Diffusion of Agricultural Information within Social Networks: Evidence on Gender Inequalities from Mali

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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.

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I. 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 2015b, BenYishay and Mobarak 2015, Duflo et al. 2008, Jack 2013; Suri 2012); 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 2007)[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).

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 exists 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 1964, Conley and Udry 2004 or Bandiera and Rasul 2006). Second, non-rival good diffusion is well documented in

[1] Alternative forms of updating may weight interactions with opinion leaders according to a social weighting eigenvector[1] (Jackson 2007), 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.

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. 2017).

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.

[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.

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

[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.

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 II by describing the social network structure of our sample villages to motivate the empirical analysis. In section III, the agricultural context, experimental design, and balancing tests for the field experiment are presented. The econometric strategy is described in detail in section IV. Section V describes the

[6] Both Emerick and Mar (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.

empirical results, and section VI concludes with a reflection on the implications of these results for allocative efficiency of new agricultural technologies.

II. 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 (2011) demonstrates 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. In 2008, while we interviewed men and women separately about their social connections, our data can only link household members to other households (not individual household members) in our census. Thus a limitation of the 2008 data is that nodes are defined only at the household level. In

[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.

2011, we used computer-assisted data collection technology which allowed us to match individuals to individuals within households. All links reported by the most knowledgeable male and female farmer (plot neighbors, house neighbors, and relatives) were pooled together by gender, and links were treated as undirected[9]. Most of the analysis is done at the level of the 'node' which is either all women or all men in a given household. Links are pooled together by gender means that plot neighbors of female 1 in the household and relatives of female 2 in the household are combined into one measure of summarizing all links between all females in one household (node) to other nodes within the village. A node with a female subscript represents all women within a household, and a node with a male subscript represents all men in a household. In doing so, we are assuming that information flows easily across individuals of the same gender within the household, while allowing the possibility that information frictions exist across genders.

The social network data from 2011 is used to calculate several measures of network centrality presented in Table 1. Measures of centrality in the social network literature include diffusion centrality, degree centrality, closeness centrality, betweenness centrality, eigenvector centrality, and Bonacich centrality (for a review, see Jackson 2008). Consensus on a preferred measure of centrality has not been established in the interdisciplinary literature. Jackson (2008) states, "Given how complex networks can be, it is not surprising that there are many different ways of viewing position, centrality, or power in a network". Padgett and Ansell (1993) use betweenness centrality to examine network structure of the Medici. Banerjee et al. (2012) use a different measure of centrality, diffusion centrality – which related to both Katz-Bonacich centrality and eigenvector

9 Undirected means that individuals A and B are treated as connected if either A or B reports a connection.

centrality[10] – and find that when information about microfinance is given to individuals with high levels of diffusion centrality in a village, there is higher overall microfinance participation in India.

In our experimental design, we focus on degree and betweenness measures of centrality. Degree measures the number of nodes to which the node is connected. Betweenness is a measure of the share of shortest paths from all pairs of nodes in the network that are connected to that node and is one measure of how influential a node is within the network. As a measure of network centrality, the betweenness measure represents how important a node is in increasing information flow. A household with very high betweenness would be one that connects two otherwise unconnected cliques (otherwise known as a bridge). To highlight how betweenness is important for information dissemination in particular, Granovetter (1973) argued that bridges were critical for the spread of job information. Betweenness centrality captures a node's role in facilitating communication in the network, and can capture how much a node serves as a bridge (Jensen et al 2015; Valente and Fujimoto 2010).

For the purpose of selecting treated nodes in the experiment, we calculated degree and betweenness in the following way. Our measure of betweenness is calculated at the household-level, combining together all links reported by men or women within the household. In the social network census collected in 2008, we only have unique identifiers at the household level rather than the individual level. Therefore, if a woman in household A indicated she was linked to a specific individual in household B, we can only link her to the entire household B. Given this limitation, we chose to

[10] Eigenvector centrality is another measure of influence within the network defined as the eigenvector of the network adjacency matrix, representing the centrality of the node as proportional to the sum of the centrality of its neighbor (Jackson 2008).

calculate betweenness at the household level. Using the 2008 data, we calculated degree based on the number of links reported by the male and female household members themselves and use this measure to determine who was treated in the experiment.

When conducting the analysis of the data, we use the 2011 social network data. Using the 2011 data, degree is based on the number of links respondents themselves report but also using any reports of links by other respondents in the village. Betweenness is calculated at the level of the node - where the social network connections of all male or female household members to other men or women in the study village. The 2011 data allows us to capture much richer measures of degree and betweenness centrality.

Table 1 provides descriptive statistics for all network nodes, comparing male and female nodes, using the 2011 network data. On average, female nodes have about 63% fewer direct contacts (degree) and are less central in the village as captured by betweenness centrality (43% lower) and eigenvector centrality (58% lower). A similar percentage of male and female nodes are not connected to anyone in the village: about 2% in both cases. This suggests that women in these villages may have less access to central nodes within the network, and if information dissemination is imperfect, targeting information to central parts of the network could have an unintended consequence of disadvantaging women's access to information. This would be consistent with the literature on job networks finding that women have less access to social networks and potentially leverage less their networks in the labor market (Lalanne and Seabright 201, Ioannides and Loury 2004, Loury 2006). For example, Beaman et al (2017) found that in Malawi, women were referred for jobs less frequently than men.

III. Context, Experimental Design and Balancing Tests

A. Context

In practice, extension agents often promote new technologies using a variety of targeting approaches directed towards changing a farmer's information set. A prominent approach in field extension-based education is to use group based trainings targeted at the village level or through targeting opinion leaders or lead farmers (Anderson and Feder 2007; Emerick and Dar 2017). Implicitly these programs assume that the farmers' social networks reinforce extension messages and increase take-up. The cost effectiveness of these interventions may be higher than direct extension visits to farmers in their fields, but less influential or vulnerable community members may be less likely to benefit due to social norms (Alesina and La Ferrara 2000) or the gender composition of the targeted groups (Kumar and Quisumbing 2011). Though extension services have largely been derided as ineffective due to low adoption of new technologies, the expansion of farmer's information sets could lead to low adoption rates due to the rational formation of beliefs that a new technology might not be profitable. Banerjee et al (2017) highlights how broadcasting information to an entire village can generate less knowledge diffusion than targeting information to particular nodes within the network.

Our experiment teaches farmers about composting. The adoption of improved soil management practices such as composting are important to long term soil fertility and productivity, but the gains from these investments rely on the complementary use of inputs and the household labor supply over a long-term period. The benefits of composting are due to increasing the stability of organic material in the soil which can change soil pH, moisture, increase biomass, and reduce water run-off (Semple, Reid & Fermor 2001, Carpenter-Bogs, Kennedy & Reganold 2000, Albiach *et al.*, 2001, Bresson *et al.*, 2001, Whalen, Hu & Liu, 2003). These benefits depend on soil characteristics before application of compost, the materials with which compost is made, and the duration of compost decomposition before application (Bationo and Mokwunye 1991, Magid & Kjærgaard 2001, McNair Bostick *et al.* 2007). Hence, benefits may accrue at a slow rate, and the returns to composting may be very heterogeneous across farmers. In this context, low adoption may be confused with low information diffusion, when in fact low profitability or profit variability for some farmers may actually explain low adoption despite high information diffusion. The goal of agricultural extension is to provide useful information about agricultural practices, not necessarily to increase adoption if other constraints to adoption are binding. We focus on understanding barriers to the flow of information within the village.

B. Experimental Design

To observe the diffusion of agricultural information within a social network, an informational placard was distributed to households in the 52 study villages. The placard was designed in the form of a wall calendar because Malians often display promotional calendars in their homes for years as decoration and conversation pieces with friends and household guests. The information distributed on the calendar provided information about how to compost and generate organic fertilizer for one's fields (see Appendix 2).

