The Efficiency of Trading in Social Networks: Experimental Measures from India

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January 16, 2014

JOB MARKET PAPER

Abstract

This paper studies whether trading in social networks allocates a new technology efficiently. I use a field experiment in Odisha India to compare decentralized trade of a new technology through networks with an approach where demand was revealed via door-to-door sales. While 84% of farmers are expected to gain from the technology, only 7% adopt in networks. Conversely, 40% of farmers adopt when demand is revealed in door-to-door sales. Using variation across the sample in estimated gains in revenue, I show that 63% of the gains from door-to-door sales are lost with decentralized trade through networks. Frictions preventing interactions between farmers from different social groups offer an explanation for the results. Sub-caste and surname association with suppliers are strong predictors of adoption in networks, but have no effect in door-to-door sales.

Keywords: Social Networks, Technology Adoption, Transaction Costs
JEL Codes: O17, L14

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I am grateful to Elisabeth Sadoulet and Alain de Janvry for their guidance on all stages of this project. I also thank Ted Miguel, Craig Mcintosh, Jeremy Magruder, Emily Oster, Kelsey Jack, Seema Jayachandran, Sofia Villas-Boas, Marshall Burke, Judson Boomhower, Ethan Ligon, and Michael Anderson for helpful comments and suggestions. I gratefully acknowledge financial support from the World Bank and the Agricultural Technology Adoption Initiative of the Bill and Melinda Gates Foundation. I thank Manzoor Dar for his help in setting up the experiment and sharing his abundant knowledge about rice production. I also thank Girija Prasad Swain, Anirudha Patra, Silu Saha, and the staff of the Balasore Social Service Society for outstanding field work.

1 Introduction

The identities of agents are usually considered to be irrelevant in the classic marketplace because buyers and sellers come together at "arm's length" to make efficient transactions. While this abstract definition of the marketplace constitutes the ideal textbook scenario, a broad set of goods are exchanged bilaterally between agents that are connected in networks (Jackson, 2009). This broad set includes informal insurance in numerous contexts (Fafchamps and Lund, 2003; De Weerdt and Dercon, 2006; Mazzocco, 2012; Attanasio et al., 2012), electronics in Japan (Nishiguchi, 1994), and fish in southern France (Vignes and Etienne, 2011).

This paper asks whether trading in networks – a common nonmarket institution – can allocate a new technology efficiently. In the absence of capacity constraints, the specific notion of efficiency is adoption by all potential buyers that have positive expected benefits from using the technology. Despite the importance of networks as a mode of exchange, the growing theoretical literature on network-based exchange (Kranton and Minehart, 2001; Elliott, 2013), and several laboratory experiments (Gale and Kariv, 2009; Cassar, Friedman, and Schneider, 2010), there is little evidence from the field on how effectively networks allocate goods (Jackson and Zenou, 2013). I present the first field experiment to measure whether network-based exchange allocates a product to everyone with demand. Ex-ante, the answer to the question is uncertain. On the one hand, the costs of adopting from suppliers coming from different social groups may create a friction and limit exchange to closely linked individuals (Elliott, 2013). Conversely, if demand is competitive, then buyers with high valuations of the technology may be induced to bear the costs of making links with sellers (Kranton and Minehart, 2001).

I exploit a unique property of a new rice variety that allows me to characterize ex-ante the potential adopters with the highest expected returns. The variety, "Swarna-Sub1", has the specific property that it only offers increases in output per hectare when fields are affected by flooding – creating variation in benefits across the sample due to variation in exposure to flooding.[1] This property has been verified in both agronomic trials (Singh, Mackill, and Ismail, 2009) and randomized experiments in farmer's fields (Dar et al., 2013b). Given that flood severity depends heavily on local topography, this flood tolerance property creates variation in expected benefits that can be used to compare the efficiency of different allocations.

While I rely on this particular agricultural technology, its most important feature is that flood exposure – the key determinant of returns – is observable. This property creates a rare opportunity to characterize the relative efficiency of different modes of exchange. Most technologies simply do not have such a property.

Overall, I find that trading in social networks does not efficiently allocate the technology. I first compare adoption in networks with two benchmarks for demand: the allocation where every farmer with positive expected returns adopts and a revealed preference measure from door-to-door sales. With respect to either benchmark, the adoption rate in networks is inferior. In contrast

[1] The technology is otherwise equivalent to Swarna, which is commonly grown throughout eastern India. For details on how the technology was developed, see Xu et al. (2006) and Bailey-Serres et al. (2010).

to this reduced adoption, trading in networks does result in a small improvement in targeting of buyers with larger expected gains. However, this improvement in targeting is not large enough to offset the reduction in adoption. The limiting of transactions to close peers is one factor that limits the ability of networks to allocate the technology. To establish this, I show that existing social relationships between buyers and suppliers – defined by caste and surname association – have significant influence on adoption in networks.

Three sources of experimental variation are used in the analysis. First, five farmers were randomly chosen in each of 82 villages to receive a small amount of the new seed variety. After a single year of production, this small amount produces a large amount of output that can potentially be used as seeds by other farmers in the village. The selection of the initial recipients of the technology is therefore akin to selection of "suppliers" because these initial recipients were effectively endowed with more than enough seeds for their own cultivation. The random selection of suppliers allows for causal identification of whether social relationships with suppliers affect adoption in networks.

Following the first year of production, the second source of variation was village-level randomization of the mode of exchange. In half of the villages nothing further was done, effectively forcing adopters to rely on suppliers for taking up the technology. I refer to this system of exchange as the "network" because trading is decentralized, non-anonymous, and thus requires at least some link between buyers and sellers.[2]

The seed was *additionally* made available via door-to-door sales in the remaining half of villages. The purpose of this intervention was to generate a revealed preference measure of demand in an environment with minimal transaction costs and no frictions due to identities of buyers and sellers. Importantly, the door-to-door intervention is not meant to simulate a potential policy, but rather to generate a benchmark of demand. Therefore, the allocation produced in these villages is a benchmark measure that can be compared to both the allocation in networks and the perfect allocation where the technology reaches all farmers with positive expected gains. Since exchange via networks could still occur in villages where sales were offered, the design allows me to address whether networked trade alone meets demand. If so, then the additional adoption resulting from access to door-to-door sales should be small.

The third source of variation was randomization of prices at which sales offers were made. Since transaction prices in networks were beyond the control of the experiment, I rely on price randomization to ensure that a comparison between the two modes of exchange can be made while holding prices constant. Thus, the design ensures that price differences can not explain the results.

The experiment produced four main results. First, the overall rate of adoption is 83% lower with networks alone. Only 7% of farmers adopted in network villages, while 40% did in door-to-door villages. Considering that 84% of farmers are expected to benefit from the technology, only about half of the optimal adoption rate is achieved in door-to-door sales. Nonetheless, the magnitude of the difference between adoption in networks and revealed demand suggests that a significant share

[2]The term "link" is used to refer to links used for the purpose of making one-shot transactions, not necessarily links for more repeated interactions such as mutual insurance.

of farmers that otherwise have positive demand for a product do not adopt when exchange occurs in social networks. An alternative explanation of this effect is that door-to-door sales met demand by simply eliminating scarcity. I show that this explanation is unlikely because the amount of seeds available to suppliers was sufficient to meet the potential demand of *more* than an entire village.

The second result speaks to how social relationships restrict trading in networks. Specifically, farmers relying on networks are more likely to adopt when the suppliers in their village belong to the same sub-caste or share the same surname. In my preferred specification, having the same surname as an additional supplier results in a 106% increase in the probability of adoption. Similarly, being part of the same sub-caste as an additional supplier leads to a 53% increase in adoption probability. Relationships with suppliers are less important for demand in door-to-door sales. An equivalent interpretation of the finding is that introducing an outside buying opportunity increases adoption, but particularly for those that are not connected to suppliers and thus would have otherwise faced barriers to adopting in networks. The result provides micro-level evidence that is consistent with the cross-country result that the diffusion of technology is slower in countries where networks are organized into distinct sub-networks or collectives (Fogli and Veldkamp, 2012). Additionally, the result empirically demonstrates the importance of network structure for trading outcomes – something that is consistent with results from laboratory experiments (Charness, Corominas-Bosch, and Frechette, 2007; Gale and Kariv, 2009).

Third, I show that while there is a moderate improvement in targeting by social networks, it is insufficient to offset the large gap between adoption and demand. I exploit the flood-tolerance property of Swarna-Sub1 to generate estimated gains in revenue using impact estimates from a randomized experiment (Dar et al., 2013b). In particular, I calculate a farmer-specific measure of expected gains from the new technology. I find that trading in social networks is moderately effective at concentrating adoption amongst farmers that have above-median gains in expected revenue. In addition, the average return of adopters decreases by approximately 23% when door-to-door sales are offered. Nonetheless, this moderate improvement in targeting by networks only offsets a small amount of the inefficiency due to reduced adoption.

As an extension to this result, I exploit the random variation in sales prices to show that increasing prices does little to improve targeting. Most simply, the average return of adopters is no larger at higher prices. If anything, the results suggest that higher prices are less effective at targeting buyers with high returns. This finding adds to the literature on the allocative efficiency of prices for distributing technologies in developing countries (Ashraf, Berry, and Shapiro, 2010; Cohen and Dupas, 2010; Cohen, Dupas, and Schaner, 2013).

Building on these first three results, my final result quantifies the magnitude of the losses resulting from trading in networks. I define these losses as the percentage of the total gains in expected revenue in the door-to-door villages that are not achieved in network-based exchange. This measure is not a measure of overall social welfare, but is a measure of the losses to buyers of having to rely on networks for adoption. The total expected gain in one-year revenue due to the new technology is almost three times larger in villages where farmers were offered door-to-door sales. More precisely, the loss due to missed trading opportunities in networks represents 63% of the total gains achieved with door-to-door sales. The magnitude of the revenue effect implies substantial losses to farmers due to trading in networks.

These results are based on the short-run allocation of the technology after a single growing season. One caveat of the results is therefore that the allocation observed over a longer time period may differ from that in the short run. In short, the proper interpretation of the findings is that in the short-run, exchange in social networks is unable to meet demand.

This finding that trade in networks does not meet demand adds new empirical evidence helping to distinguish between different models of decentralized trade in networks. If demand is competitive and the costs of making links with suppliers are sufficiently low, then the model in Kranton and Minehart (2001) shows that efficient allocations are a unique equilibrium to a noncooperative game of network formation. In contrast, there may be frictions that limit exchange. As one example, not all efficient transactions will be made if sellers have some bargaining power and links between buyers and sellers are considered as relationship-specific investments (Elliott, 2013). My results suggest that there are indeed frictions that restrict the flow of goods across social groups in networks.

The results also contribute to the literature on the barriers to the adoption of agricultural technologies in developing countries. Important barriers that limit adoption of profitable agricultural technologies include limitations to demand such as self control (Duflo, Kremer, and Robinson, 2011) and risk (Dercon and Christiaensen, 2011). In line with Suri (2011), this paper suggests that constraints on the supply side are also important for limiting technological progress in agriculture.

An important policy implication of the results is that although seemingly desirable as a low-cost method of diffusing a new technology, social networks alone may not efficiently allocate the technology. Given the push to make development interventions sustainable (Kremer and Miguel, 2007), relying on decentralized exchange through social networks seems ideal because of its low cost. Indeed, farmer-to-farmer seed exchange is common throughout the developing world (Sperling and Loevinsohn, 1993; Almekinders, Louwaars, and De Bruijn, 1994). My results suggest that this approach significantly limits the diffusion of new technologies.

The rest of the paper is organized as follows. In section 2, I provide a description of how the experiment was specifically designed to measure the efficiency of exchange in networks. Section 3 provides a model of technology adoption that lays the groundwork for the empirical analysis in section 4. After establishing the inefficiency of exchange in networks, section 5 provides further analysis that points to network structure and the tendency to transact with only close peers as one important explanation of this result. Section 5 also presents evidence that is inconsistent with some alternative explanations of the findings. Section 6 concludes.

2 Experimental Design

In this section I describe the approach to create random variation in the identities of suppliers, the mode of exchange, and transaction prices in door-to-door sales. Motivated by the questions of whether exchange in networks allocates to everybody with demand and whether social relationships with suppliers influence adoption in networks, I discuss how the three sources of variation can be used to answer these questions. Finally, I also discuss the timing of data collection.

The experiment was carried out in 82 villages in three blocks of Bhadrak district of Odisha (see Figure 1 for a map of the villages).[3] The villages were selected using satellite imagery of flooding during 2008 and 2011. The villages are located in a low-lying coastal area adjacent to the Bay of Bengal. The median elevation of the district is approximately 10 meters, and rivers flowing from adjacent higher-elevation districts make flooding frequent during the June-October rainy season. Most recently, heavy flooding occurred in 2008, 2009, and 2011.

Suppliers were randomly selected at a village meeting carried out in May 2012. Each village was visited and farmers were informed that there would be a meeting to discuss a new flood-tolerant rice variety. The meeting was open to any farmers cultivating rice. Participants were informed that five farmers would be chosen via lottery to receive a five kilogram minikit of Swarna-Sub1.[4] The meetings were attended by anywhere from 15 to 41 farmers, with average attendance being 22 – or approximately 22% of cultivating households in the village.[5] During each meeting, enumerators provided a brief overview of the characteristics of Swarna-Sub1, described its similarity to the known variety Swarna, and pointed to flood tolerance as its only known benefit. After the information was provided, each farmer provided responses to a short baseline social network survey before placing their name in a bucket for the lottery. After all data were collected, the names of the five recipients were drawn and minikits were provided. Planting occurred upon the onset of the southwest monsoon, which occurred around the second week of June.

The selection of five original recipients is akin to random selection of the "suppliers" since their role in the experiment is to multiply the seed and sell/exchange with other farmers after the harvest but prior to the following growing season. Importantly, the identities of suppliers were known to all farmers attending, thus eliminating the possibility that lack of information on identities of suppliers affected the experiment. By randomly selecting suppliers, I can compare adoption outcomes between non-recipients (henceforth "buyers") that are more or less connected to suppliers.

Most suppliers complied with the experiment by planting the seeds contained in the minikit. To verify this, enumerators returned to all villages during harvesting in November/December to collect information about production. 396 of the 410 farmers were surveyed.[6] Of the farmers surveyed, 87% indicated that the minikit had been planted.[7]

[3]The total number of villages is 84. Two villages were used for piloting of surveys and interventions and are therefore not used in the analysis.

[4]Minikits are a common approach to introducing a new seed variety in India (Bardhan and Mookherjee, 2011). Each minikit contained only five kg of Swarna-Sub1 seeds, which is enough to cultivate approximately 0.1-0.2 hectares. The minikits were identical to those provided in Dar et al. (2013b).

