. Section 5 describes the empirical results, and section 6 concludes with a reflection on the implications of these results for allocative efficiency of new agricultural technologies.

2. Network measurement and descriptive statistics

In order to measure the social networks in study villages, we collected social network data in 2008 and then again in 2011 (Appendix 1. Timeline). Within each village, all[7] household heads and their household members were fully enumerated in an initial visit. Chandrasekhar and Lewis (2016) demonstrate the limitations of using sample based measures of social networks, including the possibility that influential nodes are unobserved. Upon populating a village dictionary of household members drawn from the entire population, the most knowledgeable male and female farmer in the household were asked to list members from the village[8] that they and other adults of the same gender (if those individuals were not present in the household at the time) spoke to frequently regarding agriculture, with whom they had financial transactions, were their relatives, residential neighbors, agricultural plot neighbors, and organizations with which they were affiliated. We also collected household and individual demographic and asset information.

[3] The placards are in the form of a calendar, as Malian households like to display calendars within their houses (even when that calendar year has passed). Many microfinance institutions, political party candidates, and agricultural input suppliers use calendars as marketing tools within villages.

[4] The intended design was to include 15 villages in the betweeness treatment. One village refused to participate in the betweeness treatment and was not replaced.

[5] Within our sample, the correlation between a household's degree and betweenness is 0.5.

[6] Both Emerick and Dar (2017) and BenYishay and Mobarak (2015) find no aggregate diffusion of knowledge about an agricultural technology when using informal methods (community selection and focus groups) to select treated nodes.

[7] The average number of households per village in our sample is 35 with a standard deviation of 4.

[8] While social networks extend outside of the village, the nature of the adoption decision considered in this paper and many input decisions are predicated on the influence of farmers within their own village with whom farmers interact regularly and whose actions are observable. Farming practices are also very local in nature, given heterogeneity in agroclimatic conditions, and villages in Mali are quite distant from one another. While mobile technology is available, the cost of communication with multiple farmers outside of the village is prohibitive relative to farmers within the village.