Fifty-two villages were randomly assigned to be among one of three treatments: degree, betweenness, or random. In all villages, four individual farmers (treated nodes) were trained on composting techniques and provided some information on the benefits of composting and use of organic fertilizer and they each received 4 calendars, one for themselves and one to distribute to other households in the village. In the degree treatment, we targeted treatment to nodes with high degree (i.e. many contacts). Since men's networks and women's networks may be somewhat distinct, in each village we selected the two households with the highest degree within women's and two households with the highest degree within men's network. In the betweenness treatment, we targeted treatment to households with the highest betweenness measure, randomizing whether the recipient within the household was male or female. In the random treatment, half of the 4 treated nodes were women.[11] There are 23 random villages, 15 degree villages and 14 betweenness villages. We implemented the experiment in 30 villages in 2010 (15 random and 15 degree) and 23 (8 random and 14 betweenness) in 2011 (Appendix A: Timeline). FIGURES 2-4 HERE

After the follow-up period of approximately one month, the enumerators returned to the village to administer a short questionnaire module to all nodes within the village to measure their understanding of composting and how they directly or indirectly acquired this knowledge from the treated nodes. A ten question knowledge quiz was administered to assess information retained from the calendar. The enumerator also asked if the node received one of the distributed calendars and if so, marked down the code on the back of the calendar which links that particular calendar to a treated node. The trained farmers were also visited and asked to whom they gave their

[11] In 2010 for the allocation of the random treatment, we randomly selected households and then a female recipient was chosen from half of those households as the recipient, and a man was selected from within the remaining households. Therefore, we effectively stratified on gender within a village. In 2011, we did not stratify on gender at the village level which resulted in variation across villages in the number of female treated nodes, though the assignment rule was to allocate half of the treatment to men and half to women. Some of the households did not have female farmers who were assigned as treated female node households.

calendars. This design allows us to distinguish between the diffusion of rival (the calendar) and non-rival (composting knowledge) goods independently as well as investigate treatment effect heterogeneity by gender, as the assignment of treatment in household was randomized by gender.

Balance

Table 2 provides the results of a balancing test of household and village level variables across the treatment groups. The p value of the test of mean equivalence across groups is reported in the table's last column. The standard errors of this regression are clustered at the village level. The sample is generally balanced across household characteristics, failing to reject the null hypothesis at the 10% level of statistical significance in 10 out of the 11 variables tested. Differences in the number of households by village are statistically different across treatment groups. This will be an important variable to include in specifications to control for village size variation.

Characteristics of treated nodes

Table 3 compares observable characteristics of the treated nodes by the gender of the targeted farmer. If differences in observable characteristics exist by gender, then gender may be only one of the mechanisms, along with other characteristics of the treated node, which might influence information diffusion. Our within treatment by gender balancing tests in Table 3 illustrate that household assets, household size and experience with the primary crops grown in these villages are not statistically different by gender of the treated node at the 5% statistical significance level[12]. This is consistent across the random villages, degree treatment villages and betweenness treatment villages.

[12] The standard errors of this regression were clustered at the village level.

We also present the social network characteristics of the male and female treated nodes in Table 3. Male treated nodes are more highly connected across all treatments then female treated nodes. Though these differences are not always statistically significant, the overall trend in the data is that measures of degree, betweenness, and eigenvector centrality are higher among male treated nodes relative to female treated nodes.

Comparing the connectedness of treated nodes across treatments, we find higher degree centrality among both male and female treated nodes in the degree treatment villages relative to the male and female treated nodes in the random or betweenness treatment villages. Degree male and female treated nodes also have the highest betweenness among the three treatment groups. The betweenness treatment male nodes have similar levels of betweenness across treatment groups, though the female nodes in the betweenness treatment have lower betweenness centrality than female nodes in the degree treatment[13]. Both male and female treated nodes in the betweenness treatment have higher eigenvector centrality relative to the male and female nodes in the other treatments. Therefore our main findings do not necessarily reflect targeting betweenness specifically but more broadly targeting central nodes (and their associated characteristics, which are not randomly assigned).

[13] This likely occurred since in the 2008 census data we were only able to identify high betweenness households, and then randomly selected a male or female node within those households. The data in Table 3 is from the 2011 census data, where we can construct betweenness at the node-level within each household.

Women and men's access to treated nodes

The targeting strategies in the experimental design created different access to treated nodes for male and female nodes across villages. Figure 1 shows the distribution of distance between nodes to the closest treated node in the sample. On average, women are further from treated nodes than men. In Table 4, we present the network characteristics of all nodes by treatment assignment.[14] Across treatments, we find similarity in network structure with respect to degree, betweenness and eigenvector centrality when we consider the complete network of male and female nodes and disaggregated men's and women's networks[15]. Disaggregating these network characteristics by gender reveals differences between male and female network characteristics. Female nodes have smaller network sizes as measured by degree and are less influential in their networks as measured by either betweenness or eigenvector centrality. Men's network size is 2.7, 2.8, and 3 members larger relative to women's network size in the betweenness, degree and random treatments. Male network size is 2.3, 2.6 and 2.1 times more influential using betweenness measures or 1.9, 1.8, and 1.7 times more influential using eigenvector centrality measures in the betweenness, degree, and random treatments.

Table 4 also presents distance calculations of male and female nodes to the treated nodes. These variables represent the number of links a node must pass through in a network to access the treated node. As summary statistics of these distance variables, we also calculate the percentage of

[14] Network characteristics are reported unadjusted or raw and normalized in Table 4. The normalized network characteristics are normalized to be mean 0 and standard deviation 1.

[15] The only network characteristic that is not balanced across treatment is men's eigenvector centrality at the 10% level.

indirect nodes and not connected nodes in the network relative to the total number of nodes in a household's network. Indirect nodes are those that do not directly connect to a treated node. Consistent with the social network characteristics, male nodes have shorter average distances to treated nodes relative to female nodes in all treatment groups. A key descriptive is that the difference between indirect male and female nodes is higher in the betweenness treatment than the difference between male and female nodes in the other treatments. The number of not connected or isolated nodes is very low and similar across treatments (1-3% of nodes) – hence the important dimension of variation in the data is whether a node is a direct or indirect connection to a treated node.

In Figures 2-4, three network maps of villages are presented to illustrate visually the differences in social network structure across villages and how the treatments affected information diffusion within a few selected villages. For graphical clarity, these figures demonstrate links across households, not nodes. Green circles represent the households who initially received the calendars. Yellow circles represent households to whom calendars were diffused by treated households. Gray circles illustrate households to whom no calendar was given by a treated household, but to whom information through word of mouth may or may not have spilled over. The figures also demonstrate that there is heterogeneity in network structure across villages.

IV. Econometric strategy

The objective of the empirical analysis is to understand (1) how the calendar diffuses through the social networks of the 52 study villages, and (2) how information about composting is aggregated into knowledge. Our first step is to estimate how an outcome – either the likelihood of receiving a calendar or the knowledge score – is related to the men or women's social network distance to the closest knowledge source, i.e. nodes who we trained on composting. The distance to treated nodes is calculated as the closest distance to any treated node. We consider nodes in the same household (i.e. groups of male and female household members) as connected with a distance of 1. Figure 1 highlights that the vast majority of nodes are either direct contacts (social distance 1) or friends-of-friends (social distance 2) of treated nodes. Given there are not many nodes that are a distance of 3-6 from a treated node, we pool together all indirect links (social distance of 2 or more) in our preferred specification. We show the disaggregated results by social network link distance in Appendix tables A1 and A2[16].

Our specification when looking at the receipt of the calendar compares nodes that are directly linked to treated nodes in other households to those indirectly connected or not connected. We know all treated nodes received calendars, and the treated nodes were instructed to give extra calendars to other households. Therefore we exclude treated nodes, counterfactual treated nodes (high degree and high betweenness) and treated nodes' household members from the analysis. This specification provides an effect of social distance on a rival good, the calendar. The specification is:

$$y_{ghj} = \alpha + \beta_1 indirect_{ghj} + \beta_2 unconnected_{ghj} + \beta_3 female_{hj}$$
$$+\beta_4 SNcontrols_{ghj} + d2011_j + \epsilon_{ghj} \qquad (1)$$

[16] The alternative specification reported in the Appendix regresses the outcome on whether a respondent is distance 1, 2, 3, …, 6 or unconnected to an treated node. Being distance 1 implies that the respondent is a direct contact of a treated node, either by sharing a household or being named as linked (by either party) in the social network survey. Distance 2 links are friends-of-friends. Distance 3 links are friends-of-friends-of-friends, etc.

We define y_{ghj} for calendar receipt as an indicator for whether any individual of gender g in household h in village j has received a calendar directly from a treated node. The reference group is comprised of individuals who are directly connected to a treated node but not members of the same household. The variable $indirect_{ghj}$ is an indicator for the male or female network in household h having at least one indirect social network connection to a treated node. The $unconnected_{ghj}$ variable is an indicator for the male or female network which has no path that connects them to the treated node household and are therefore socially isolated, while the $female_{hj}$ indicates that node within the household is female. The variable $d2011_j$ is an indicator for whether the experiment was conducted in 2011 (compared to 2010) to control for average differences across years.

Our specification estimating the effect of social distance on information diffusion (i.e. composting knowledge) differs somewhat from specification (1):

$$y_{ghj} = \alpha + \beta_1 direct_{ghj} + \beta_2 indirect_{ghj} + \beta_3 unconnected_{ghj} + \beta_4 female_{hj} + \beta_5 SNcontrols_{ghj} + d2011_j + \epsilon_{ghj} \qquad (2)$$

where y_{ghj} is the male or female composting knowledge score of an individual of gender g in household h in village j[17]. The reference group in this specification is comprised of treated nodes. And here, the variable $direct_{ghj}$ is an indicator of at least one male or female, g, direct social network connection to any treated node. Direct contacts of node g, in household h are either

[17] Composting knowledge was collected from the lead male and female farmer in each household. We implicitly assume that knowledge within gender is shared whereas knowledge between gender may not be shared.

household members, nodes who named h as a contact, or nodes within households that h named as a contact. The other variables are the same as in equation (1).