[5]The households in the sample are fairly representative of the villages. The average share of the population that is Scheduled Caste is 20% in both the sample and the matched 2001 census of villages. Average household size and male literacy are also similar between the sample and the census.

[6]14 of the 410 suppliers could not be reached because either the household had moved from the village or household members were away for work during survey visits.

[7]The most common reason reported for not cultivating the minikit was that the seedbed was damaged by drought

The amount of seed provided to suppliers produced enough output to eliminate any concern that demand could not be met with the harvest. The average harvest of Swarna-Sub1 at the village level was approximately 1.8 tons. This amount was sufficient to meet potential demand because most farmers use approximately 5-10 kg of seed during their first year of cultivation and there is an average of 103 farmers per village. As I discuss in further detail in Section 5, alternative uses of output were no more profitable to suppliers, indicating that suppliers had no incentives to use the output in other ways.

Prior to randomization of the mode of exchange, a survey was administered to 1,151 randomly selected potential buyers during February-April 2013.[8] There were four purposes of this survey. First, a plot-level record of the duration of past flooding events during the previous five years was collected in order to estimate the expected returns of the new technology. I return to the estimation of expected returns using these data below. Second, farmers were also reminded about the new variety and the potential to obtain it from other farmers in the village. These reminders limit the possibility that farmers chose not to adopt simply because they had forgotten or did not know about the technology. Third, all potential buyers were again informed about the flood tolerance property of Swarna-Sub1 and that it is most effective during flooding of 5-15 days. Fourth, another social network survey was administered, thus allowing for analysis of whether stated network relationships responded to selection of suppliers.

The mode of exchange was randomized at the village level prior to planting for the 2013 season. In half of the villages, no intervention was carried out and thus decentralized trade between farmers was the only channel for adoption. The transactions between farmers in these villages could be sales, exchanges, or outright gifts – the latter likely occurring with some expectation of future reciprocity.[9] The randomization of the mode of exchange was stratified by block – an administrative unit two levels above villages – and the relative importance of suppliers to buyers.[10]

In the remaining half of villages, farmers were additionally given the opportunity to purchase the technology from NGO staff. The NGO staff went directly to the homes of farmers to make sales offers at pre-determined village-level prices. Except for telling the farmers about availability of the technology, the staff gave farmers no additional details about its benefits. Since farmers knew about the technology from the village meeting and previous surveys, there is little chance that increased awareness could drive the results. Nonetheless, I return to this possible explanation in Section 5.

or cows. The common method of planting rice in the area is transplanting, which involves preparing a small seedbed and uprooting the small seedlings approximately 3-4 weeks after emergence. The uprooted seedlings are then bundled and planted in the main field. Lack of water is particularly problematic for the seedbed.

[8] In villages with more than 15 potential buyers, a random sample of 15 names was drawn from the list of remaining farmers from the original village meeting. All buyers were selected if there was less than 15 names remaining.

[9] The ability to exchange seeds is an advantage of the networked market if farmers face liquidity constraints at the time right before planting.

[10] Suppliers were defined as being relatively more important when the ratio of average degree of suppliers to the average degree of buyers was larger than the sample median. The degree is simply the number of links of a farmer, where two farmers are defined to be linked if either farmer stated that they would go to the other farmer for seeds, fertilizers, or other inputs.

Since five suppliers were selected in all villages, network-based exchange was equally possible in all villages. Therefore, taking door-to-door sales as a method for eliciting demand, the question being addressed by random provision of door-to-door buying opportunities is whether exchange through networks alone leaves significant demand unmet. If so, then a large number of farmers will be "crowded in" when door-to-door sales are available.

Returning to prices, the prices were randomized in order to approximate the prices paid in transactions between farmers. Farmers often exchange seeds directly or sell at prices that are approximately equal to prices of harvested rice. Since the opportunity cost to the seller of such a transaction is the value of output, a sensible benchmark is the output price of rice for consumption. The minimum support price set by the Indian government for the 2012-2013 season was 12.5 Rs per kg (1 USD $\approx$ 58 Rs). Many farmers also sell to private traders at prices ranging from 10-12 Rs. Using these values as a benchmark, prices were randomly set at 3 levels: 10, 12, and 14 Rs per kg. Since most network transactions are one-to-one exchanges of Swarna-Sub1 for a different variety of seeds, these prices are reasonable proxies for prices paid in network transactions. Therefore, I can effectively hold prices constant by estimating the main treatment effects at the average price in farmer-to-farmer transactions.

A final endline survey was carried out in all villages in July 2013 to track adoption and area planted. The survey was administered to all farmers in order to verify transactions from both buyers and suppliers. A total of 1,150 of the previously surveyed buyers and 394 of the previously surveyed suppliers were reached. I use adoption from this survey as the main outcome variable throughout the remainder of the paper.

Summary statistics indicate that the experimental groups are comparable on observable characteristics. Panel A of Table 1 shows mean values of baseline observable characteristics for the suppliers and randomly selected buyers. Observable characteristics of suppliers appear similar to those of buyers, suggesting that the randomization in the field was successful at generating a random group of suppliers. Focusing on the social network measures, two farmers are defined to have an information link if either farmer indicated they would go to the other farmer to talk about rice farming. Similarly, two farmers have a sharing link if either farmer indicated that the other farmer is somebody they would hypothetically go to for seeds, fertilizers, or other inputs. Each farmer has on average 5 information links and 4.25 sharing links.

Village-level statistics from the 2001 census are presented in Panel B of Table 1. The villages are fairly small, with an average of 165 households, 103 of which are engaged in cultivation. The average elevation of five meters shows that the villages are located in a coastal low-lying area. Importantly for the design, the share of suppliers not cultivating the seeds provided and the aggregate Swarna-Sub1 harvest are balanced across network and door-to-door villages, suggesting that any differences in adoption can not be attributed to differences in production of suppliers.[11]

[11] Another useful test is the test of whether any differences between suppliers and buyers are greater in door-to-door villages as compared to network villages. In results not reported, I regress each characteristic in Panel A of Table 1 on village-level treatment, a supplier indicator, and the interaction of these two variables. The F-statistics of these 11 regressions range from 0.29 to 1.19 and thus the three variables do not jointly explain variation in any of the farmer

3 Model of Technology Adoption in Networks

In this section I formulate a model of adoption of a new technology in networks. In contrast to a model where networks function to spread information, I focus on how network relationships create variation in costs of adopting across the population. I then use the model to help show how targeting of buyers with high expected benefits may vary between networks and a setup where these costs are eliminated in door-to-door sales.

3.1 Simple Example

Before formulating the adoption choice of buyers, I present a simple example that is meant to convey the ways in which trading in networks may vary from the outcome when door-to-door sales are offered. Figure 2 displays the network structure for one of the sample villages, where two farmers are assumed to have a link if they share a common surname, an assumption I provide support for in Section 5. The dark nodes (S1-S5) represent the five farmers that were selected as suppliers and the remaining nodes (B1-B15) are potential buyers. Since the harvest of suppliers is enough to meet demand, and there are no alternate uses of the output that are more profitable, the first-best allocation would require each buyer with positive demand to adopt. As an example, if B5 has a high valuation for the technology, then she faces a tradeoff of going to a supplier outside of her network, or not adopting. As the theoretical literature suggests, it is not obvious as to whether these transactions will take place (Kranton and Minehart, 2001; Elliott, 2013).

The link pattern is inconsequential when demand is revealed via door-to-door sales because all potential costs of transacting are eliminated. As a result, network structure imposes no barriers to B5 adopting the technology. If network relationships present barriers to adoption, then the amount demanded from door-to-door sales will be significantly larger for those farmers that are unconnected to suppliers. In contrast, if networks work efficiently for exchange, then B5 should adopt regardless of the mode of exchange.

3.2 Model Setup

The main benefit to the farmer of adopting the new technology is improved flood tolerance. To formalize this, denote α_i as the probability that farmer i is affected by flooding. The agronomic return of the technology when flooding occurs is $r_i > 0$. Conversely, the return under non-flood conditions is zero – an assumption consistent with the experimental results in Dar et al. (2013b). Therefore, the expected return of the technology is $R_i = \alpha_i r_i$.

In addition to the returns due to flood exposure, there is an idiosyncratic term, u_i, which measures benefits that are observed to the farmer, but not to the econometrician. For instance, some farmers may have stronger preferences for trying new technologies. I assume that u_i is mean zero and independent of both R and c. Since R_i can be approximated with data on past exposure to

characteristics.

flooding and u_i is unobservable, the door-to-door sales treatment serves the purpose of generating a measure of overall demand that is based on both terms.

The difference in prices between the old and new technologies is v. I consider prices to be fixed. While there is a large literature on bargaining between buyers and sellers in networks (Corominas-Bosch, 2004; Manea, 2011; Abreu and Manea, 2011), I focus on network structure and costs of exchange as potential barriers to adoption. The lack of significant variation in prices and the prevalence of exchanging seeds at a rate of one-for-one suggests that bargaining is not an important consideration in this context.

The costs of exchange in networks can be decomposed into two terms. The first term, $\underline{c}$, is the inconvenience of having to leave the house to obtain seeds. While likely important in many contexts, $\underline{c}$ is likely to be less important in this sample due to the close proximity of houses. Half of the households in the sample have a supplier that lives within 42 meters of their household. Also, over 90% of buyers are located within 300 meters of a supplier.

The second term, c_i, denotes the costs to the buyer of making a trading link with a supplier. The value of c_i varies across the population because of varying degrees of connectedness to suppliers. As an example, a low caste farmer may find it very costly to adopt from a higher caste supplier. However, it need not be the case that $c_i > 0$. For instance, a farmer may *benefit* from trading in networks if peers extend credit or allow for other types of flexible payments.[12]

In contrast to a conventional market, door-to-door sales eliminate both $\underline{c}$ and c_i by making transactions anonymous and bringing seeds directly to farmers. A standard market with some transportation costs would eliminate c_i, but not $\underline{c}$. I use various measures of connectedness to suppliers to show empirically that c_i is quantitatively important.

I assume that c, R, and u are distributed multivariate normally where the means of c and R are μ_c and μ_R. The parameter ρ denotes the correlation between R and c. The idiosyncratic term u has a mean of zero and is uncorrelated with both R and c.

Combining all benefits and costs, the probability of adopting the new technology in networks is $P\{R + u > v + c + \underline{c}\}$. Introducing door-to-door sales causes the adoption probability to be $P\{R + u > v\}$. In addition to differences in adoption, there may be a targeting effect where the quality of adopters varies between the two modes of exchange.

3.3 Targeting

The expected return of adopters is a natural measure of targeting effectiveness. Conditional on the overall rate of adoption, the average return of adopters is a direct measure of how efficiently the technology is allocated. As shown in the appendix, the expected return of adopters when trading

[12]See Kranton (1996) and Aoki and Hayami (2001) for discussion of some of the benefits of reciprocal exchange through networks.

occurs in networks is

$$E(R|R+u-c>v+\underline{c}) = \mu_R + \frac{\sigma_R(\sigma_R-\rho\sigma_c)}{\sqrt{\sigma_R^2+\sigma_u^2+\sigma_c^2-2\rho\sigma_R\sigma_c}} * M\left(\frac{v+\underline{c}-\mu_R+\mu_c}{\sqrt{\sigma_R^2+\sigma_u^2+\sigma_c^2-2\rho\sigma_R\sigma_c}}\right), \quad (1)$$

where $M(z) = \frac{\phi(z)}{1-\Phi(z)}$ is the inverse Mill's ratio. The expected return of adopters is above the average in the population if $-1 \leq \rho < \frac{\sigma_R}{\sigma_c}$. Intuitively, if returns and costs of adopting are negatively correlated, then the farmers facing the fewest barriers to adopting in networks are those with the highest returns. Therefore, on average, the adopters have higher returns than the overall population. On the other hand, if the correlation between costs and returns is sufficiently large, then targeting in networks is less effective because the farmers with high costs are those with high returns.

The expected return of adopters in door-to-door sales is

$$E(R|R+u>v) = \mu_R + \frac{\sigma_R^2}{\sqrt{\sigma_R^2+\sigma_u^2}} * M\left(\frac{v-\mu_R}{\sqrt{\sigma_R^2+\sigma_u^2}}\right). \quad (2)$$

Comparing equations (1) and (2), the average return of adopters will be larger in door-to-door sales if $\rho > \frac{\sigma_R}{\sigma_c}$. In this case, door-to-door sales crowd in farmers with high returns that did not adopt in networks. Conversely, if ρ is held constant, and μ_c is large relative to σ_c, then adoption in networks sends a stronger signal that returns are large because the farmer is willing to make the costly investment of adopting from other farmers.[13] Expected returns of adopters in networks will be larger in this case.

Overall, the model predicts that the difference in the average return of adopters between the two modes of exchange will depend upon the magnitudes of μ_c, σ_c^2, and ρ. However, the experimental design causes c and R to be uncorrelated when conditioning on network size. This results because random selection of suppliers generates random variation in connectedness to suppliers. Applying this to the model, the targeting effectiveness of exchange in networks will depend only on the distribution of costs. If barriers to exchange in networks are irrelevant, then costs will be small and the average returns of adopters in networks will be similar to that in door-to-door sales. This prediction is considered in detail in the empirical analysis.

4 Results

I first report in Section 4.1 the results showing that exchange in social networks results in lower adoption, crowding out of farmers with fewer connections to suppliers, and a small improvement in targeting. These results build up to an overall measure of efficiency losses discussed in Section 4.2.

[13] To see this, note that $M(z)$ increases monotonically with z. Therefore, as μ_c increases and σ_c decreases, both M and $\frac{\sigma_R(\sigma_R-\rho\sigma_c)}{\sqrt{\sigma_R^2+\sigma_u^2+\sigma_c^2-2\rho\sigma_R\sigma_c}}$ increase.

Section 4.3 considers whether adoption effects vary across the population. Finally, in Section 4.4, I take advantage of the random variation in prices to show that increasing prices is not effective at screening the pool of adopters.

4.1 Adoption, Peer Effects, and Targeting

I first show that exchange via social networks alone results in significantly lower adoption when compared to villages where door-to-door sales were used to reveal demand. In order to estimate the magnitude of this effect while holding prices constant, I rely on random price variation to estimate the effect at the average price observed in network transactions between farmers. Formally, the regression specification is

$$adoption_{ij} = \beta_0 + \beta_1 door\ to\ door_j + \beta_2 door\ to\ door_j * (price_j - 12.4) + \varepsilon_{ij}, \tag{3}$$

where $adoption_{ij}$ is an indicator for adoption by farmer i in village j, $door\ to\ door_j$ is an indicator for door-to-door villages, and $price_j$ is the random offer price in door-to-door villages.[14] Since the average price of transactions between farmers is 12.4 Rs per kg[15], the coefficient β_1 measures the gap between network adoption and revealed demand at a price equivalent to an average network transaction.