Households that have more contacts are mechanically more likely to be close to a treated node, even in villages where the treated node was randomly selected. Households with many connections may also be systematically different than those with few connections, and in particular they could have a higher baseline knowledge of composting. Specifications (1) and (2) therefore include controls for social network characteristics ($SNcontrols_{ghj}$), which are of two types. First, we include the male or female node's degree, the number of male or female node links of distance 2, distance 3, distance 4, distance 5, distance 6, and distance 7 or more. This addresses the issue that an individual with lots of connections will mechanically be more likely to be close to a treated node. Second, in betweenness and degree villages, we would also be concerned that the nodes which are close to central nodes would have more knowledge, independent of whether those central nodes were actually trained on composting. Therefore, we also include an indicator for whether a node would have been a betweenness or degree treated node, independent of treatment status, and 2 additional indicators for whether a node is a direct or indirect connection to these counterfactual treated nodes. Standard errors are clustered at the village level, to reflect any correlation in the error term induced by the targeting experiment.

Differences in the diffusion process may be driven by more than just differences in social distance. For example, not all nodes with distance 2 will share information equally. Men and women may be able to leverage their indirect contacts in different ways, especially if indirect contacts are of different genders. If this is the case, the diffusion process would differ beyond the "mechanical" social network differences in social distances that targeting more central nodes would be expected to generate by altering a women's distance to the treated node. We investigate this hypothesis by testing whether the diffusion process differs by treatment, using a specification which interacts social distance with treatment indicators.

We next investigate how targeting information to important nodes within the social network affects knowledge diffusion and aggregation and if this varies by the gender of the respondent. Our primary econometric specification investigates the effect of village level treatment based on either degree or betweenness targeting.

$$y_{ghj} = \alpha + \beta_1\, Td_j + \beta_2\, Tb_j + \beta_3\, Female_{ghj} + \beta_4\left(Td_j \times Female_{ghj}\right) + \beta_5\left(Tb_j \times Female_{ghj}\right) + \gamma X + \epsilon_{ghj} \quad (3)$$

where y_{ghj} is composting knowledge score of gender g in household h in village j. The variable $Female_{ghj}$ indicates a female node in household *h* in village *j*. The variable Td_j is an indicator for whether the treated node farmers were selected according to degree while Tb_j is the equivalent variable for the betweenness treatment villages. Treated nodes and the nodes that would have been treated nodes in betweenness or degree villages (counterfactual treated nodes) are not in these regressions. Standard errors are clustered at the level of the village to reflect the clustered treatment design. The additional controls (X) includes: the number of treated nodes that were, according to the randomization, allocated to female networks within the household[18]; fixed effects of the

[18] There was some replacement of treated nodes in the field, and occasionally a male household member was used instead of the intended female treated node. However we control for the intended number of female treated nodes.

number of female treated nodes and interaction terms of those indicators with whether the female network was selected in a particular household[19]; and the reciprocal of number of households in the village.[20] The reciprocal of village size is included as a control because we distributed the same number of calendars per village; therefore, there is on average less diffusion in larger villages. Additionally, our balancing tests also indicate a significant difference in village size across treatments.

Women are just one group that we expect to be socially excluded from information flows within the village. We also use the social network data to identify households which are more socially connected to see if they benefit systematically from targeting well-connected treated nodes. We focus on three measures of a household's social status in the village: degree (number of connections), betweenness, and eigenvector centrality. Eigenvector centrality was not used in the experimental protocol but is frequently used in Economics and more broadly (see Google PageRank) as a measure of how important a node is within a network. The fourth specification, similar to equation 3, looks at heterogeneous treatment effects of targeting by the social network characteristics of the farmer's household.

$$y_{ghj} = \alpha + \beta_1\, Td_j + \beta_2\, Tb_j + \beta_3\, SN_{ghj} + \beta_4\, (Td_j \times SN_{ghj}) + \beta_5\, (Tb_j \times SN_{ghj}) + \gamma X + \epsilon_{ghj} \quad (4)$$

[19] This set of interactions include an indicator for having one female treated node x respondent is female up to an indicator for having 4 female treated nodes x female indicator. Therefore we are estimating 8 coefficients to reflect the variation across villages in the number of treated female nodes assigned to the village. Seventy-five percent of villages received exactly 2 female and male treated nodes.

[20] Our results are robust to alternative specifications that include the number of households and their square directly.

To ease interpretation, the three SN characteristics in specification 4 are normalized to be mean 0 and standard deviation 1. The X characteristics are as described above, and standard errors continue to be clustered at the level of the village.

V. Empirical Results

A. *Effect of Training, Calendar Diffusion, and Knowledge Aggregation*

We first present evidence that the calendar and short training infused new information about composting to the treated nodes. If treated nodes did not benefit from the composting training and understand how to interpret the graphic drawings depicting the composting process, then incorrect composting knowledge could diffuse within the village or limit the diffusion process due to incomprehension. To measure treated node knowledge, we use a simple specification regressing knowledge of composting from the follow up survey on whether the male or female respondent was a treated node. We restrict the analysis to only random villages to identify the causal effect of being treated. The composting knowledge aggregate was constructed using a simple count of correct responses given to 10 composting knowledge questions.[21]

We find in Table 5, that the treated nodes have more composting knowledge than other nodes in the network: on our ten point scale, treated nodes scored 3 points higher, representing a 53% increase in knowledge.

B. *Information Diffusion and Gender*

[21] The 10 composting knowledge questions included questions about the timing, benefits and process of making compost which were linked to information found on the promotional calendar.

We next investigate whether social distance has an effect on calendar receipt and knowledge aggregation. Table 6 reports the relationship between social distance and calendar receipt (specification 1), and Table 7 contains the estimates of the analogous regression (specification 2) when the knowledge test is the outcome variable[22]. Column (1) of Table 6 provides the pooled regression results of the effect of distance on calendar diffusion, while the second and third columns restrict the sample by male and female subsamples respectively.

As social network distance to the treated node increases, nodes are less likely to receive a calendar. Nodes which are directly connected to the treated node (the reference group) have a 30% probability of receiving a calendar. That rate goes down by 9.4 percentage points (33%) for nodes which have an indirect link to the treated node, and 31.9 percentage points when the node is not connected to the treated node. This suggests that diffusion of the rival good (the calendar) is strongly related to proximate social distance to the treated node. The patterns of calendar receipt are different for men and women's social networks (Columns 2 and 3). First, men are overall much more likely to receive a calendar than women. Among nodes that were eligible to receive a calendar (excluding treated nodes), only 5% of the female nodes in our sample received a calendar compared to 23% of male nodes. Table 6 shows that among men with a direct link to a treated node, 40% receive a calendar; this figure is 13% for female nodes. Column 2 shows that when men are indirectly linked to the treated node, the probability of calendar receipt is 11 percentage points less likely than for directly linked male nodes. The decline in the probability of calendar receipt

[22] The sample size in Table 5 is lower than in Table 4 as non-response excluded some observations from the sample if either the most knowledgeable male or female was not available at the time of interview to respond to the knowledge quiz.

for indirectly linked female nodes is 6 percentage points (column 3), though this is not statistically different from the effect for men (p=.30). Being entirely unconnected with the treated node is associated with being 51 percentage points less likely to receive the calendar for male nodes, while this figure is only 16 percentage points for unconnected female nodes (the coefficients in columns 2 and 3 are statistically different with a *p* value of .002). But recall only 2% of the sample are unconnected. Hence there is a stronger slope on social distance to the treated node for men then for women, but that may be because women are so unlikely to receive a calendar.

The calendars provide a way for us to directly and physically observe how diffusion occurs in the village. But nodes, particularly female nodes, which did not receive a calendar may still receive the necessary knowledge to conduct composting as information diffuses through social networks. There may be a difference in the effect of social distance frictions in the diffusion of rival and non-rival goods by gender. The aggregation of information may also differ by gender, if information aggregation within similar social distances is not the same by gender, i.e. a wife's husband's friends may distribute information differently than the husband's friend of a friend. We measure composting knowledge and the effect of social distance using specification (2) in Table 7. In this specification, the reference group is the treated nodes. Direct links include individuals who are in the same household as treated nodes and direct contacts of the treated nodes.

Columns (1)-(3) show that as social distance from the treated node increases, knowledge of composting decreases on average. Column 1 shows that direct links' composting scores are 2.8 points lower than the treated nodes, representing a 31% decline in knowledge. Indirect links score 3.3 points lower than treated nodes, and this difference is statistically different from the coefficient on the direct link (p<.01). Those with no connections to a treated node score 6 points, or 66%, lower than the treated nodes. We cannot reject, however, that the knowledge of those not connected to the treated nodes is different from those indirectly connected to treated nodes (p=.261). The estimate on the effect of being not connected is estimated with considerable noise (se=2.4) likely reflecting that there is not a large number of such nodes in the sample, demonstrated by Figure 4.

Columns (2) and (3) divide the analysis into subsample by gender. In the full sample, males have about 20% higher composting knowledge than females (p<.01; not shown in table), though this could reflect pre-existing differences in knowledge prior to the experiment. Column (2) estimates knowledge decay with social distance for men. Men who are direct links have a 26% lower score than treated nodes, and those with indirect links have 31% lower scores. The difference in knowledge between men with direct versus indirect links is statistically different (p<.01). Unconnected male nodes have dramatically less knowledge (9 points) on composting, which despite the controls for the number of contacts a household has, could reflect that unconnected male nodes are just systematically different than households who are connected to the giant component of the social network in the village. For women, column (3) shows that female nodes with a direct link to a treated node score 35% lower than female treated nodes, while female nodes with an indirect link score 40% lower score than treated nodes. These differences between women with direct and indirect links are again statistically different (p<.01). Knowledge among women who are unconnected is 3.4 points lower than the treated nodes but the difference is not statistically significant – either compared to treated nodes or compared to female nodes with direct and indirect links. The pattern of decay for those who are further and further away from the treated node is statistically different for men versus women. Male treated nodes have higher knowledge scores than women, and women who are direct links to the treated nodes also have differentially larger declines in knowledge than men who are direct links to treated nodes (-3.07 for women vs -2.42 for men; p=.04; not shown in table). Similarly, the decline in knowledge relative to treated nodes for indirect connections is larger for women than it is for men (-3.530 vs -2.868; p=.05; not shown in table).

In columns (4)-(6) of Table 7, we restrict the sample to nodes that did not receive a calendar. This is a selected sample, but this specification provides suggestive evidence on whether there was knowledge diffusion even for nodes that did not directly benefit from the physical descriptions of how to do composting. We estimate similar effect sizes for the pooled and gender disaggregated specifications. Therefore the non-rival knowledge about composting is diffusing even among those who did not receive the rival good, the calendar.

Columns (7) and (8) demonstrate that the decay of knowledge along social distance is different in the betweenness treatment than in the random (and degree) treatment. In particular, women who are direct and indirect contacts of high betweenness treated nodes have less knowledge than women who are direct and indirect contacts of randomly selected and high degree treated nodes. This is consistent with the idea that women may have a hard time "activating" links they may have, or that the strength of links may differ even at the same distance, when those links are to specific types of individuals - in this case those who have high betweenness in the village.

As a robustness check, a finer definition of distance to the treated node is used in an alternative specification, the results of which are in Appendix tables A1 and A2. We also present the results of specification (2) without the *SNcontrols*. Disaggregating indirect links into finer social network distances does not change the paper's main results. The results are qualitatively similar with and without social network controls, though the estimated decay in calendar receipt is steeper without social network controls. In Table A2, the point estimate of knowledge decay are broadly similar with and without social network controls. The one exception is that the reduction in knowledge associated with being unconnected is a little over half the size when no social network controls are included.

C. Targeting within the Network

In this section we investigate how targeting information to specific nodes within a network affects the diffusion of knowledge about composting and whether the less central nodes within the network, particularly women, are adversely affected by this targeting strategy.

In column (1) of Table 8, we see that there are no average differences in composting knowledge in villages which targeted high-degree or high-betweenness treated nodes, compared to villages where the treated nodes were randomly selected. Column (2) shows that informational inequality is stark in the betweenness treatment villages. Women in all treatment groups had lower overall knowledge relative to men (57% lower), but this informational inequality is particularly pronounced in the betweenness treatment. The gap in women's knowledge relative to men in the betweenness treatment group is 10% larger than in the random group (p=.10). As seen in Table 4, women are farthest from treated nodes than men in betweenness villages[23]. As demonstrated in

[23] There are a fixed number of calendars that is the same in all villages, so we do not look at calendar distribution as an outcome of specification (3). We also investigated whether the total number of calendars received by women within each village is a function of the targeting strategy. This analysis generates very noisy estimates. On average, only 2 of the calendars – out of 12 distributed in each village – were given to women who were not treated nodes.

Table 7, the social network targeting may affect diffusion not only through social distance, but because information aggregation may differ among nodes of similar social distance. More central nodes may share information differentially with men and women of the same social distance. No statistical differences are observed between the degree and random group with respect to knowledge, and we reject the equality of coefficients of the degree-female and betweenness-female interactions with p-value 0.003.

Columns (3)-(7) demonstrate robustness given a *p* value close to .10 in column (2). In columns (3) and (4), we demonstrate the robustness of this initial result by restricting the sample to villages which were randomly assigned 2 female treated nodes. In these villages we do not need to estimate the coefficients on the 8 indicators for the (i) number of female treated nodes assigned to the village and (ii) the interactions of each indicator for the number of female treated nodes assigned to the village with whether the respondent is a female but the sample size is reduced. In columns (5) and (6), we again use the full sample but include controls only for the number of female treated nodes assigned to the village and its interaction with gender – making a functional form assumption but potentially gaining power. In the last column, we use an indicator for whether half of the treated nodes were female and its interaction with the respondent being female. In all specifications, we observe that women in the betweenness treatment have the lowest level of knowledge of composting.

Therefore there may just be too little variation in the dependent variable to detect an effect on calendar receipt given the number of villages in our experiment.

Table 9 presents the estimation results of equation (4). Thus far we have focused on women as a potentially vulnerable group. Here we instead look at nodes that are less socially integrated, as captured by their number of contacts (degree), and how connected they are - betweenness and eigenvector centrality (EVC) - as listed in the table column heading. All of these measures are constructed so that a larger value means more social connectedness. The specification is otherwise similar to equation (4). The coefficient "SN Characteristic" is degree in column (1), betweenness in column (2) and EVC in column (3).

Columns (1)-(3) show that among all nodes in the village, nodes who are more central themselves, using any of the three measures, have more knowledge about composting. Part of this strong correlation is driven by gender differences. Since women have lower average values of degree, betweenness and eigenvector centrality than men, we focus this analysis primarily on variation in the social connectedness of men.

Columns (4)-(6) of Table 9 suggest male nodes which are the least connected have lower knowledge in the betweenness treatment than in the random treatment. Column (6) suggests that nodes with high eigenvector centrality benefit from the targeting high-betweenness nodes. Even average eigenvector centrality (.12) are worse off in the betweenness villages than if their village had random targeting of information. Hence, targeting composting training to those most influential within social networks leads to more knowledge dissemination to other male nodes who are fairly well connected. This is consistent with the finding that female nodes are made worse off in betweennes villages. Columns (7)-(9) show the same analysis for women, but we find no precisely estimated differences by treatment for women who are relatively more connected compared to women who are relatively less connected. This may be because women have lower levels of EVC and the standard deviation of EVC among women is smaller.

VI. Conclusion

Low adoption rates of agricultural technologies could be due either to low expected profitability of a technology or imperfect information about these returns which forms farmer expectations. There are few – if any – agricultural technologies which should be universally adopted by all farmers in all weather conditions. Instead, the objective of agricultural extension should be to provide correct information to farmers so they can make decisions that are best for them. We therefore focus on the diffusion of agricultural information to farmers and farmers' aggregation of that knowledge to better understand how social networks influence the information set of farmers, particularly when adoption rates are low. Given there are many ways to disseminate information, we seek to know the consequences of targeting information to influential nodes within a network and whether there are distributional consequences to that type of targeting.

Our methodological approach is key to identification of the effects of social network targeting on calendar receipt and composting knowledge, two measures of rival and non-rival good diffusion in our experiment. We find information diffusion declines with social distance, suggesting frictions in the diffusion of information. Aggregate knowledge about the technology did not increase when the most-connected individuals were targeted. However, women were disadvantaged: women in villages where composting information was targeted to network nodes with high betweenness had significantly lower knowledge than women in the degree and random treatment groups.

The results caution that while policymakers may be able to use social networks to spread information cheaply and efficiently, the choice of *who* to target within a network has implications for *who* will benefit from the information. We showed that information does not diffuse to people who are far from the initial recipients of information. Since different types of people are located in different parts of the network, the choice of targeting strategy will determine which types of people receive the information. In particular, targeting central nodes within a network will tend to leave out the periphery, including women.