The estimates in column 1 of Table 2 show that when holding price constant, the demand revealed by door-to-door sales is higher by 33 percentage points. The rate of adoption of 40% in door-to-door sales is larger than the adoption in networks by over five times. Focusing on the ratio of the two estimated coefficients in column 1, the price charged in door-to-door sales would need to approximately double to result in the same adoption rate observed in networks alone. The coefficient changes little when including control variables (column 2). Further, as shown in column 3, adoption in networks fell far below demand at all three price levels, even at the highest price, which is larger than the prices of almost all farmer-to-farmer transactions.

One potential explanation for the low adoption in networks is that exchange tends to be limited to farmers from the same social groups, effectively crowding out farmers without links to suppliers. I rely on the random selection of suppliers to test whether relationships between buyers and suppliers are more important in networks. The estimating equation is

$$\begin{aligned} adoption_{ij} =& \beta_0 + \beta_1 door\ to\ door_j + \beta_2 suppliers_{ij} + \beta_3 degree_{ij} + \beta_4 suppliers_{ij} * door\ to\ door_j \\ &+ \beta_5 degree_{ij} * door\ to\ door_j + \varepsilon_{ij}, \end{aligned} \tag{4}$$

[14] I focus on a binary adoption rate throughout the paper because the amount used is only relevant for a single year. After one year, the harvest produced from only 1-2 kg of seed is enough to cultivate the average farmer's entire landholdings. In door-to-door villages, the adoption indicator is set to 1 if *either* the farmer purchased from an NGO representative, or adopted from a peer.

[15] The dominant transaction type is direct exchanges of Swarna-Sub1 for a different variety of rice. The price for these exchanges is valued at the output price of rice. I use the most conservative estimate, which is the government-supported price of 12.5 Rs per kg.

where $suppliers_{ij}$ is the number of peers of farmer i that were selected as suppliers and $degree_{ij}$ is the total number of peers of farmer i. Peers are defined using either the baseline social network survey, common surnames, or belonging to the same sub-caste.[16] Importantly for identification of β_2 and β_4, the random introduction of the technology guarantees that the number of suppliers that are connected to a given farmer is as good as randomly assigned when conditioning on the total number of connections, thus avoiding the classic reflection problem discussed in Manski (1993).

The results in Table 3 show that stated relationships with suppliers from the baseline social network survey have little impact on adoption in both types of villages. The effect of being linked to an additional supplier in social networks is small and not statistically significant across all specifications in columns 1-3. As seen by the estimate of β_4, adding door-to-door sales does little to change this effect.

In contrast, sharing surnames with suppliers is significantly more important for obtaining the technology when trading occurs in networks. In column 4, sharing the same surname with an additional supplier results in a 3.5 percentage point, or 50%, increase in the probability of adoption in networks. Adding door-to-door sales causes this effect to decrease significantly by 7.5 percentage points. The negative effect of 4 percentage points in door-to-door sales represents an approximate 10% decrease in adoption, but the effect is not statistically significant (p=0.24). The results do not change substantially when adding household controls (column 5). Turning to column 6, the effects are somewhat larger when village fixed effects are added.[17] Having the same surname as a single additional supplier results in a 106% increase in the likelihood of adoption in networks. Again, the effect in door-to-door sales is slightly negative, but not statistically significant. Holding network size constant, a farmer would need to share the same surname as an additional 4.5 suppliers in order to have the same likelihood of adopting as when door-to-door sales are available. A natural explanation for the difference between surname association and stated network links is that farmers have some flexibility to adopt from others that are not their closest peers, but that establishing a trading link with another farmer from a different social group is too costly.

Belonging to the same subcaste as suppliers is also a significant determinant of adoption in networks. In column 7, having one additional supplier from the same subcaste leads to a 4 percentage point increase in the probability of adoption, representing a 57% effect. The estimated coefficient on the interaction between the door-to-door indicator and the number of suppliers belonging to the same sub-caste is negative and of similar order of magnitude as the effect in networks. Thus, the effect of belonging to the same subcaste as suppliers becomes effectively zero when door-to-door sales are made. As shown in columns 8 and 9, the results are similar when adding control variables and village fixed effects.

[16] There is substantial variation in surnames within villages. The average number of unique surnames per village is 5.6. Therefore, each farmer in the sample shares a surname with approximately 3.3 other farmers in the sample.

[17] This likely occurs because the villages with little variation in adoption and where most farmers share the same surname receive less weight in the identification. In Table A1 I show that the estimated peer effects are much larger in the sample of villages where there was at least one adopter (columns 1 and 2). This is mostly due to very low adoption in one of the three blocks (columns 3 and 4). The results are also more similar to fixed effects results when discarding the 5% of observations where over 15 of the farmers in the village have the same surname (not shown).

The estimated effects of relationships with suppliers are robust to two natural alternative estimation approaches. First, accounting for the dichotomous nature of the dependent variable by using a probit specification has little impact on the estimates (columns 5 and 6 in Table A1). Second, an alternative way of measuring relationships with suppliers is to use the share of connected farmers that were selected as suppliers. As shown in Table A2, using this approach actually improves precision of the estimates.

Compared to the existing literature on peer effects, this result highlights a different mechanism through which peers influence behavior. Namely, when products can be directly traded through networks, one may gain access to a new product via their peers. The literature on peer effects consistently points to peers as a source of learning about new technologies or products (Foster and Rosenzweig, 1995; Munshi, 2004; Bandiera and Rasul, 2006; Kremer and Miguel, 2007; Conley and Udry, 2010; Oster and Thornton, 2012; Cai, de Janvry, and Sadoulet, 2012; Bursztyn et al., 2012). In contrast to this learning channel where peers help to overcome information barriers, the presence of peer effects in trading networks creates *inefficiencies* by limiting trading opportunities.

The results up to this point suggest that adoption in social networks falls short of revealed demand and that this adoption gap is larger for farmers with fewer connections to suppliers. The immediate next question to ask is whether targeting is any more or less effective in networks.

As a first step in answering this, I use data on flooding during the past five years to generate a measure of expected returns for each farmer in the sample,

$$return_{ij} = \frac{\frac{1}{5} * \sum_{p=1}^{P_{ij}} \sum_{t=2008}^{2012} R(d_{ijpt}) * area_{ijp}}{\sum_{p=1}^{P_{ij}} area_{ijp}}. \tag{5}$$

The term d_{ijpt} represents the duration of flooding for farmer i in village j on plot p during year t, P_{ij} is the total number of plots cultivated, and the function $R(\cdot)$ is the expected agronomic return of Swarna-Sub1, relative to Swarna. The units of measurement of R are kilograms per hectare cultivated. I use estimates of R that were generated using data from a randomized experiment carried out in nearby villages during 2011. Specifically, I use nonparametric estimates of the treatment effect of Swarna-Sub1 as a function of flood duration.[18] The density of estimated returns for the sample of buyers is shown in the left panel of Figure 3. The right panel shows the density of deviations between estimated returns and village means. Variation in topography, and hence flood exposure, generates substantial variation in estimated returns both across and within villages.[19]

Following Galasso and Ravallion (2005), I first measure overall targeting performance using a measure that is equivalent to the correlation in a 2 x 2 contingency table. In particular, the measure

[18]See the middle panel of Figure 1 in Dar et al. (2013b) for the estimates.

[19]One caveat is that this approach measures *agronomic* returns rather than *economic* returns. Dar et al. (2013a) show that access to Swarna-Sub1 causes farmers to change several production practices, leading to increases in yield even during years when flooding does not occur. Increases in investment are generally larger for farmers that have more farmers in their peer group also cultivating the variety. Since networks favor adoption by peers, one advantage of farmer-to-farmer exchange is that it could facilitate these behavioral changes.

ϕ is

$$\phi = (a_b - a_{nb}) * \sqrt{\frac{s(1-s)}{a(1-a)}}, \tag{6}$$

where $a_b - a_{nb}$ is the difference in adoption rates between farmers with positive net benefits and those with negative or zero benefits, a is the overall adoption rate in the sample, and s is the share of farmers with positive net benefits. This measure offers two advantages. First, it is neutral to scale, thus allowing an easier comparison between targeting effectiveness in the two treatments where overall adoption varies widely. Second, it is related directly to the objective of a planner that can only observe returns due to flooding. That is, ϕ approaches one if the technology is perfectly allocated to all farmers with positive net benefits. Conversely, ϕ approaches -1 as adoption becomes more concentrated amongst farmers that do not benefit from the technology.

The results in Table 4 suggest some slight differences in targeting between the two experimental groups. Neither networks or door-to-door sales are particularly successful at concentrating adoption on farmers with positive expected returns. While the rates of adoption of farmers with positive expected gains are higher by 2.9 and 7.2 percentage points in networks and door-to-door sales, respectively, neither ϕ coefficient is statistically significant. However, social networks are somewhat effective at concentrating adoption amongst farmers with above-median returns. Focusing on the third row of the table, the adoption rate in networks is higher by 5 percentage points – i.e. an increase from 4% to 9% – for farmers with above-median expected returns. This targeting difference is also statistically significant. In contrast, the ϕ coefficient for above-median returns in door-to-door villages is less than half of the size and is not statistically significant.

While door-to-door sales tended to induce adoption by farmers experiencing severe flooding more recently, exchange in social networks induced adoption more by those experiencing flooding in the more distant past. I focus on areas flooded for 7-14 days because this is the range where Swarna-Sub1 has a statistically significant advantage in yield over Swarna (Dar et al., 2013b). As shown in the fourth row of Table 4, farmers with land flooded for 7-14 days during the 2011 floods were 11.4 percentage points more likely to adopt from the door-to-door salespersons. This targeting difference is statistically significant. In contrast, farmers experiencing flooding from 7-14 days during 2008 were over twice as likely to adopt in networks. Taken together, these results suggest that if anything, targeting is slightly more effective in networks.

As an additional measure of targeting effectiveness across the entire support of expected returns, Figure 4 shows nonparametric fan regressions of adoption on expected returns. Adoption in both treatment arms is positively correlated with expected returns. However, other than for the lowest values of estimated returns, the difference in adoption between networks and door-to-door sales is fairly constant. Following the binary targeting results from Table 4, Panel B uses the area weighted average flood duration on the farmer's land during the most recent flood in 2011. Adoption in the door-to-door villages shows a quadratic relationship with flood duration, where the maximum adoption occurs around 12 days. This contrasts with networks where adoption is not strongly correlated with 2011 flood intensity. The pattern is quite remarkable given that impact estimates show that agronomic returns during flooding are maximized at approximately 13 days.

The positive correlation between adoption and estimated returns and the quadratic relationship between adoption and flood intensity in 2011 rule out a story where misunderstanding the benefits of the technology drives the results. If farmers did not understand the benefits of the technology, then there would be no reason to expect adoption to be highest in areas exposed to heavy flooding. Farmers appear to have used a combination of available information and their past experiences with flooding, particularly during 2011, to base adoption decisions.

Regression results in Table 5 are consistent with the graphical results. The correlation between adoption and expected returns in networks alone is positive, but not quite statistically significant (column 1).[20] An increase from the 25th to 75th percentile in the expected returns distribution leads to an increase in the probability of adoption by 3 percentage points, or 43%. Adding door-to-door sales results in an increase in the correlation between returns and adoption, but the interaction term is not statistically significant. However, the overall effect in door-to-door sales is statistically significant. Moving from the 25th to 75th percentiles of the expected returns distribution in door-to-door sales leads to a 7.5 percentage point (19%) increase in adoption. The results in column 2 verify that the quadratic relationship between adoption and 2011 flood severity is highly statistically significant in door-to-door sales, but not in networks alone.

I consider the average return of adopters as the most direct measure of targeting effectiveness that maps directly to the calculation of efficiency losses. Figure 5 displays the densities of estimated returns for adopters across the different treatment groups. Visually, the distribution of estimated returns in network villages shifts to the right when compared to villages where door-to-door sales were made.

OLS regression estimates also suggest a moderate improvement in targeting by exchange in networks. The regression results in column 1 of Table 6 show that the average return of adopters in door-to-door sales is smaller by 40 kg per hectare, an approximate 23% decrease.[21] The effect is reasonably large, but not quite statistically significant (p=0.11). The average return across the entire sample of 124 kg per hectare can be taken as the return of adopters if the technology had been provided free of cost. Therefore, the average return of adopters in networks (the constant term) represents a 40% improvement over free distribution. This difference is statistically significant (p=0.029).

Focusing on column 2, very similar results are obtained when using a self-reported measure of

[20]Two sets of standard errors are used to make statistical inference. First, OLS standard errors are reported in parentheses. Second, bootstrapped standard errors that correct for expected returns being a regressor generated from a separate sample are reported in brackets. The issue is similar to two sample instrumental variables, where authors have calculated standard errors using either the covariance matrix in Murphy and Topel (1985), the delta method, or by bootstrapping (Inoue and Solon, 2010). Following Björklund and Jäntti (1997), I use the bootstrapping method. I draw 200 samples (clustered at the village level) from both the main estimation sample and the sample in Dar et al. (2013b). For each sample the nonparametric fan regression relating returns of Swarna-Sub1 to the duration of flooding is re-estimated and expected returns in the sample drawn from the estimation sample are re-calculated using this new mapping between flood duration and estimated returns. I then estimate the regression with these new values of estimated returns. Bootstrapped standard errors for each parameter are calculated as the standard deviations of the 200 estimates.

[21]Strata fixed effects are dropped in this regression in order to avoid absorbing selection effects.

flood risk for the plot where the new variety would be planted. Farmers were asked to assess on a scale from 1-10 how prone their Swarna-Sub1 plot is to flooding. The average value amongst adopters in networks was 5.25. The predicted decrease with door-to-door sales is 0.85, or 16.2%. The estimated effect with this separate measure is qualitatively similar, but also not statistically significant (p=0.11).

Columns 3 and 4 show that the results become more precisely estimated when dropping the two farmers that were provided Swarna-Sub1 free of cost from a local disaster management office. These results are largely consistent with the targeting differentials in Table 4. Namely, the estimated returns are slightly larger for adopters in networks because there is a larger mass of adopters with expected returns that exceed the median.

Taken together, the results on targeting suggest that improved targeting from exchange in networks will offset a small portion of the inefficiency due to the adoption gap. I next turn to a measure that combines these effects to estimate the overall losses in expected revenue.

4.2 Efficiency Loss

As a first step in quantifying the magnitude of the losses to farmers due to trading in networks, I define the gain in expected gross revenue for farmer i as $gain_i = adoption_i * return_i * hectares_i$, where $return_i$ is converted to monetary units by multiplying by the government supported output price of 12.5 Rs per kg. The total gain in expected revenue is then calculated by summing $gain_i$ across farmers. Following the results on peer effects, farmers in network villages are further split into two groups: farmers with one or zero suppliers sharing their surname, and farmers having the same surname as two or more suppliers.[22] I also present potential gains for a scenario where every farmer with positive expected gains adopts.[23] The aggregate gains are then re-weighted to ensure that the total number of observations is held constant across the groups.