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Tables

Table 1: Network Characteristics of all Network Nodes by Gender

	Male	Female
Degree	9.47	6.66
	[4.15]	[3.04]
Betweenness	111.70	48.52
	[141.46]	[83.28]
Eigenvector Centrality	0.12	0.07
	[0.08]	[0.06]
Not connected nodes	0.02	0.02
Observations (nodes)	1,775	1,775

Note: These statistics are based on the 2011 social network census data used in our empirical analysis. Standard deviations in brackets.

Table 2: Household Covariate Balancing Tests

Variable	Degree Treatment	Betweenness Treatment Mean (Std. Dev)	Random Treatment	N	*p value*
Household Size (2008)	11.56	11.83	10.93	3342	0.38
	(8.72)	(8.44)	(7.29)		
Number of Women in HH (2008)	5.63	5.82	5.39	3342	0.42
	(4.53)	(4.46)	(4.03)		
Total Number of Livestock (2008)	17.54	19.95	19.77	3544	0.53
	(19.33)	(21.34)	(21.05)		
Number of Different Household Assets Owned (2008)	9.58	9.43	9.46	3580	0.95
	(4.68)	(4.28)	(4.04)		
Number of Different Farm Assets Owned in 2008	6.07	6.42	6.29	3464	0.40
	(2.51)	(2.24)	(2.25)		
HH has mud floors (1=Yes)	0.82	0.90	0.86	3330	0.03
	(0.39)	(0.29)	(0.34)		
HH uses well for drinking water (1=Yes)	0.45	0.51	0.54	3332	0.80
	(0.50)	(0.50)	(0.50)		
Number of HH buildings in concession	4.13	4.47	3.95	3332	0.17
	(3.26)	(3.69)	(3.07)		
Number of men's agricultural plots	1.99	1.98	1.66	3239	0.22
	(1.84)	(1.69)	(1.44)		
Millet is main agricultural crop (1=Yes)	0.28	0.39	0.32	2664	0.71
	(0.45)	(0.49)	(0.47)		
Rice is main agricultural crop (1=Yes)	0.32	0.28	0.25	2664	0.79
	(0.46)	(0.45)	(0.44)		
Number of Households in Village (2008)	41.73	24.00	36.26	52	0.02
	(13.52)	(21.30)	(16.79)		
Number of Households in Village (2011)	42.20	23.79	35.17	52	0.02
	(13.43)	(17.16)	(20.04)		

These statistics are based on the 2008 social network census which was the data used to randomize treatment. The pvalue is the result of the test of the null hypothesis that the variables are balanced across treatments by regressing a degree and betweenness indicator on each variable in the table. Standard errors in this regression were corrected for village level clustering.

Table 3: Treated node Covariates Balancing Tests by Gender - Random Treated node Balancing Test

Household Characteristic	Male Treated Node	Female Treated Node	*p value*
Livestock Count	26.02	25.48	0.919
	(21.67)	(24.23)	
Agricultural Capital Count	6.96	6.85	0.827
	(1.58)	(1.93)	
Adult Equivalent Household Size	6.87	5.79	0.114
	(2.79)	(2.42)	
Experience with Irrigated Rice (1=Yes)	0.52	0.45	0.442
Experience with Millet (1=Yes)	0.57	0.50	0.454
Experience with Sorghum (1=Yes)	0.61	0.50	0.265
Social network characteristics			
Degree	9.13	8.53	0.542
	(4.51)	(2.98)	
Betweenness	28.48	24.69	0.571
	(35.27)	(30.77)	
Eigenvector Centrality	0.18	0.19	0.784
	(0.10)	(0.10)	

Degree Treated node Balancing Test

	Male Treated Node	Female Treated Node	*p value*
Livestock Count	33.41	27.66	0.246
	(27.62)	(23.09)	
Agricultural Capital Count	7.15	7.71	0.012
	(1.03)	(1.30)	
Adult Equivalent Household Size	7.01	8.24	0.158
	(2.48)	(2.46)	
Experience with Irrigated Rice (1=Yes)	0.57	0.57	0.964
Experience with Millet (1=Yes)	0.50	0.37	0.206
Experience with Sorghum (1=Yes)	0.61	0.47	0.199
Social network characteristics			
Degree	12.24	10.23	0.002
	(3.28)	(2.84)	
Betweenness	48.54	40.95	0.431
	(39.87)	(53.26)	
Eigenvector Centrality	0.23	0.19	0.094
	(0.08)	(0.08)	

Table 3: Continued: Between Treated Node Balancing Test

	Male Treated Node	Female Treated Node	*p value*
Livestock Count	28.50	23.89	0.528
	(24.93)	(26.32)	
Agricultural Capital Count	7.35	7.47	0.665
	(1.35)	(1.07)	
Adult Equivalent Household Size	7.04	6.94	0.887
	(2.32)	(3.09)	
Experience with Irrigated Rice (1=Yes)	0.38	0.40	0.880
Experience with Millet (1=Yes)	0.65	0.50	0.088
Experience with Sorghum (1=Yes)	0.65	0.55	0.492
Social network characteristics			
Degree	10.35	9.15	0.397
	(4.08)	(3.48)	
Betweenness	40.47	19.63	0.344
	(71.75)	(29.26)	
Eigenvector Centrality	0.31	0.30	0.534
	(0.10)	(0.12)	

These statistics are based on the 2008 social network census which was the data used to randomize treatment. Means are reported with standard deviations in parenthesis. The pvalue is the result of the test of the null hypothesis that the variables are balanced across treatments by regressing a degree and betweenness indicator on each variable in the table. Standard errors in this regression were corrected for village level clustering.

Table 4: Network Characteristics of all Network Nodes by Treatment Assignment

	Village Treatment Assignment					
	Betweenness Treatment		Degree Treatment		Random Treatment	
	Raw	Normalized	Raw	Normalized	Raw	Normalized
Degree	7.89	-0.02	7.88	-0.02	8.29	0.08
	(3.56)	(0.92)	(3.91)	(1.01)	(4.02)	(1.04)
Degree Female	6.56	-0.37	6.40	-0.41	6.92	-0.27
	(2.87)	(0.74)	(3.05)	(0.79)	(3.08)	(0.79)
Degree Male	9.21	0.32	9.37	0.36	9.67	0.44
	(3.68)	(0.95)	(4.10)	(1.06)	(4.36)	(1.13)
Betweenness	64.39	-0.12	83.94	0.04	83.59	0.04
	(113.76)	(0.96)	(123.32)	(1.04)	(120.03)	(1.01)
Betweenness Female	38.75	-0.34	46.50	-0.28	54.12	-0.21
	(74.83)	(0.63)	(75.80)	(0.64)	(91.43)	(0.77)
Betweenness Male	90.03	0.09	121.37	0.36	113.05	0.29
	(137.86)	(1.16)	(147.94)	(1.25)	(136.88)	(1.16)
Eigenvector centrality	0.12	0.35	0.08	-0.08	0.09	0.01
	(0.09)	(1.15)	(0.07)	(0.92)	(0.08)	(1.03)
Eigenvector Female	0.08	-0.07	0.06	-0.43	0.07	-0.33
	(0.07)	(0.95)	(0.05)	(0.64)	(0.06)	(0.82)
Eigenvector Male	0.15	0.76	0.11	0.28	0.12	0.34
	(0.09)	(1.19)	(0.08)	(1.01)	(0.08)	(1.11)
Male node dist to treated node	1.39		1.72		1.68	
	(0.81)		(0.83)		(0.87)	
Women node dist to treated node	1.73		1.98		1.93	
	(0.85)		(0.93)		(0.96)	
Indirect connection	0.50		0.64		0.63	
Indirect connection-Female	0.30		0.35		0.34	
Indirect connection-Male	0.20		0.29		0.28	
Not connected nodes	0.01		0.03		0.02	
	Above 75 p	Below 75p	Above 75 p	Below 75p	Above 75 p	Below 75p
Degree, dist to initial node	1.15	1.73	1.29	2.08	1.40	2.02
	(0.65)	(0.86)	(0.64)	(0.88)	(0.66)	(0.97)
Betweenness, dist to initial node	1.53	1.57	1.67	1.92	1.60	1.88
	(0.76)	(0.86)	(0.82)	(0.91)	(0.82)	(0.95)
Eigenvector centrality, dist to initial node	1.00	1.89	1.25	2.02	1.30	1.97
	(0.58)	(0.80)	(0.64)	(0.88)	(0.66)	(0.94)
Observations (Household-gender)	666		1,270		1,614	

These statistics are based on the 2011 social network census data used in our empirical analysis. *Degree* is the number of contacts a respondent has; *Betweenness* is the individual's betweenness centrality, and *Eigenvector centrality* is the respondent's eigenvector centrality. The distance to treated node variable is calculated based on the shortest number of nodes necessary to connect a household to the treated node. Indirect connection is an indicator that a respondent has an indirect connection to at least 1 treated node. Indirect connection: Female is an indicator for female respondents that they have an indirect connection to at least 1 treated node. Standard deviations are in parentheses.