Panel A of Figure 6 shows that the smallest gains from the technology were amongst the relatively less connected farmers that relied on trading in networks. The total gain in revenue in this group was 16,800 Rs. The gains were 32,800 Rs – or nearly twice as large – amongst the better connected farmers. The aggregate gain in revenue with door-to-door sales is 61,700 Rs. Therefore, approximately 35.6% of the revenue gap between less connected farmers in networks and farmers receiving door-to-door visits can be explained by limited connectivity. Averaging across all network villages, the total gain across all farmers was 23,000 Rs. Thus, the aggregate losses in short-term revenue due to trading in networks represent approximately 63% of the aggregate expected returns generated by door-to-door sales.

While making transactions costless by adding door-to-door sales increases expected revenue, there is still a large gap between door-to-door sales and the allocation where every farmer with positive returns adopts. This is driven by the fact that only 40% of farmers adopt in door-to-

[22]This threshold is used because the increased adoption in networks is strongest for farmers that have two or more suppliers with the same surname.

[23]Since cultivated area is not observed for non-adopters, it is imputed with average cultivated area of adopters when calculating the aggregate gain in expected revenue for the efficient scenario.

door villages even though around 84% of farmers are expected to gain from Swarna-Sub1. Not surprisingly, regardless of the exchange environment, some farmers are likely to wait until additional information about the technology comes available before making adoption decisions.

While there are clear losses from trading in networks, the absolute magnitude of the losses during the first year is small. In particular, the overall loss of 38,700 Rs represents approximately 1.14 USD per farmer. This results for two reasons. First, farmers only cultivate a small amount of the new variety during the first year. Second, the agronomic gains do not account for the changes in farm investment that are induced by the reduction in risk.

Focusing on investments, we show in a related paper that farmers with Swarna-Sub1 increase investment in inputs and cultivate more land during the second year of using the technology (Dar et al., 2013a). More specifically, farmers use more fertilizer and are more likely to utilize a more modern planting technique. Both behaviors are channels through which the technology enhances productivity in non-flood years. Overall, the reduced form effect of access to the technology on yield during normal years is 283 kg per ha, an approximate 10% increase. In addition, farmers with the technology increase *total* area cultivated by an average of 0.1 hectares. Finally, the amount of area cultivated with Swarna-Sub1 increases from 0.1 to 0.33 hectares during the second year.

I use these parameters to estimate gains from the technology over a two year period. The expected gains in revenue during the first year are set equal to the agronomic gains, i.e. those in Panel A of the figure. During the second year, the yield and area cultivated are assumed to increase according to the parameters above.[24] The important assumption underlying this calculation is that any additional adoption prior to the second year will be balanced across network and door-to-door villages.

The results in Panel B of Figure 6 show much larger gains in expected revenue over a two-year period. Specifically, the net gain with trading in networks is 220,300 Rs. When adding door-to-door sales, the total gains increase by 1.01 million Rs. The per-farmer increase in expected revenue represents approximately 30.73 USD. Thus, when considering all of the measurable benefits of the new technology, there are substantial economic losses to buyers from trading in social networks.

4.3 Heterogeneity

Are there some groups that are better off when trading occurs in networks, or is the gap between revealed demand and adoption in networks similar across the population of farmers? As shown in Table A4, the gain in adoption from adding door-to-door sales is smaller for lower caste (SC) farmers, smaller for the better educated, but larger for those cultivating Swarna – the variety that is otherwise identical to Swarna-Sub1. Put differently, networks are relatively more effective for the lowest caste farmers, the better educated, and farmers not cultivating Swarna.

One implication of this result is that introducing door-to-door sales increases efficiency, but has a smaller effect on equity because lower caste farmers are less likely to be induced to adopt with door-to-door sales. An affirmative action policy that introduces more formal buying opportunities

[24] Expected gains during the second year are discounted using a discount factor of 0.9.

at the same time as favoring lower castes in seed distribution could limit the negative effects on equity because the lower caste farmers would benefit more from peer-to-peer exchange if more of the initial adopters came from their caste group.

4.4 Prices as an allocation mechanism

I next use the random variation in prices across door-to-door villages to investigate whether higher prices are more effective at allocating the technology to farmers with the highest returns. I start by estimating the degree to which the demand elasticity is dependent upon estimated returns. I then show how the average return of the pool of adopters varies with prices. Understanding whether prices can be used to more effectively allocate the technology has implications for choosing the most efficient allocation mechanism.

Table 7 displays demand estimates. In this analysis, the 4.5% of farmers that adopted from peers in door-to-door villages are considered as non-adopters. The purpose of this is to ensure that the demand analysis reflects only responses to the random price offers. While the linear demand estimates in column 1 imply a demand elasticity of 0.84 when price is 12 Rs per kg, a perfectly inelastic demand curve can't be rejected. This results because power is limited to detect price effects because there is significant clustering in adoption and the number of villages is small.[25] The estimated differences in demand at the lower prices are large, as shown in column 2, but the estimates remain statistically imprecise.

Demand is significantly more responsive to price for farmers with larger expected returns. Turning to column 3, the specification includes interaction terms between the two price indicators and estimated returns. Door-to-door sales crowd in farmers with the highest expected returns only when prices are low. The increase in adoption induced by a decrease in price from 14 to 10 is expected to be higher by 16.8 percentage points when estimated returns are at the 75th percentile as compared to when returns are zero. The order of magnitude is similar for a decrease in price from 14 to 12, suggesting that demand at low prices is fairly inelastic across the entire population.[26]

Not surprisingly given these demand estimates, increasing price does not increase the average return of adopters. The regression estimates in columns 1 of Table 8 show that if anything, increasing price from 10 to 14 Rs leads to a *decline* in the average return of adopters. The results again become more precise when focusing on the sample of adopters from either peers or door-to-door sales. Focusing on column 3, the average return of adopters at all three price levels is not statistically distinguishable from 1.24 quintiles per ha, which is the overall average across all farmers in the sample. Thus, charging positive prices or increasing those prices does not clearly improve targeting outcomes above the outcome that would be achieved by free distribution. However, decentralized exchange through networks does produce a better targeted pool of adopters.

[25] Village-level prices were chosen to avoid perceptions of unfairness and to create a uniform price situation that more closely mimics real-world pricing. The loss in power was acceptable since estimates of demand were of secondary interest.

[26] The quadratic relationship between adoption and 2011 flood intensity is also much more prevalent at low prices (see Figure A1).

The policy implication of this finding is that in this context, higher prices are not an effective tool for targeting adoption to farmers with the highest expected benefits. While prices are theoretically desirable as a screening tool, this argument relies heavily on the equality of willingness to pay and ability to pay. There is indeed some evidence in the literature that higher prices are an effective tool for targeting the adoption of health products (Ashraf, Berry, and Shapiro, 2010; Cohen, Dupas, and Schaner, 2013). In contrast, Cohen and Dupas (2010) find that varying price subsidies has little effect on targeting of insecticide-treated bed nets in Kenya. The results in this paper are most consistent with this finding and thus add additional evidence suggesting that in some contexts prices may not always be an effective mechanism for screening.

5 Why is exchange in networks inefficient?

As a final exercise, I investigate potential explanations for the inefficiency of exchange in social networks. Section 5.1 presents additional evidence suggesting that transactions were limited to family members and close friends and that farmers failed to establish trading links with other farmers. Section 5.2 considers four alternative explanations: supply effects, quality differences, ineffective choice of suppliers, and increased salience of the technology. I find no evidence consistent with any of these alternative explanations.

5.1 Relationships limit trading

Evidence from the final survey with suppliers suggests that only close family and friends approached suppliers to obtain the technology. As displayed in Figure A2, the most popular reason given by suppliers for not selling or exchanging seeds is that nobody asked. There are two candidate explanations: networks failed to disseminate information on identities of suppliers and farmers knew the identities of suppliers, but failed to establish trading links. The first explanation is unlikely because suppliers were publicly identified at the beginning of the experiment when seeds were disseminated via lottery.

When asked, suppliers openly recognize that existing relationships were important for choosing trading partners. Specifically, 63% and 39% report that trading partners were close friends and close family, respectively. These responses are consistent with the results in Table 3 showing that relationships with suppliers are more important for adoption in networks. Interestingly, suppliers clearly expected buyers to initiate trades: only 8% of suppliers reported actively seeking buyers.

In addition to the survey evidence from suppliers, followup social network data indicate that buyers did not make greater contact with suppliers. While suppliers did become more central in the network, this is almost entirely due to additional stated links with other suppliers. To establish increased importance of suppliers, I estimate

$$degree_{ij} = \beta_0 + \beta_1 supplier_{ij} + \beta_2 baselinedegree_{ij} + x_{ij}\delta + \alpha_j + \varepsilon_{ij}, \tag{7}$$

where $degree_{ij}$ is the number of links of farmer i in village j during the follow-up survey, $supplier_{ij}$ is an indicator for suppliers, and x_{ij} is a vector of control variables. Regression results are reported in Table 9. In columns 1 and 2 degree is measured as the total number of links, regardless of which farmer reported the link. Being randomly selected as a supplier of the technology leads to one additional link, which represents an approximate 14% increase. Columns 3 and 4 show that increases in in-degree – the number of links reported by *other* farmers – account for approximately half of this effect.

I use a dyadic regression model of network formation to investigate whether links at followup were concentrated between buyers and suppliers. The baseline specification is

$$link_{ikj} = \beta_0 + \beta_1 onesupplier_{ikj} + \beta_2 twosupplier_{ikj} + \alpha_j + \varepsilon_{ikj}, \tag{8}$$

where $link_{ikj}$ is an indicator variable equal to one if farmer i stated that he would go to farmer k for sharing seeds, or if farmer k made the equivalent statement for farmer i. The variables $onesupplier_{ikj}$ and $twosupplier_{ikj}$ are indicators for buyer-supplier and supplier-supplier dyads, respectively.[27] Randomization generates exogenous variation in the likelihood that a dyad consists of one or two suppliers. Therefore, both β_1 and β_2 can be interpreted causally. If buyers make new contacts with suppliers, then β_1 should be positive and large.

Results in Table 10 show that most of the increase in the degree of suppliers is due to links between suppliers, not links between buyers and suppliers. Specifically, two farmers that were both selected as suppliers are 18.2 percentage points – or 48% – more likely to report being linked. An intuitive explanation for the result is that farmers cultivating the same variety are more likely to go to each other for sharing information, inputs, or even seeds. Conversely, the effect of one farmer in the dyad being a supplier is small.

Homophily – the tendency of farmers to interact with other farmers having similar characteristics – is present in the data. Turning to the coefficient estimates in column 2, farmers belonging to the same sub-caste are 3.5 percentage points – or 9% – more likely to be linked. Similarly, farmers sharing the same surname are 12.4 percentage points – or 32% – more likely to be linked.[28] As shown in Table A5, there is significant correlation between common surnames, sub-caste association, and geographic proximity. While networks are formed according to all of these characteristics, sharing a common surname is the most robust predictor of link formation.

Taken together, the results suggest that farmers did not invest effort in establishing trading relationships. Instead, trading was more likely to be limited to existing well-defined social groups. This tendency to transact only with close family and friends therefore explains some of the inability

[27]The symmetry requirement of dyadic regressions with undirected networks is met by definition since $w_{ikj} = w_{kij}$ for all $i \neq k$ (Fafchamps and Gubert, 2007). Also, standard errors in dyadic regressions must be adjusted for correlation of error terms across observations. Observations in the same dyad are obviously correlated, leading to artificially low OLS standard errors. Fafchamps and Gubert (2007) propose a covariance matrix that corrects for correlated observations within dyads. I instead cluster the standard errors at the village level, an approach that is taken in Attanasio et al. (2012). The advantage gained from this approach is that standard errors are robust to arbitrary correlation of error terms between dyads in the same village.

[28]Similar results were found in network data from southern India (Maertens and Barrett, 2012)

of trading in networks to meet demand.

5.2 Alternative Explanations

Supply effects and prices

One explanation of the ineffectiveness of trading in networks is that the quantity of seeds available to suppliers was insufficient to meet demand. If scarcity caused low adoption in networks, then having access to door-to-door sales would naturally lead to increased adoption.

The experiment was designed specifically to avoid any effects of scarcity. While only 25 kg of seed were initially provided to suppliers, the average quantity produced with this amount was approximately 1.8 tons – an amount sufficient to meet demand of approximately 180 farmers. As verification, Figure 7 shows the distribution of the differences between the Swarna-Sub1 harvest of suppliers during the first year and the total amount of Swarna-Sub1 planted in the village *after* door-to-door sales were made. The total amount planted by all farmers – including suppliers and other farmers outside the sample – was smaller than the total harvest in 40 of the 41 door-to-door villages. In other words, the door-to-door sales did not fill in a gap in supply that could not have been met by suppliers. The average amount harvested exceeded the amount planted by 14 times. Further, the amount harvested by suppliers was more than double the amount planted in all but two villages. Therefore, scarcity can not explain the results.

The limited number of seed transactions can not be explained by output being more valuable under alternative uses. In addition to being used as seeds, the harvest could be consumed or sold as grain for consumption. Since the eating quality of Swarna-Sub1 is identical to Swarna, and the average output price amongst farmers selling for consumption was 10.4 Rs per kg, output could have been sold or exchanged with other farmers without decreasing welfare of suppliers. These transfers were simply not made.

Price differences can not explain the results. In short, the technology was not under-priced in door-to-door sales. The price interval from 10 to 14 Rs covers the range of prices for transactions between farmers. Using the government's minimum support price of 12.5 Rs per kg as a conservative estimate of the price for direct exchanges, the average price of the technology across all farmer-to-farmer transactions was 12.4 Rs. The range of prices in door-to-door sales covers this value and therefore allows for the main effects to be estimated at a price that is equivalent to an average farmer-to-farmer transaction. Further, there is still significant demand at prices *above* the prices in farmer-to-farmer transactions, suggesting that welfare could have been improved if these transactions had been made.

Quality differences

Seed quality is the only potential product attribute that could have varied between networks and door-to-door sales. The seeds that were exchanged between farmers were second generation, i.e. output from the 2012 harvest, while the seeds sold in door-to-door sales were produced by a private seed company in a neighboring state. If farmers fail to produce quality seeds, this could potentially explain low adoption in networks.[29] Descriptively, 16% of suppliers reported that seed quality was the reason they chose not to exchange with others (Figure A2).[30]

I use two proxy measures for quality preferences to investigate whether networks only crowd out farmers with stronger preferences for quality seeds. First, approximately 42% of farmers purchased certified seeds from local government offices for the 2012 season.[31] Given the higher quality standards for certified seeds, this serves as a revealed preference measure of demand for seed quality. As a second measure, I use responses to a question asking whether more Swarna-Sub1 seeds would hypothetically be purchased when certified seeds are available at local government offices as compared to when seeds are only available from other villagers. I define those who indicated that a larger quantity of certified seeds would be procured as having a preference for seed quality. This group represents approximately half of the sample. If quality explains the results, then networks should crowd out farmers that either revealed or stated preferences for higher quality seeds.

There is no evidence that exchange in networks differentially crowded out farmers that preferred quality seeds. Table A6 shows that the correlation between the two measures of quality preference and adoption in networks is small and statistically insignificant. Further, adding door-to-door sales did not lead to significantly larger increases in adoption for these farmers. Overall, the results provide suggestive evidence that differential seed quality does not explain the results.

Selection of suppliers

Another possible explanation is that adoption is low in network villages because suppliers were not selected strategically. A different method commonly used by NGO's would involve a more targeted approach of selecting the most "progressive" or "lead" farmers as initial users of the new technology. In theory, this could result in greater adoption if the more central farmers are either better at demonstrating the technology or if other farmers look to them for the best varieties to cultivate.

I exploit the random selection of suppliers to investigate whether trading in networks is more effective when suppliers are relatively more important, where importance is defined by average degree. I partition villages into two groups according to the ratio of the average degree of suppliers to that of buyers. Villages where suppliers are more central are defined as those where this ratio is

[29] As an example, if seed is stored without proper drying, then germination ability and vigor of seedlings are negatively affected. Other practices that farmers can do to improve seed quality and purity are hand sorting to remove weeds and seeds of other varieties, winnowing to remove empty grains and chaff, and careful storage to avoid moisture absorption and damage by pests.

[30] Common reasons for poor seed quality were that drought affected production, seeds became wet during harvesting, and that Swarna-Sub1 was mixed with other rice varieties after harvesting.

[31] Seeds that are certified are produced following certain guidelines that ensure purity and higher quality.

greater than the sample median.[32] The regression specification is

$$adoption_{ij} = \beta_0 + \beta_1 door\ to\ door_j + \beta_2 important_j + \beta_3 door\ to\ door_j * important_j + x_{ij}\delta + \varepsilon_{ij}, \quad (9)$$

where $important_j$ is an indicator for villages where suppliers were relatively more important than buyers.[33]

The data rule out that networks were more effective at diffusing the technology when suppliers were more central. Focusing on column 1 of Table 11, the adoption rate in networks was 4.7 percentage points lower when suppliers were relatively more important. While the estimated coefficient is not statistically significant, large positive effects of importance of suppliers can effectively be ruled out, suggesting that the low adoption in networks is not due to the nonstrategic way in which suppliers were selected.[34] The results in column 2 show that there is no evidence that trading in networks was more effective at increasing adoption when suppliers were relatively larger farmers.

The aggregate demand revealed in door-to-door sales is however larger when suppliers are relatively more important. Returning to column 1, the predicted increase in adoption from adding door-to-door sales is 26 percentage points when suppliers are less important and 41 percentage points when suppliers are relatively more important. This approximate 60% increase in the effect is statistically significant at the 10% level. Two plausible explanations are that farmers learn more effectively from important farmers in the village or that farmers prefer to cultivate the same variety as these farmers. While recent work suggests that both channels are important (Cai et al., 2012; Bursztyn et al., 2012), separation of these channels is outside the scope of this paper.

Salience of the technology

Simply going door-to-door to sell Swarna-Sub1 could have increased awareness about the technology or sent a signal to farmers about its potential value. Increasing salience of the technology is therefore an additional possible explanation for the larger take up in door-to-door sales. Reminding farmers about the technology and its flood tolerance property during the midline survey served the purpose of reducing potential effects of increased salience.

To test salience effects, I take advantage of the fact that while door-to-door visits were only made to a randomly selected group of 15 farmers per village, it was well known that NGO staff were moving between houses to offer seeds. Houses in the sample villages are small and located in close proximity. For instance, there is an average of over two other houses in the sample within a 25 meter radius of each sample household. If door-to-door visits increased salience, then farmers that

[32] Randomization of village-level treatment was stratified by the degree ratio for purposes of investigating heterogeneity with respect to importance of suppliers. Using the ratio of average degrees carries one additional advantage since the social network in each village was only partially sampled. Chandrasekhar and Lewis (2011) show that the bias in average degree due to partial sampling of network data is proportional to the sampling rate. Using the ratio of average degrees should therefore minimize concerns regarding biases.

[33] The specification uses block fixed effects rather than strata fixed effects because randomization was stratified by block and the relative importance of suppliers.

[34] The 95% confidence interval for β_2 is (-0.122,0.028).

were outside of the sample would have become aware of the technology and increased purchases from suppliers.

There is no evidence of salience effects in the data. I use data from the final survey with suppliers to test whether suppliers in door-to-door villages transacted with a larger number of farmers from outside the sample. Table A7 shows that the effect of door-to-door sales on the number of trading partners from outside the sample is negative and statistically insignificant. Moreover, increases in the number of trading partners of over approximately 30% can be rejected. These results provide some evidence that salience effects are not an important driver of the large gap between revealed demand and adoption in networks.

Summary

Combining the analyses on other possible explanations, the lack of strong evidence for any of these explanations, along with the stronger peer effects in networks, suggest that barriers to exchanging with socially distant farmers represent one important explanation of the inability of decentralized trade in networks to meet demand. The pattern of existing relationships appears to prevent some transactions that otherwise would have been made if buyers and sellers had been anonymous.

6 Conclusions

Many products are exchanged directly between individuals that are connected in networks. Put differently, not all goods and services change hands in the textbook marketplace where the identities of buyers and sellers are irrelevant. This paper used a randomized experiment with a new agricultural technology in India to shed light on whether a system of exchanging the technology via networks is able to meet demand. The question is motivated by the idea that network structure may impede the ability of decentralized trade to allocate goods. If transacting with people from other social groups is costly or difficult, then this may present an important friction that limits the ability of buyers and sellers to come together to make transactions.

The results indicate strongly that trading in networks is inefficient. The rate of adoption of the technology was lower by 83% in networks. Trading patterns showed stronger peer effects when exchange occurred in networks. A farmer with a single additional supplier belonging to his sub-caste was approximately 50% more likely to adopt the technology when trading occurred in networks. Similarly, a farmer with one additional supplier having his surname was over twice as likely to adopt from peers. In contrast, being connected to suppliers did not have a positive effect on adoption in villages where farmers had the opportunity to purchase from door-to-door salespersons. However, targeting of farmers with higher expected returns to cultivating the technology was moderately more effective in social networks. In combination, the large decrease in adoption, combined with the only moderate improvement in targeting, cause the aggregate loss due to trading in networks to represent over 60% of the gains from exchange that were achieved with door-to-door sales.

The strong peer effects in networks are consistent with two types of trading frictions. First, there are likely non-trivial costs of interacting with farmers from other social groups. Second, if the flow of information between social groups is limited, then this could limit exchange between farmers from different groups. While information about the technology was provided to all farmers to limit the latter explanation, and five farmers demonstrated the variety in all villages, the experimental design does not fully rule out information as a barrier to exchange. Estimating the extent to which information campaigns can facilitate exchange in networks is an important area for future investigation.

The main contribution of this paper is the quantitative measure of the inefficiency of decentralized trade through networks. Such an exchange environment is common across a variety of situations, including contracting for inputs and trading of informal insurance between family and friends in developing countries. In contrast to a classic marketplace, social relationships are important for decentralized allocation of goods through social networks. Put simply, relationships matter in this exchange environment and this has negative consequences for those with limited connections to suppliers.

An important policy implication of the findings is that dissemination of new technologies using decentralized exchange through networks may be practically desirable, but it is inefficient. Introducing new seed varieties and relying on social networks for diffusion seems desirable in practice because it is an extremely low cost approach to diffusing a product. If the allocation achieved by exchange in networks is efficient, then networks could be relied upon as a sustainable method of ensuring efficient spread of technologies, particularly in the absence of anonymous markets. In terms of agricultural seed varieties, informal exchange between peers is the status quo in many remote areas where formal markets are absent. Introducing more formal channels for adoption can increase access and thus increase efficiency.

One caveat of this result is that the experiment was carried out over a single year, and thus it has little to say about the effectiveness of social networks in allocating the technology over a longer time horizon. Nonetheless, in an environment where farmers commonly learn about the benefits of new technologies from each other, there are clear benefits of having the technology demonstrated in a wide variety of conditions during the initial years. Further, there are short-run benefits to farmers from using a superior technology. My results suggest that taking a hands off approach by relying on trading in networks will leave significant demand unmet and therefore limit these short-run benefits from using the technology.

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Figures

Figure 1: Location of villages in Bhadrak district

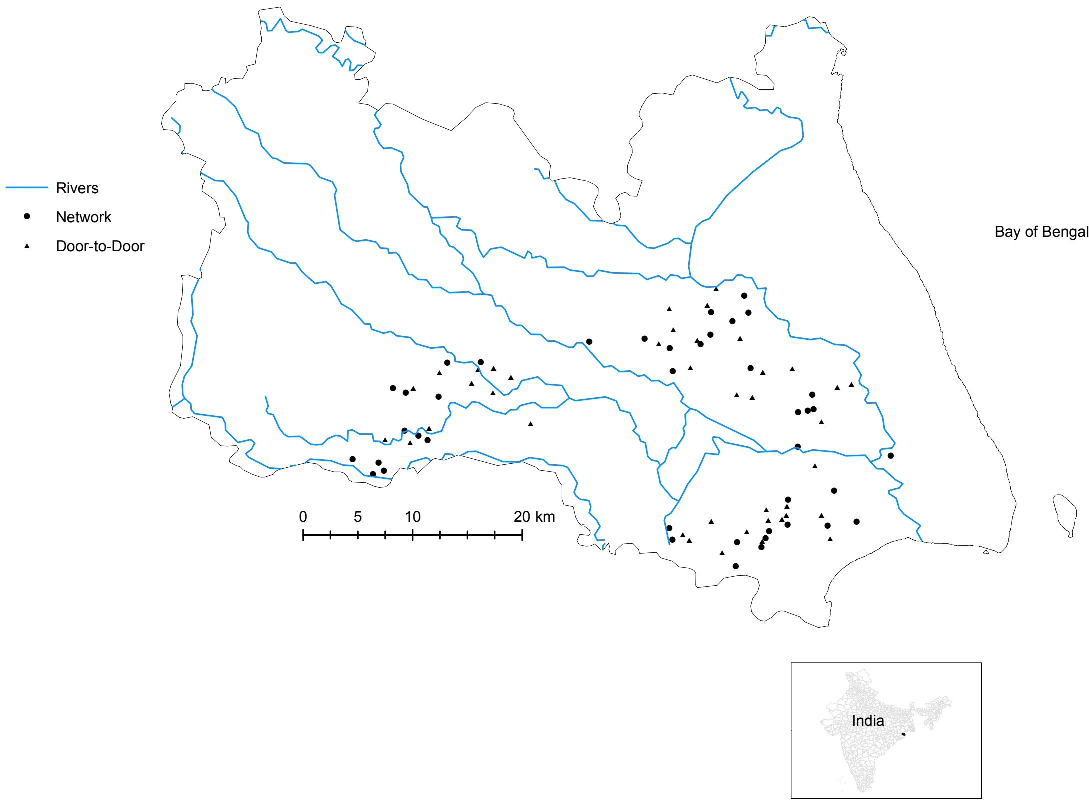
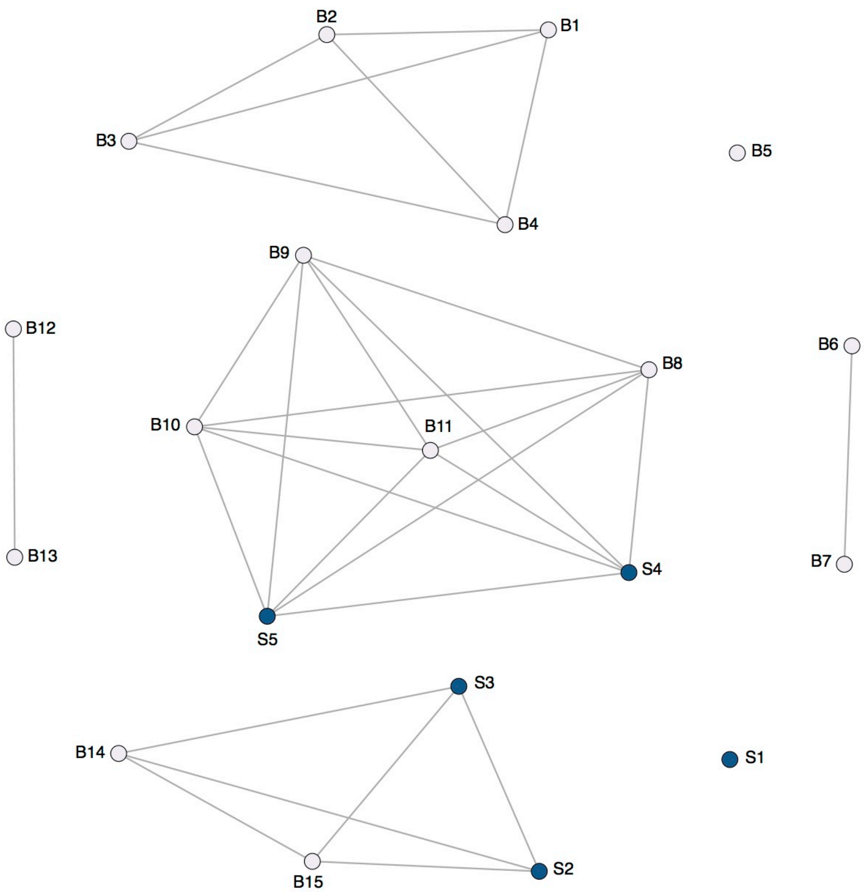
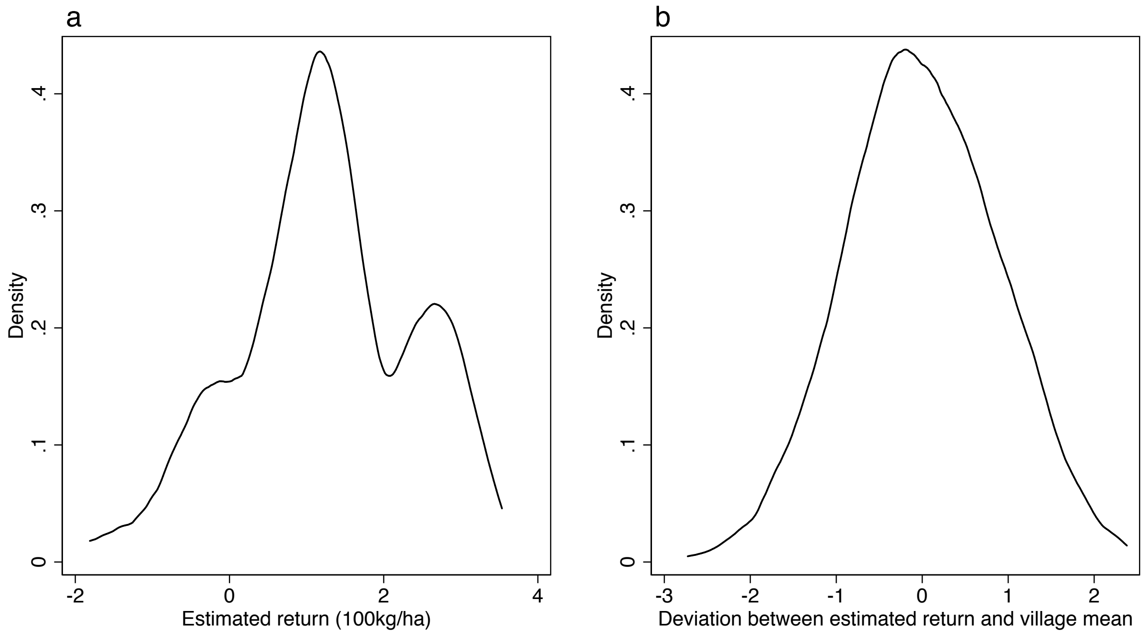