Table 5: Do the Treated Nodes Know More?

	(1)	
Treated Node	3.016	***
	(0.253)	
Observations	1391	
Composting Knowledge Mean	5.646	
SD	2.887	

Notes

1 Only 'Random villages' are included in this sample. The composting knowledge mean is the mean of the random village sample of all treated and untreated nodes.

Table 6: Diffusion of Calendars

	(1)		(2)		(3)	
Indirect Link	-0.094	***	-0.111	***	-0.064	**
	(0.022)		(0.035)		(0.026)	
Not Connected	-0.319	***	-0.506	***	-0.158	**
	(0.052)		(0.085)		(0.065)	
1 If Female	-0.156	***				
	(0.028)					
N	2561		1282		1279	
Gender	All		Male		Female	
Mean of Treated Nodes	0.304		0.401		0.131	
SD of Treated Nodes	0.460		0.491		0.338	
p value: Indirect vs Not connected	0.000		0.000		0.108	

Notes

1 Treated nodes and counterfactual treated nodes (high degree and high betweenness) are excluded. The excluded group is individuals who are directly connected to a treated node. Individuals who are in the same household as a treated node are also excluded because treated nodes were instructed to share the calendar with individuals outside their own household.

2 Standard errors clustered at the village level.

3 Additional controls include: 2011 indicator, and controls for the individual's position in the social network (degree, # of links of distance 2, # of links of distance 3, # of links of distance 4, # of links of distance 4, # of links of distance 5, # of links of distance 6, and # of links of distance 7 or more). Also included are indicators for whether the respondent is indirectly linked to a counterfactual betweenness and/or degree treated nodes.

Table 7: Knowledge of Composting

	(1)		(2)		(3)		(4)		(5)		(6)		(7)		(8)	
Direct Link	-2.779	***	-2.419	***	-3.071	***	-3.032	***	-2.58	***	-3.299	***	-2.495	***	-2.777	***
	(0.207)		(0.202)		(0.312)		(0.237)		(0.266)		(0.350)		(0.286)		(0.415)	
Indirect Link	-3.295	***	-2.868	***	-3.530	***	-3.446	***	-2.92	***	-3.649	***	-2.466	***	-2.978	***
	(0.251)		(0.260)		(0.338)		(0.265)		(0.312)		(0.363)		(0.388)		(0.428)	
Not Connected	-5.984	**	-9.198	***	-3.395		-5.504	**	-9.207	***	-3.201		-6.648	**	-1.434	
	(2.400)		(2.151)		(2.469)		(2.488)		(2.191)		(2.389)		(2.580)		(2.472)	
1 If Female	-1.253	***					-1.144	***								
	(0.165)						(0.186)									
Direct link * Betweenness													-0.340		-1.687	*
													(0.556)		(0.945)	
Indirect Link * Betweenness													-2.151	**	-2.716	***
													(0.840)		(0.910)	
Not connected * Betweenness													-3.469	**	-5.483	***
													(1.699)		(1.229)	
Direct link * Degree													0.670		0.361	
													(0.453)		(0.551)	
Indirect Link * Degree													0.085		0.117	
													(0.653)		(0.543)	
Not connected * Degree													1.667		3.973	
													(3.034)		(2.404)	
N	2571		1282		1289		2138		932		1206		1282		1289	
Gender	All		Male		Female		All		Male		Female		Male		Female	
Sample Restriction			None - Full Sample						No Calendar Recipients				None - Full Sample			
p value: Direct vs Indirect Link	0.000		0.003		0.007		0.001		0.045		0.055		0.890		0.375	
p value: Indirect vs Not connected	0.261		0.004		0.956		0.408		0.005		0.851		0.114		0.532	

Notes
1 Sample includes all households, including treated nodes which are the comparison, excluded, group.
2 Standard errors clustered at the village level.
3 Col (1)-(3) includes the full sample restricted only in Col (2) to the male subsample and Col (3) to the female subsample. Col (4)-(6) is restricted to the subsample of nodes who did not receive a calendar for the full sample (4), male subsample (5), and female subsample (6). Columns (7) and (8) include type of link (direct, indirect or not connected) by treatment indicators in the regression for the same subsample as Col (2) and (3).
4 Additional controls include in all regressions: 2011 indicator, and controls for the individual's position in the social network (degree, # of links of distance 2, # of links of distance 3, # of links of distance 4, # of links of distance 4, # of links of distance 5, # of links of distance 6, and # of links of distance 7 or more). Also included are indicators for whether the respondent is a counterfactual betweenness and/or degree treated node, and indicators for having a direct or indirect link to the counterfactual degree and betweenness treated nodes.

Table 8. Village-level Treatments: Knowledge and Gender

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
1 If Treated Using Degree	0.162	-0.069	-0.051	-0.255	0.232	-0.070	0.026
	(0.246)	(0.275)	(0.235)	(0.274)	(0.266)	(0.284)	(0.294)
1 If Treated Using Betweenness	0.016	0.299	-1.681	-1.494	-0.239	0.173	-0.036
	(1.239)	(1.202)	(1.335)	(1.331)	(1.107)	(1.079)	(1.129)
1 If Female	-3.219 ***	-2.647 ***	-1.082 ***	-1.209 ***	-2.606 ***	-2.343 ***	-1.263 ***
	(0.671)	(0.751)	(0.152)	(0.251)	(0.664)	(0.628)	(0.229)
Degree Treatment * Female		0.454		0.423		0.586 **	0.470 *
		(0.274)		(0.287)		(0.268)	(0.266)
Betweenness Treatment * Female		-0.572 *		-0.753 *		-0.851 **	-0.770 **
		(0.337)		(0.410)		(0.362)	(0.311)
Less Than Half of Initial Nodes are Female							-0.645
							(1.068)
Less Than Half of Initial Nodes are Female * Female							-1.137 ***
							(0.286)
N	2445	2445	2204	2025	2445	2445	2445
Mean of Random Villages	5.65		5.65		5.65		
SD	2.89		2.89		2.89		
p value: Degree * Female vs. Betweenness * Female		0.003		0.002		0.000	0.000

Notes

1 The comparison, excluded, group is Random Villages. Treated nodes and individuals who are betweenness and degree counterfactual nodes are not included in the analysis sample in these regressions. Standard errors clustered at the village level.

2 Columns (1)-(2) have the following controls: 2011 indicator, the reciprocal of village size, and indicators for the number of female treated nodes assigned to the village, and interactions of each indicator for the number of female initial nodes assigned to the village with whether the respondent is a female.

3 Columns (3)-(4) restrict the sample to only villages which were randomly assigned 2 female treated nodes. The specification also includes a 2011 indicator and the reciprocal of village size.

4 Columns (5)-(6) have the following controls: 2011 indicator, the reciprocal of village size, the number of female treated nodes assigned to the village, and interaction of the number of female treated nodes assigned to the village with whether the respondent is a female.

5 Columns (7) has the following controls: 2011 indicator, the reciprocal of village size, an indicator for whether half of the treated nodes were women, and an interaction term with whether the respondent is a female.

Table 9. Village-level Treatments: Knowledge and Social Distance

	Pooled			Men			Women		
	Degree	Bet	EVC	Degree	Bet	EVC	Degree	Bet	EVC
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
1 If Treated Using Degree	0.160	0.137	0.108	0.159	0.215	0.105	0.073	0.019	0.024
	(0.235)	(0.219)	(0.221)	(0.314)	(0.249)	(0.287)	(0.233)	(0.252)	(0.250)
1 If Treated Using Betweenness	-0.218	-0.180	-0.390	-0.739	-0.573	-1.227	0.062	0.269	0.203
	(1.199)	(1.214)	(1.209)	(1.125)	(1.098)	(1.222)	(1.295)	(1.408)	(1.222)
SN Characteristic	0.211	0.150	0.220 **	0.094	0.091	0.123	0.222	0.049	0.155
	(0.151)	(0.096)	(0.095)	(0.139)	(0.092)	(0.099)	(0.159)	(0.115)	(0.149)
SN Characteristic * Degree Treatment	-0.077	-0.183	-0.065	0.137	-0.063	0.162	-0.048	-0.115	-0.060
	(0.184)	(0.121)	(0.150)	(0.206)	(0.099)	(0.189)	(0.183)	(0.225)	(0.212)
SN Characteristic * Betweenness Treat	0.126	0.135	0.641 *	0.281	-0.072	0.945 ***	-0.332	0.309	0.278
	(0.254)	(0.464)	(0.347)	(0.327)	(0.448)	(0.331)	(0.507)	(0.817)	(0.620)
N	2178	2178	2178	1075	1075	1075	1103	1103	1103
Mean Knowledge of Random Villages	5.65			6.34			4.96		
SD	2.89			2.51			3.07		
p value: SN Char*Degree = SN Char & Betweenness	0.375	0.482	0.035	0.653	0.983	0.026	0.567	0.620	0.568

Notes

1 The comparison, excluded, group is Random Villages. Treated nodes and individuals who are counterfactual betweenness and degree treated nodes are not included in the analysis sample in these regressions.