Figure 2: A Sample Network



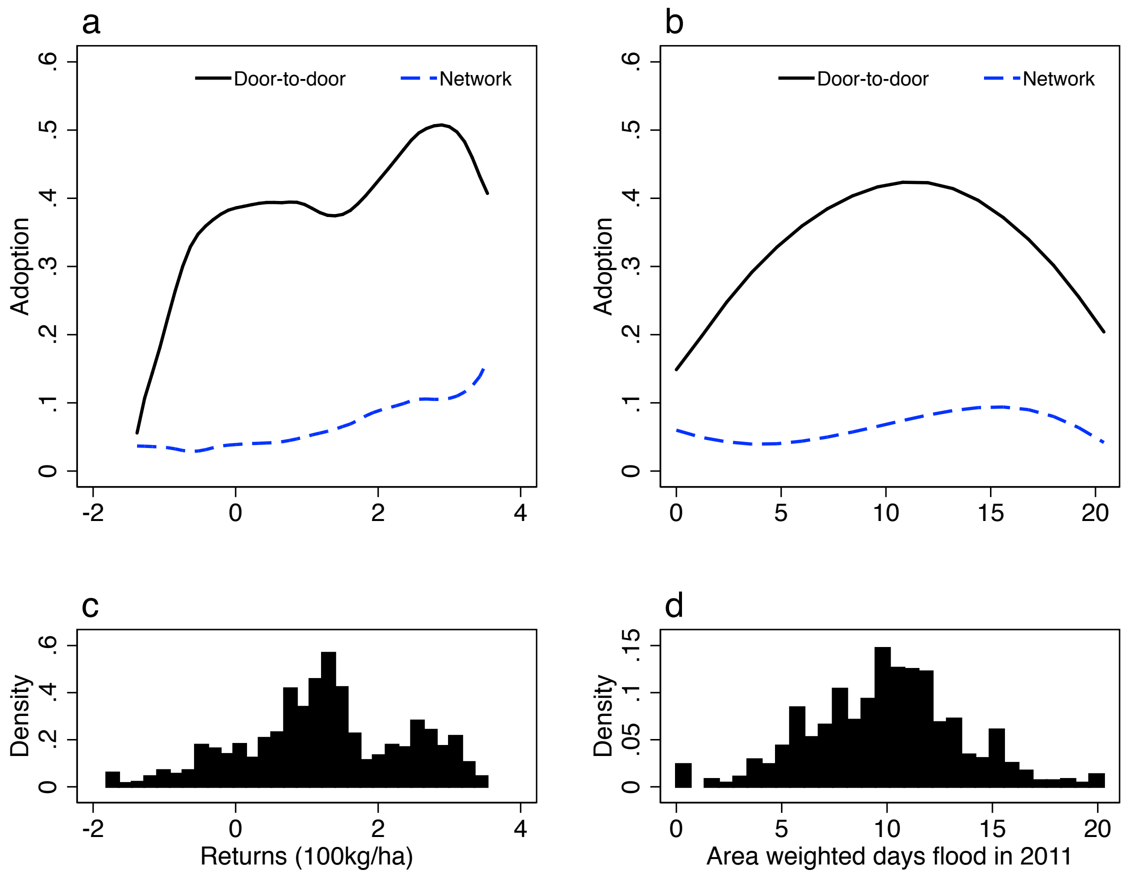
Notes: Figure displays a network diagram for one of the 82 sample villages. Dots (nodes) represent individual farmers and edges (lines) represent connections, where connections are assumed if the farmers share a common surname. The shaded nodes, marked S1-S5 are farmers that were randomly selected as suppliers. The unshaded nodes, marked B1-B15, were randomly selected as buyers.

Figure 3: Distribution of expected returns of Swarna-Sub1



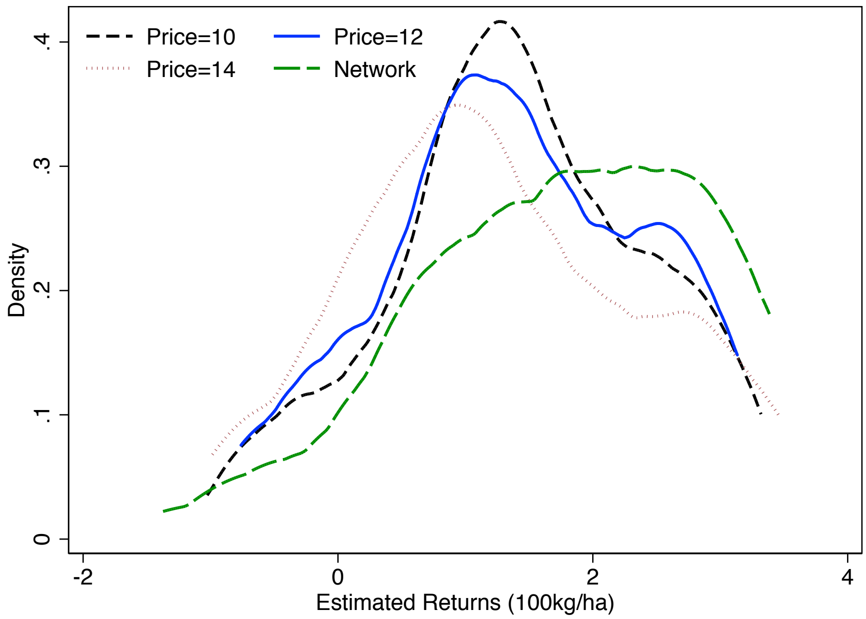
Notes: Figure shows densities of raw estimated returns (Panel A) and deviations between estimated returns and village averages (Panel B). Plot-level recall on flood duration and impact estimates in Dar et al. (2013b) were used to calculate expected returns for each farmer in the sample. The only source of variation in expected returns using this methodology is exposure of the farmers' land to flooding.

Figure 4: Relationship between estimated returns and adoption, by treatment



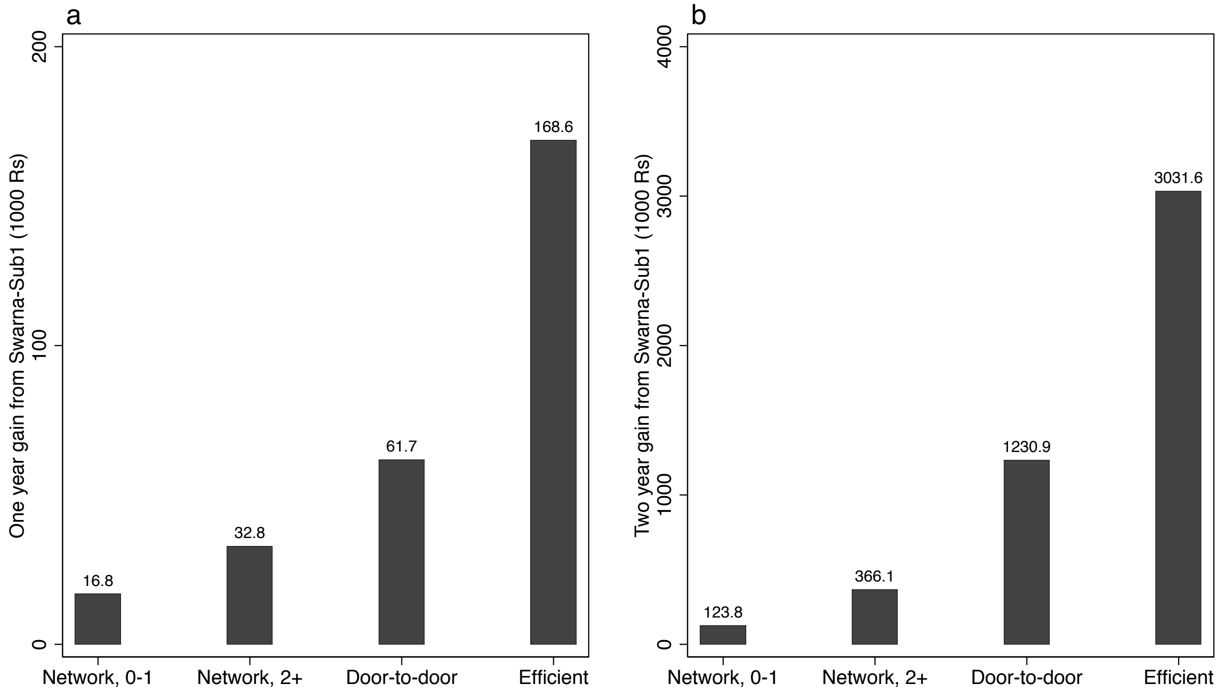
Notes: **(a)** Nonparametric fan regression of adoption on estimated returns. **(b)** Nonparametric fan regression of adoption on area weighted duration of flooding during 2011 floods. **(c)** Density of estimated returns. **(d)** Density of area weighted flood duration in 2011.

Figure 5: Densities of estimated returns of adopters, by treatment



Notes: Figure displays kernel densities of estimated returns, by treatment group. Densities are estimated only for adopters.

Figure 6: Losses in expected revenue due to trading in social networks



Notes: Height of bars is the total gain in expected revenue due to adoption of Swarna-Sub1. Bar labels are as follows. Network, 0-1 and Network, 2+ refer to farmers in network villages with 0-1 suppliers having the same surname and 2 or more suppliers having the same surname, respectively. Door-to-door is for door-to-door villages and Efficient refers to a scenario where every farmer with positive expected returns adopts. **(a)** Bars represent total gain in expected revenue due to Swarna-Sub1 *during the first year of cultivation*. Cultivated area for non-adopters is imputed with average cultivated area of adopters for computation of total gains from the efficient network. **(b)** Plot displays total gain in expected revenue *over two years*. The only gains in revenue during the first year are the agronomic gains due to improved flood tolerance, i..e those in Panel A. Following the results in Dar et al. (2013a), farmers are assumed to make changes in investment patterns during the second year of cultivation. First, farmers are assumed to cultivate 0.33 hectares with Swarna-Sub1. Second, average yield of Swarna-Sub1 is expected to increase by 283 kg per ha due to investments in fertilizer and modern planting techniques. Third, farmers increase total cutivated area by 0.1 ha. The expected gains in revenue during the second year are discounted using a discount factor of 0.9.

Figure 7: Distribution of difference between total harvest of Swarna-Sub1 in year 1 and amount planted in year 2 in door-to-door villages

Notes: Data are for door-to-door villages. Figure shows the kernel density of difference between total year 1 harvest of Swarna-Sub1 by suppliers and aggregate amount of Swarna-Sub1 planted in village during year 2 (in kg). The amount planted during year 2 includes amount purchased from door-to-door sales, amount obtained directly from suppliers (by all farmers, not only farmers in the sample), and amount planted by suppliers.

Tables

Table 1: Summary Statistics

	(1) Buyer	(2) Supplier	(3) p-value: (1)-(2)
Panel A: Farmer Level Statistics (N=1584)			
Rice acres in Kharif 2011	3.88	3.80	0.53
Acres flooded 4 days or less in Kharif 2011	1.25	1.25	0.94
Acres flooded 5 days or more in Kharif 2011	2.63	2.56	0.52
Acres grown with Swarna in Kharif 2011	1.95	1.88	0.34
Farmer is Scheduled Caste (SC)	0.20	0.18	0.46
Age of farmer	48.96	49.07	0.86
Farmer is lead farmer	0.09	0.11	0.29
Information degree	4.89	5.02	0.40
Sharing degree	4.19	4.37	0.21
Information in-degree	2.31	2.44	0.36
Sharing in-degree	1.94	2.16	0.08*
Panel B: Village Level Statistics (N=82)	Network	Door-to-door	
Total households	149.68	180.60	0.26
Total cultivators	89.41	117.33	0.13
Total Ag. laborers	46.80	55.42	0.46
Persons per household	5.84	5.90	0.64
Share Scheduled Caste (SC)	0.21	0.17	0.29
Literacy Rate	0.63	0.65	0.26
Approximate elevation (m)	5.29	4.28	0.19
Share of farmers not cultivating minikit	0.11	0.14	0.54
Estimated village harvest of Swarna-Sub1	1647.71	2066.22	0.20

Asterisks indicate statistical significance at the 1% ***, 5% **, and 10% * levels. Column 1 in Panel A is for buyers. Column 2 in Panel A is for suppliers. Column 1 in Panel B is for network villages, while column 2 in Panel B is for villages where door-to-door sales were made. All farmer level statistics are from the baseline survey in May-June 2012. Information degree is the number of links (undirected) where a link occurs if either farmer lists the other farmer as somebody with which they talk about rice farming. Sharing degree is the number of links (undirected) where a link occurs if either farmer lists the other farmer as somebody with which they would go to if they needed seeds, fertilizers, or other inputs. Information in-degree is the number of *other* farmers in the village naming this farmer as an information contact. Sharing in-degree is equally defined for sharing seeds, fertilizers, or other inputs. The first six village level variables are from the 2001 census. Approximate elevation is calculated at the center of the village using SRTM global elevation layer (resolution 250m). The share of farmers not cultivating the minikit and the estimated village harvest of Swarna-Sub1 are taken from the November-December 2012 follow-up with original recipients.

Table 2: Estimated difference between adoption in networks and demand revealed in door-to-door sales

	(1)	(2)	(3)
Door-to-door treatment	0.327***	0.328***	
	(0.042)	(0.041)	
Door-to-door treatment*(Price-12.4)	-0.026	-0.026	
	(0.024)	(0.024)	
Door-to-door and Price=10			0.385***
			(0.078)
Door-to-door and Price=12			0.351***
			(0.067)
Door-to-door and Price=14			0.280***
			(0.059)
Farmer is SC		-0.058	-0.057
		(0.041)	(0.040)
Farmer has BPL card		-0.056*	-0.056*
		(0.031)	(0.030)
Land cultivated in 2012		0.005	0.005
		(0.007)	(0.007)
Ag. cooperative member		-0.019	-0.019
		(0.023)	(0.023)
Swarna user in 2012		0.087***	0.086***
		(0.033)	(0.032)
Strata Fixed Effects	Yes	Yes	Yes
Mean of Dep Variable: Network	0.07	0.07	0.07
Number of Observations	1150	1134	1134
R squared	0.190	0.208	0.209

Dependent variable is 1 if farmer adopted Swarna-Sub1 for 2013 wet season. *Door-to-door treatment* is 1 for villages where farmers had the opportunity to obtain the technology from a door-to-door salesperson. Land cultivated in 2012 is measured in acres. Standard errors are clustered at the village level. Asterisks indicate statistical significance at the 1% ***, 5% **, and 10% * levels.

Table 3: Effects of social relationships with suppliers on adoption

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Door-to-door	0.346***	0.341***		0.332***	0.327***		0.367***	0.362***	
Treatment	(0.068)	(0.067)		(0.056)	(0.055)		(0.065)	(0.062)	
Door-to-door	0.002	-0.000	-0.026						
Treatment * Baseline links with suppliers	(0.033)	(0.033)	(0.031)						
Door-to-door	-0.003	-0.001	-0.002						
Treatment * Baseline degree	(0.016)	(0.016)	(0.013)						
Baseline links with	-0.007	-0.006	-0.004						
suppliers	(0.011)	(0.012)	(0.013)						
Baseline degree	0.005	0.003	0.003						
	(0.008)	(0.008)	(0.007)						
Door-to-door				-0.075*	-0.072*	-0.109**			
Treatment * Number suppliers w/ same surname				(0.043)	(0.042)	(0.045)			
Door-to-door				0.021	0.020	0.035**			
Treatment * Total number w/ same surname				(0.014)	(0.014)	(0.014)			
Number suppliers w/				0.035	0.027	0.074**			
same surname				(0.026)	(0.027)	(0.032)			
Total number w/ same				-0.008	-0.004	-0.023**			
surname				(0.008)	(0.009)	(0.009)			
Door-to-door							-0.056*	-0.058*	-0.053
Treatment * Number suppliers same sub-caste							(0.030)	(0.030)	(0.036)
Door-to-door							0.011	0.011	0.014
Treatment * Total number same sub-caste							(0.009)	(0.010)	(0.010)
Number suppliers							0.040*	0.024	0.037*
same sub-caste							(0.021)	(0.023)	(0.021)
Total number same							-0.010	-0.007	-0.011
sub-caste							(0.007)	(0.008)	(0.007)
Strata Fixed Effects	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No
Village Fixed Effects	No	No	Yes	No	No	Yes	No	No	Yes
Household controls	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Mean of Dep Variable: Network	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07
Number of Observations	1148	1132	1132	1135	1134	1134	1135	1134	1134
R squared	0.185	0.203	0.413	0.191	0.209	0.419	0.192	0.210	0.413

Dependent variable is 1 if farmer adopted Swarna-Sub1 for 2013 wet season. *Door-to-door treatment* is 1 for villages where farmers had the opportunity to obtain the technology from a door-to-door salesperson. Control variables are indicator for SC, indicator for holding BPL card, land area cultivated in 2012 wet season, indicator for member of agricultural cooperative, and indicator for Swarna cultivator in 2012 wet season. Standard errors are clustered at the village level. Asterisks indicate statistical significance at the 1% ***, 5% **, and 10% * levels.

Table 4: Targeting effectiveness of social networks and door-to-door sales

	Networks			Door-to-door sales		
	Targeting Differential	ϕ	p-value	Targeting Differential	ϕ	p-value
Returns greater than:						
0	0.029	0.043	0.302	0.072	0.052	0.212
25^{th} percentile	0.043	0.077	0.067	0.035	0.030	0.476
50^{th} percentile	0.050	0.100	0.017	0.042	0.042	0.312
Flooding 7-14 days during:						
2011	0.011	0.022	0.601	0.114	0.105	0.012
2009	0.015	0.030	0.485	0.009	0.009	0.834
2008	0.050	0.087	0.040	0.044	0.033	0.427

Notes: Targeting differential is the difference in adoption rates between farmers with estimated returns above and below the given threshold. For example, farmers with positive estimated returns are 2.9 percentage points more likely to adopt in social networks when compared to farmers with zero or negative returns. ϕ represents the phi coefficient from the relevant contingency table. Farmers that were flooded for 7-14 days were identified using area-weighted average flood duration collected during survey visits. P-values are calculated using the χ^2 statistic from the relevant 2x2 contingency table.

Table 5: Estimated correlation between expected returns and adoption

	(1)	(2)
Door-to-door treatment	0.300***	0.130
	(0.049)	(0.126)
	[0.065]	
Door-to-door treatment*Expected Returns	0.031	
	(0.025)	
	[0.024]	
Expected Returns	0.019	
	(0.013)	
	[0.014]	
2011 Area weighted days flood		0.007
		(0.011)
2011 Area weighted days flood^2		-0.000
		(0.000)
Door-to-door treatment*2011 Area weighted days flood		0.044**
		(0.018)
Door-to-door treatment*2011 Area weighted days flood^2		-0.002***
		(0.001)
Strata Fixed Effects	Yes	Yes
Household controls	Yes	Yes
Mean of Dep Variable: Network	0.07	0.07
Number of Observations	1134	1126
R squared	0.212	0.213

Dependent variable is 1 if farmer adopted Swarna-Sub1 for 2013 wet season. *Door-to-door treatment* is 1 for villages where farmers had the opportunity to obtain the technology from a door-to-door salesperson. Conventional standard errors that are clustered at the village level are reported in parentheses. Bootstrapped standard errors that correct for *Expected Returns* being a generated regressor are in brackets. Asterisks (pertaining to conventional standard errors) indicate statistical significance at the 1% ***, 5% **, and 10% * levels.

Table 6: Effect of exchange environment on the average return and self-reported flood risk of adopters

	All adopters		Adopters from peers or door-to-door	
	(1) Return	(2) Flood severity (1-10)	(3) Return	(4) Flood severity (1-10)
Door-to-door treatment	-0.402	-0.846	-0.542***	-0.979*
	(0.248)	(0.527)	(0.165)	(0.507)
Door-to-door treatment*(Price-12.4)	-0.037	-0.069	-0.037	-0.069
	(0.061)	(0.109)	(0.061)	(0.109)
Constant	1.742***	5.250***	1.882***	5.382***
	(0.219)	(0.464)	(0.117)	(0.442)
Mean of Dep Variable: Network	1.742	5.250	1.882	5.382
Number of Observations	266	267	264	265
R squared	0.018	0.029	0.031	0.037

Dependent variable in columns 1 and 3 is the expected return of Swarna-Sub1, measured in quintiles (1 quintile = 100kg) per hectare. Dependent variable in columns 2 and 4 is a subjective measure of the flood severity of the plot where Swarna-Sub1 was being planted. This variable ranges from 1-10 and was collected during the final follow-up survey with all potential buyers. *Door-to-door treatment* is 1 for villages where farmers had the opportunity to obtain the technology from a door-to-door salesperson. Standard errors are clustered at the village level. Asterisks indicate statistical significance at the 1% ***, 5% **, and 10% * levels.

Table 7: Estimated demand functions in door-to-door sales

	(1)	(2)	(3)
Expected Returns	0.048**	0.049**	-0.003
	(0.022)	(0.022)	(0.034)
	[0.024]	[0.023]	[0.027]
Price	-0.025		
	(0.024)		
	[0.031]		
Price = 12		0.101	-0.001
		(0.081)	(0.104)
		[0.096]	[0.154]
Price = 10		0.100	0.001
		(0.095)	(0.121)
		[0.126]	[0.211]
Price=12*Expected Returns			0.086*
			(0.049)
			[0.051]
Price=10*Expected Returns			0.079*
			(0.047)
			[0.062]
Strata Fixed Effects	Yes	Yes	Yes
Household controls	Yes	Yes	Yes
Mean of Dep Variable	0.362	0.362	0.362
Number of Observations	569	569	569
R squared	0.116	0.118	0.125

Data are limited to 41 villages where door-to-door sales were made. Dependent variable is 1 if farmer adopted Swarna-Sub1 for 2013 wet season. Conventional standard errors that are clustered at the village level are reported in parentheses. Bootstrapped standard errors that correct for *Expected Returns* being a generated regressor are in brackets. Asterisks (pertaining to conventional standard errors) indicate statistical significance at the 1% ***, 5% **, and 10% * levels.

Table 8: Effects of random price variation on the screening of adopters

	All adopters		Adopters from peers or door-to-door	
	(1)	(2)	(3)	(4)
	Return	Flood severity (1-10)	Return	Flood severity (1-10)
Price=10	-0.323	-0.850	-0.464***	-0.982*
	(0.250)	(0.528)	(0.167)	(0.508)
Price=12	-0.367	-0.485	-0.507**	-0.617
	(0.284)	(0.693)	(0.215)	(0.679)
Price=14	-0.472	-1.150*	-0.612**	-1.282**
	(0.311)	(0.589)	(0.249)	(0.572)
Constant	1.742***	5.250***	1.882***	5.382***
	(0.220)	(0.464)	(0.118)	(0.442)
Mean of Dep Variable: Network	1.742	5.250	1.882	5.382
Number of Observations	266	267	264	265
R squared	0.018	0.047	0.032	0.054

Dependent variable in columns 1 and 3 is the expected return of Swarna-Sub1, measured in quintiles (1 quintile = 100kg) per hectare. Dependent variable in columns 2 and 4 is a subjective measure of the flood severity of the plot where Swarna-Sub1 was being planted. This variable ranges from 1-10 and was collected during the final follow-up survey with all potential buyers. *Door-to-door treatment* is 1 for villages where farmers had the opportunity to obtain the technology from a door-to-door salesperson. Standard errors are clustered at the village level. Asterisks indicate statistical significance at the 1% ***, 5% **, and 10% * levels.

Table 9: Estimated effect of being selected as a supplier on follow-up social network status

	Sharing degree		Sharing in-degree	
	(1)	(2)	(3)	(4)
Supplier	0.998***	1.003***	0.497**	0.473*
	(0.227)	(0.221)	(0.246)	(0.242)
Baseline sharing degree	0.147***	0.148***		
	(0.052)	(0.050)		
Baseline sharing in-degree			0.181***	0.180***
			(0.067)	(0.068)
Farmer is SC		-0.627		-0.872***
		(0.379)		(0.325)
Land cultivated in 2012		0.108**		0.046
		(0.044)		(0.039)
Farmer has BPL card		0.015		-0.004
		(0.156)		(0.162)
Village Fixed Effects	Yes	Yes	Yes	Yes
Mean of Dep Variable	7.28	7.29	3.92	3.92
Number of Observations	1544	1542	1547	1545
R squared	0.341	0.347	0.198	0.204

Asterisks indicate statistical significance at the 1% ***, 5% **, and 10% * levels. Standard errors are clustered at the village level. Degree is the total number of links reported by either the surveyed farmer or other farmers in her village. The in-degree is the total number of *other* farmers in the village that reported a contact with the farmer. Land cultivated in 2012 is measured in acres

Table 10: Dyadic regressions of network formation at follow-up

	(1)	(2)
One farmer is seller	0.013	0.022
	(0.014)	(0.015)
Both farmers are sellers	0.182***	0.207***
	(0.030)	(0.035)
Same sub-caste		0.035*
		(0.018)
Same surname		0.124***
		(0.018)
Houses within 25 m		0.006
		(0.017)
Plots within 100 m		0.009
		(0.015)
Village Fixed Effects	Yes	Yes
Mean of Dep Variable	0.380	0.385
Number of Observations	27633	24837
R squared	0.073	0.088

Data are from follow-up social network survey of all farmers. Dependent variable is 1 if either farmer in the dyad indicated a sharing link (i.e. an undirected network). Standard errors are clustered at the village level. Asterisks indicate statistical significance at the 1% ***, 5% **, and 10% * levels.

Table 11: Heterogeneous effects according to baseline importance of suppliers

	(1)	(2)
Door-to-door treatment	0.256***	0.309***
	(0.063)	(0.065)
1 if supplier degree / buyer degree > median	-0.047	
	(0.038)	
Door-to-door treatment*1 if seller degree / buyer degree > median	0.157*	
	(0.088)	
1 if supplier size / buyer size > median		-0.057
		(0.036)
Door-to-door treatment*1 if seller size / buyer size > median		0.063
		(0.089)
Farmer is SC	-0.071*	-0.058
	(0.041)	(0.038)
Farmer has BPL card	-0.061*	-0.067**
	(0.032)	(0.033)
Land cultivated in 2012	0.004	0.005
	(0.007)	(0.007)
Ag. cooperative member	-0.025	-0.019
	(0.024)	(0.024)
Swarna user in 2012	0.074**	0.078**
	(0.032)	(0.033)
Block Fixed Effects	Yes	Yes
Mean of Dep Variable: Network	0.07	0.07
Number of Observations	1134	1119
R squared	0.199	0.195

Dependent variable is 1 if farmer adopted Swarna-Sub1 for 2013 wet season. 1 if supplier / buyer degree > median is a village-level indicator for ratio of average sharing degree of suppliers to average sharing degree of buyers being larger than the median. 1 if supplier size / buyer size > median is a similar indicator, but using average land cultivated during 2012 rather than sharing degree. *Door-to-door treatment* is 1 for villages where farmers had the opportunity to obtain the technology from a door-to-door salesperson. Land cultivated in 2012 is measured in acres. Standard errors are clustered at the village level. Asterisks indicate statistical significance at the 1% ***, 5% **, and 10% * levels.