2 Standard errors clustered at the village level.

3 Additional controls include: 2011 indicator, the reciprocal of village size, and indicators for the number of female treated nodes assigned to the village, and interactions of each indicator for the number of female treated nodes assigned to the village with whether the respondent is a female.

4 *Degree* is the number of contacts a respondent has; *Bet* is the individual's betweenness centrality, and *EVC* is the respondent's eigenvector centrality. All measures are normalized.

Figures

Figure 1: Distance from the Treated node

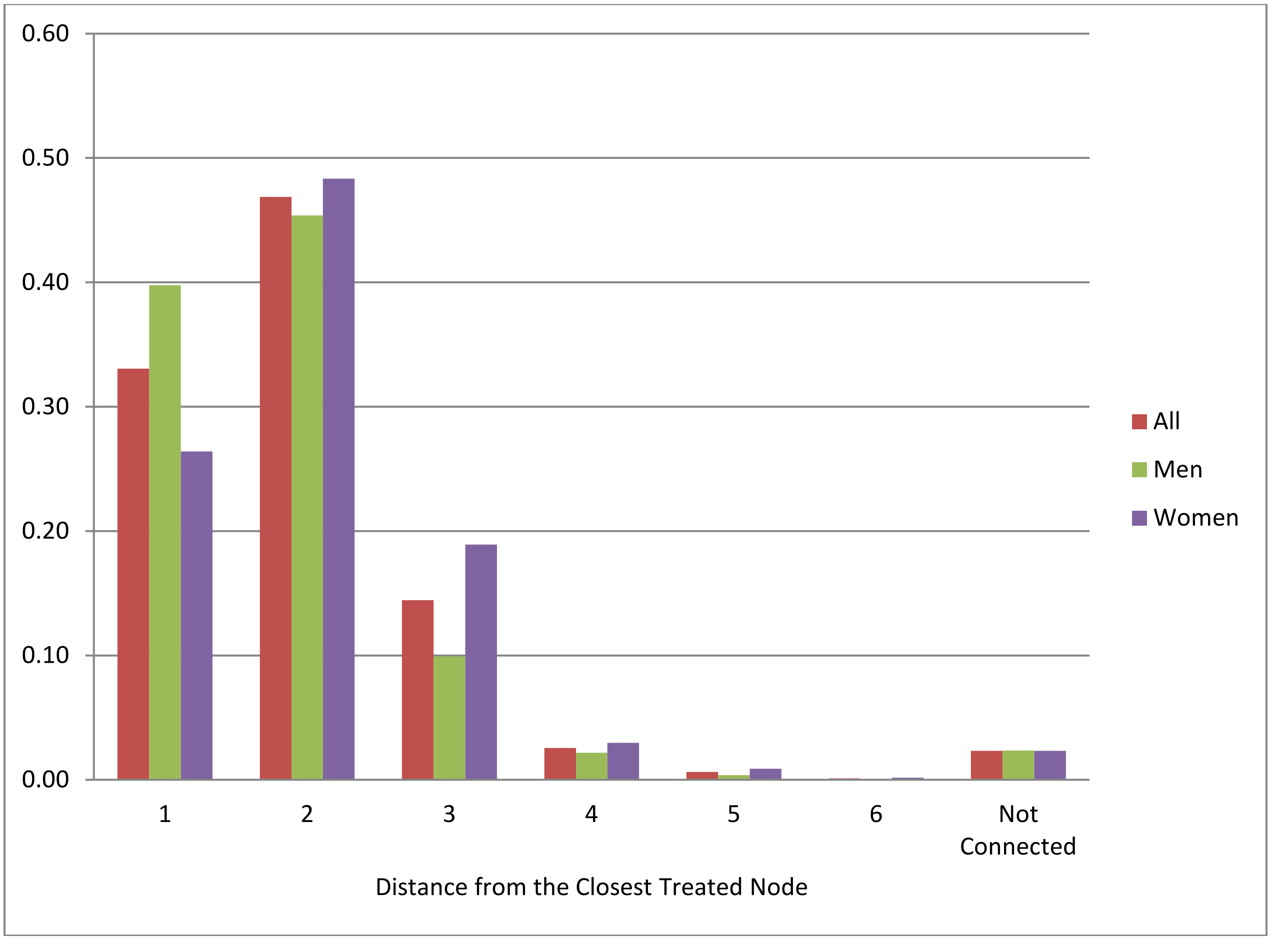
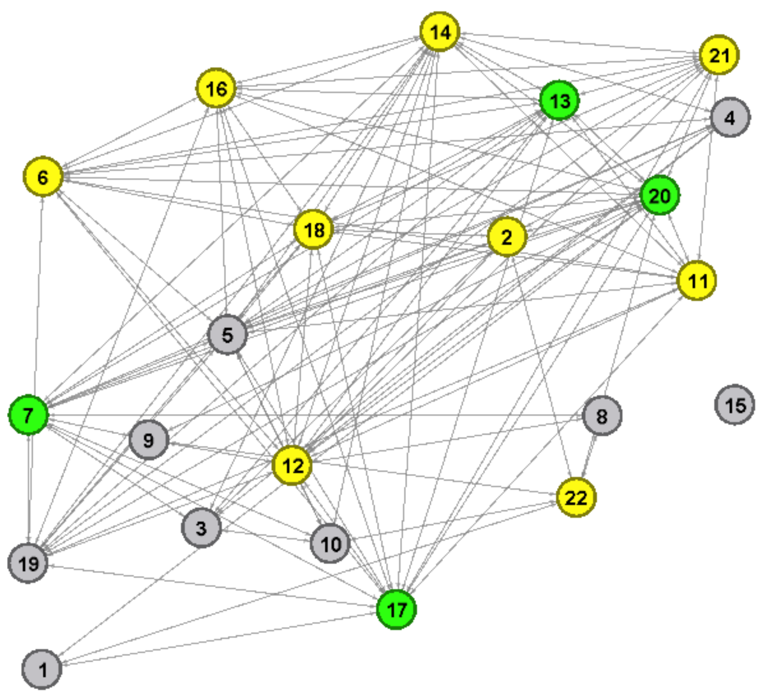


Figure 2: Betweenness Village



Note: Lines represent links as determined by the social network census while circles are households. Green circles represent the households which initially received the calendars. Yellow circles represent households which were given calendars by treated households. Gray circles illustrate households that were not given a calendar by a treated household.

Figure 3: Random Village

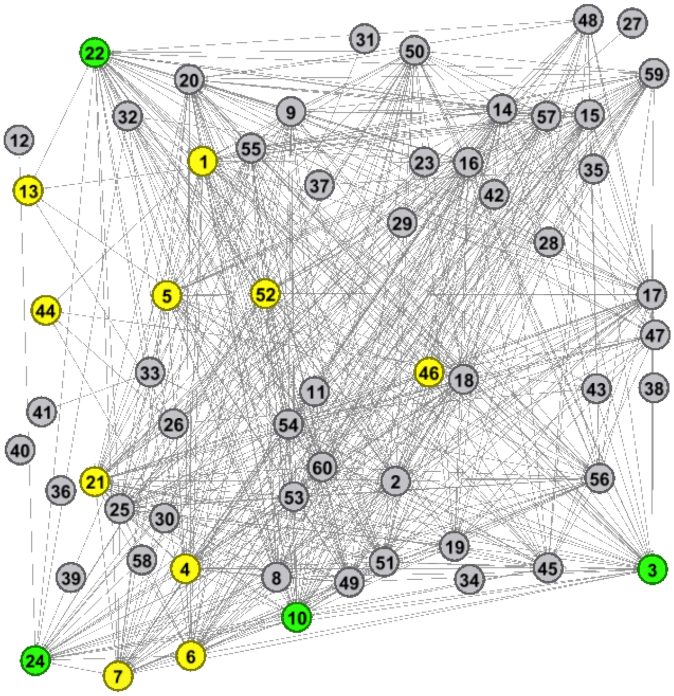
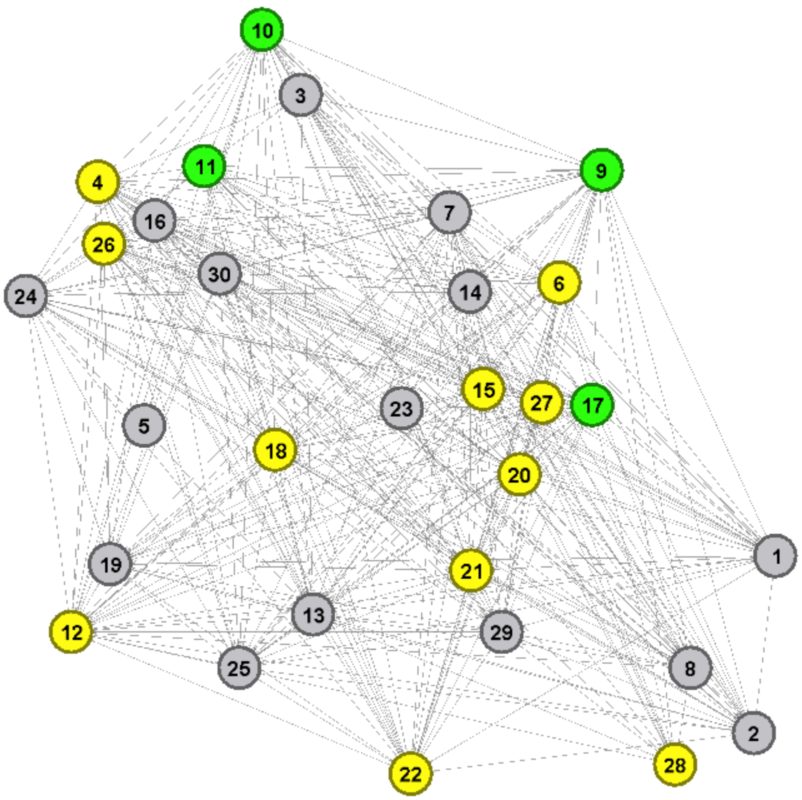
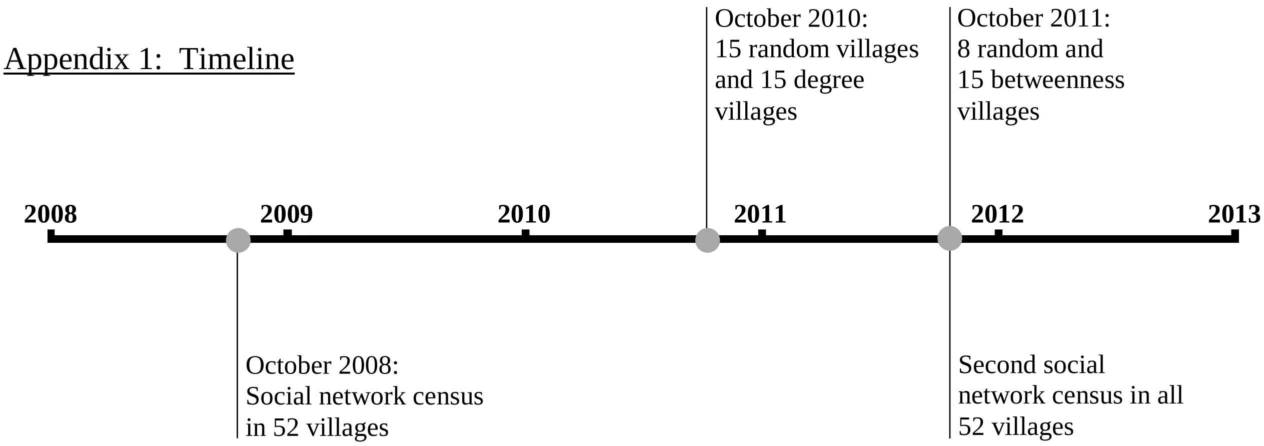


Figure 4: Degree Village



Appendices

Appendix 1: Timeline



Note: Two rounds of social network data were collected in 2008 and 2011 in similar seasons and in the same 52 villages. The 2008 social network data was used as the basis for randomization of the 2010 and 2011 villages since the 2011 network data was not available in time to determine treated nodes. The 2011 social network data was used as the basis for the creation of the social network variables in our analysis.

Appendix 2: Calendar

Appendix Table A1: Diffusion of Calendars Disaggregated by Social Distance

	(1)		(2)		(3)		(4)		(5)		(6)	
Distance 2	-0.097	***	-0.155	***	-0.113	***	-0.190	***	-0.065	**	-0.091	***
	(0.023)		(0.017)		(0.035)		(0.027)		(0.026)		(0.022)	
Distance 3	-0.071	**	-0.176	***	-0.093	**	-0.256	***	-0.056		-0.097	***
	(0.028)		(0.021)		(0.045)		(0.035)		(0.037)		(0.026)	
Distance 4	-0.069	*	-0.199	***	-0.090		-0.272	***	-0.069	*	-0.112	***
	(0.039)		(0.026)		(0.083)		(0.048)		(0.039)		(0.033)	
Distance 5	-0.184	***	-0.225	***	-0.374	**	-0.351	***	-0.112	***	-0.132	***
	(0.057)		(0.022)		(0.169)		(0.030)		(0.038)		(0.025)	
Distance 6	-0.221	***	-0.236	***			-0.456	***	-0.153	***	-0.132	***
	(0.034)		(0.046)				(0.059)		(0.055)		(0.026)	
Not connected	-0.322	***	-0.241	***	-0.497	***	-0.324	***	-0.168	**	-0.131	***
	(0.052)		(0.026)		(0.085)		(0.044)		(0.065)		(0.026)	
1 If Female	-0.155	***	-0.157	***								
	(0.028)		(0.024)									
SN Controls	Yes		No		Yes		No		Yes		No	
N	2561		3169		1282		1581		1279		1588	
Mean	0.29		0.29		0.38		0.38		0.13		0.13	
SD	0.45		0.45		0.49		0.49		0.34		0.34	

Notes

1 Treated nodes and counterfactual treated nodes (high degree and high betweenness) are excluded. The excluded group is individuals who are directly connected to a treated node. Individuals who are in the same household as a treated node are also excluded because treated nodes were instructed to share the calendar with individuals outside their own household.

2 Standard errors clustered at the village level.

3 Additional controls include: 2011 indicator, and controls for the individual's position in the social network (degree, # of links of distance 2, # of links of distance 3, # of links of distance 4, # of links of distance 4, # of links of distance 5, # of links of distance 6, and # of links of distance 7 or more). Also included are indicators for whether the respondent is indirectly linked to a counterfactual betweenness and/or degree treated nodes.

Appendix Table A2: Knowledge of Composting Disaggregated by Social Distance

	(1)		(2)		(3)		(4)		(5)		(6)	
Distance 1 (direct links)	-2.773	***	-2.911	***	-2.410	***	-2.564	***	-3.066	***	-3.270	***
	(0.209)		(0.231)		(0.203)		(0.258)		(0.326)		(0.306)	
Distance 2	-3.251	***	-3.650	***	-2.828	***	-3.277	***	-3.464	***	-3.886	***
	(0.253)		(0.359)		(0.266)		(0.410)		(0.320)		(0.293)	
Distance 3	-3.537	***	-3.949	***	-3.206	***	-3.401	***	-3.816	***	-4.337	***
	(0.321)		(0.405)		(0.391)		(0.496)		(0.372)		(0.330)	
Distance 4	-3.806	***	-3.763	***	-3.800	***	-3.321	***	-3.818	***	-4.143	***
	(0.629)		(0.586)		(0.953)		(1.062)		(0.729)		(0.636)	
Distance 5	-4.620	***	-5.277	***	-4.684		-4.719	***	-4.623	***	-5.562	***
	(1.530)		(0.708)		(3.021)		(0.993)		(1.536)		(1.344)	
Distance 6	-7.595	***	-7.135	***					-6.088	**	-6.850	***
	(1.740)		(0.398)						(2.704)		(2.649)	
Not connected	-6.275	**	-5.090	***	-9.236	***	-5.202	***	-3.697	**	-4.887	***
	(2.358)		(0.834)		(2.131)		(0.981)		(1.455)		(0.733)	
1 If Female	-1.248	***	-1.190	***								
	(0.164)		(0.146)									
SN Controls	Yes		No		Yes		No		Yes		No	
N	2571		2592		1282		1292		1289		1300	
Mean	8.98		8.98		9.14		9.14		8.78		8.78	
SD	1.00		1.00		0.86		0.86		1.11		1.11	

Notes

1 Sample includes all households, including treated nodes which are the comparison, excluded, group.

2 Standard errors clustered at the village level.

3 Additional controls include: 2011 indicator, and controls for the individual's position in the social network (degree, # of links of distance 2, # of links of distance 3, # of links of distance 4, # of links of distance 4, # of links of distance 5, # of links of distance 6, and # of links of distance 7 or more). Also included are indicators for whether the respondent is a counterfactual betweenness and/or degree treated node, and indicators for having a direct or indirect link to the counterfactual degree and betweenness treated nodes.