Appendix

Derivation of expected returns of adopters

The expected return of adopters in social networks is $E(R|R+u-c > v+\underline{c})$. Using properties of the multivariate normal distribution, this is written as

$$E(R|R+u-c > v+\underline{c}) = \mu_R + \sigma_R\tilde{\rho}E\left(\frac{R+u-c-\mu_r+\mu_c}{\sqrt{\sigma_R^2+\sigma_c^2+\sigma_u^2-2\rho\sigma_c\sigma_R}}\middle| R+u-c > v+\underline{c}\right), \quad \text{(A1)}$$

where $\tilde{\rho}$ is the correlation between R and $R+u-c$. This expression can be rewritten as

$$\begin{aligned} E(R|R+u-c > v+\underline{c}) =& \mu_R + \frac{\sigma_R}{\sqrt{\sigma_R^2+\sigma_c^2+\sigma_u^2-2\rho\sigma_c\sigma_R}}\tilde{\rho}E(R+u-c|R+u-c > v+\underline{c}) \\ & - \frac{\tilde{\rho}\sigma_R(\mu_R-\mu_c)}{\sqrt{\sigma_R^2+\sigma_c^2+\sigma_u^2-2\rho\sigma_c\sigma_R}}. \end{aligned} \quad \text{(A2)}$$

Given that $R+u-c$ is distributed normally, $E(R+u-c|R+u-c > v+\underline{c})$ can be written as

$$\mu_R - \mu_c + \sqrt{\sigma_R^2+\sigma_u^2+\sigma_c^2-2\rho\sigma_R\sigma_c} * M\left(\frac{v+\underline{c}-\mu_R+\mu_c}{\sqrt{\sigma_R^2+\sigma_u^2+\sigma_c^2-2\rho\sigma_R\sigma_c}}\right), \quad \text{(A3)}$$

where $M(z) = \frac{\phi(z)}{1-\Phi(z)}$ is the inverse Mill's ratio. Reinserting this into Equation A2 gives

$$E(R|R+u-c > v+\underline{c}) = \mu_R + \tilde{\rho}\sigma_R M\left(\frac{v+\underline{c}-\mu_R+\mu_c}{\sqrt{\sigma_R^2+\sigma_u^2+\sigma_c^2-2\rho\sigma_R\sigma_c}}\right). \quad \text{(A4)}$$

Since $\tilde{\rho}$ is the correlation between R and $R+u-c$, $\tilde{\rho}$ simplifies to

$$\tilde{\rho} = \frac{\sigma_R - \rho\sigma_c}{\sqrt{\sigma_R^2+\sigma_u^2+\sigma_c^2-2\rho\sigma_R\sigma_c}}. \quad \text{(A5)}$$

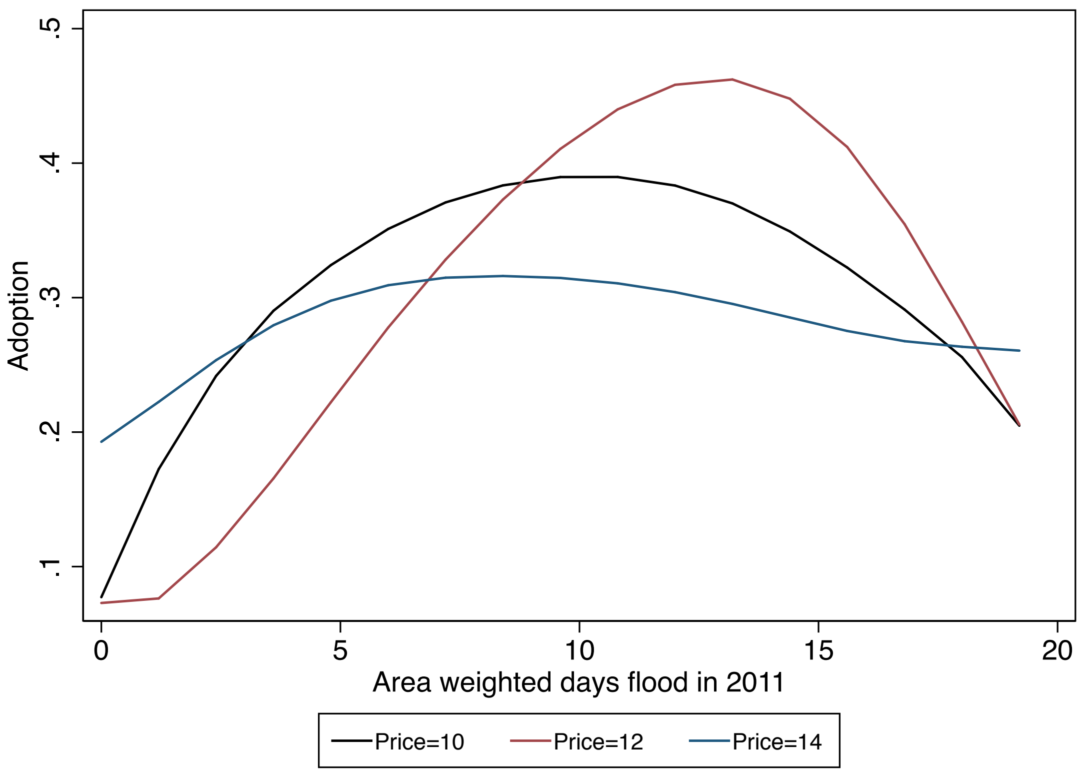
Combining Equations A4 and A5,

$$E(R|R+u-c > v) = \mu_R + \frac{\sigma_R(\sigma_R-\rho\sigma_c)}{\sqrt{\sigma_R^2+\sigma_u^2+\sigma_c^2-2\rho\sigma_R\sigma_c}} * M\left(\frac{v+\underline{c}-\mu_R+\mu_c}{\sqrt{\sigma_R^2+\sigma_u^2+\sigma_c^2-2\rho\sigma_R\sigma_c}}\right). \quad \text{(A6)}$$

This establishes the result. A similar derivation is used to verify the formula for $E(R|R+u > v)$ in the main text.

Appendix Figures and Tables

Figure A1: Nonparametric relationship between flooding intensity in 2011 and adoption for 3 different price levels



Notes: Figure shows estimates from nonparametric fan regressions of adoption on area weighted days flood in 2011. Data are limited to door-to-door villages.

Table A1: Robustness of estimated peer effects to different subsamples and nonlinear model

	Variation in adoption		Drop Dhamanagar block		Full sample	
	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) Probit	(6) Probit
Door-to-door Treatment	0.268*** (0.080)	0.206** (0.095)	0.316*** (0.069)	0.328*** (0.085)	0.349*** (0.055)	0.357*** (0.059)
Door-to-door Treatment * Number suppliers w/ same surname	-0.159** (0.061)		-0.155*** (0.052)		-0.076** (0.036)	
Door-to-door Treatment * Total number w/ same surname	0.034** (0.016)		0.048*** (0.016)		0.021 (0.014)	
Number suppliers w/ same surname	0.110** (0.053)		0.061 (0.038)		0.027* (0.016)	
Total number w/ same surname	-0.015 (0.011)		-0.017 (0.011)		-0.010 (0.013)	
Door-to-door Treatment * Number suppliers same sub-caste		-0.120** (0.045)		-0.092** (0.035)		-0.063** (0.027)
Door-to-door Treatment * Total number same sub-caste		0.031* (0.017)		0.026*** (0.010)		0.017 (0.012)
Number suppliers same sub-caste		0.075* (0.041)		0.053** (0.023)		0.024* (0.013)
Total number same sub-caste		-0.024 (0.017)		-0.018** (0.007)		-0.014 (0.012)
Strata Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Household controls	Yes	Yes	Yes	Yes	Yes	Yes
Mean of Dep Variable: Network	0.18	0.18	0.09	0.09	0.07	0.07
Number of Observations	744	744	800	800	1134	1134
R squared	0.120	0.118	0.204	0.197		

Data in columns 1 and 2 are limited to villages where at least one farmer adopted Swarna-Sub1 for 2013 wet season. Data in columns 3 and 4 are for villages in Chandabali and Tihidi blocks. Dependent variable in all columns is 1 if farmer adopted Swarna-Sub1 for 2013 wet season. Columns 3 and 4 present marginal effects calculated from probit coefficients, along with standard errors calculated from the delta method. *Door-to-door Treatment* is 1 for villages where farmers could either obtain the technology from door-to-door sales or from peer suppliers. Control variables are indicator for SC, indicator for holding BPL card, land area cultivated in 2012 wet season, indicator for member of agricultural cooperative, and indicator for Swarna cultivator in 2012 wet season. Standard errors are clustered at the village level. Asterisks indicate statistical significance at the 1% ***, 5% **, and 10% * levels.

Table A2: Robustness of estimated peer effects to measurement of peer influence in shares rather than levels

	(1)	(2)	(3)	(4)	(5)	(6)
Door-to-door	0.435^{***}	0.439^{***}		0.435^{***}	0.439^{***}	
Treatment	(0.049)	(0.047)		(0.057)	(0.054)	
Door-to-door	-0.364^{***}	-0.373^{***}	-0.346^{***}			
Treatment * Share of same surname that are suppliers	(0.115)	(0.112)	(0.130)			
Share of same	0.207^{**}	0.206^{**}	0.202^{**}			
surname that are suppliers	(0.079)	(0.080)	(0.095)			
Door-to-door				-0.384^{**}	-0.398^{**}	-0.411^{**}
Treatment * Share of same sub-caste that are suppliers				(0.172)	(0.167)	(0.184)
Share of same				0.175^{**}	0.125	0.174^{*}
sub-caste that are suppliers				(0.082)	(0.090)	(0.099)
Strata Fixed Effects	Yes	Yes	No	Yes	Yes	No
Village Fixed Effects	No	No	Yes	No	No	Yes
Household controls	No	Yes	Yes	No	Yes	Yes
Mean of Dep Variable: Network	0.07	0.07	0.07	0.07	0.07	0.07
Number of Observations	1009	1008	1008	1056	1055	1055
R squared	0.202	0.220	0.435	0.199	0.218	0.434

Dependent variable in all columns is 1 if farmer adopted Swarna-Sub1 for 2013 wet season. *Door-to-door Treatment* is 1 for villages where farmers could either obtain the technology from door-to-door sales or from peer suppliers. Control variables are indicator for SC, indicator for holding BPL card, land area cultivated in 2012 wet season, indicator for member of agricultural cooperative, and indicator for Swarna cultivator in 2012 wet season. Standard errors are clustered at the village level. Asterisks indicate statistical significance at the 1% ***, 5% **, and 10% * levels.

Table A3: Estimated peer effects using stated social networks at followup

	(1)	(2)
Door-to-door	0.316^{***}	
Treatment	(0.066)	
Door-to-door	0.009	-0.019
Treatment * Followup links with suppliers	(0.027)	(0.021)
Door-to-door	0.001	0.004
Treatment * Followup degree	(0.010)	(0.008)
Followup links with	0.002	0.014
suppliers	(0.015)	(0.013)
Followup degree	0.006	0.001
	(0.005)	(0.003)
Strata Fixed Effects	Yes	No
Village Fixed Effects	No	Yes
Household controls	Yes	Yes
Mean of Dep Variable: Network	0.07	0.07
Number of Observations	1134	1134
R squared	0.207	0.413

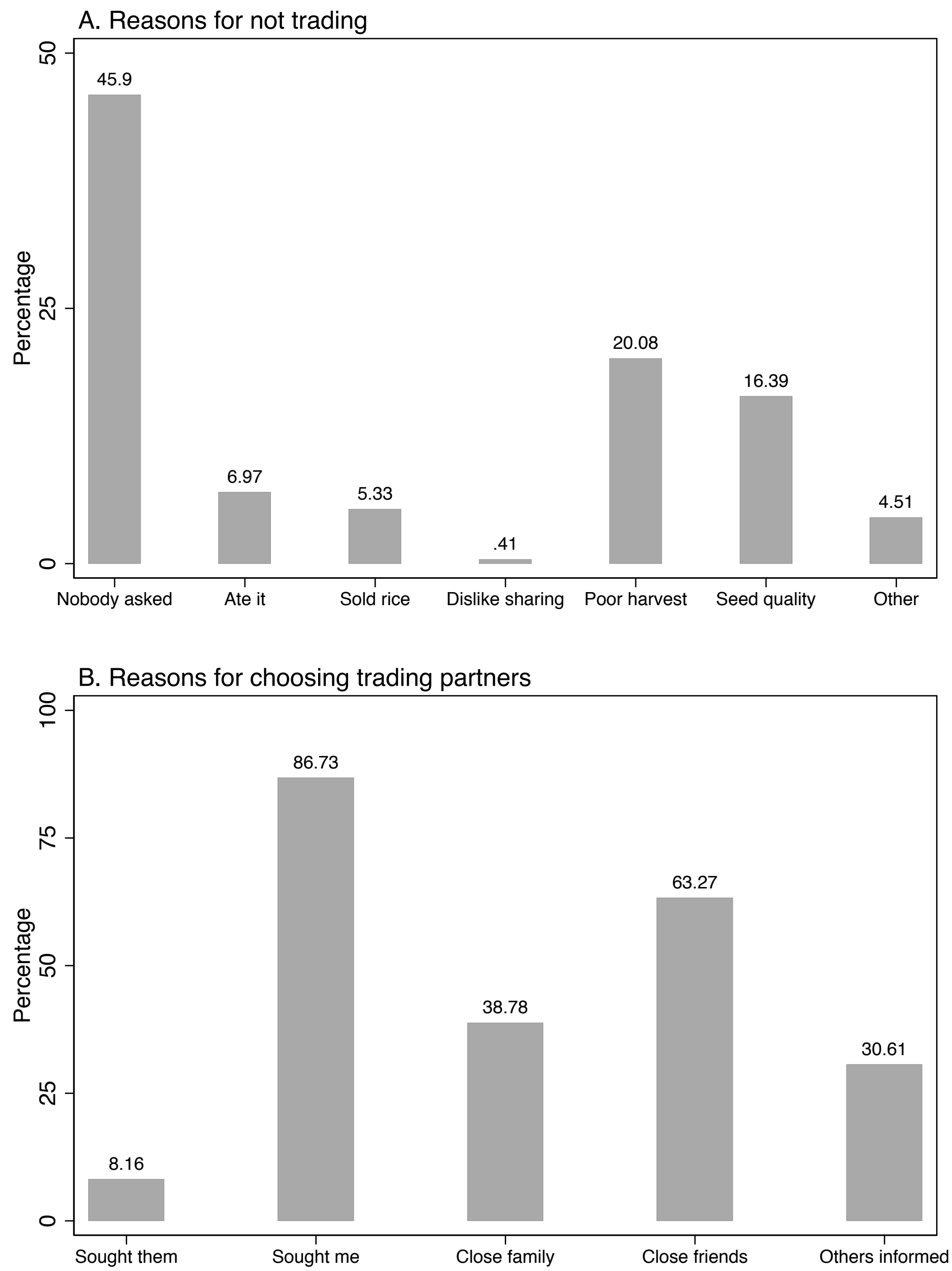
Dependent variable is 1 if farmer adopted Swarna-Sub1 for 2013 wet season. *Door-to-door Treatment* is 1 for villages where farmers could either obtain the technology from door-to-door sales or from peer suppliers. Control variables are indicator for SC, indicator for holding BPL card, land area cultivated in 2012 wet season, indicator for member of agricultural cooperative, and indicator for Swarna cultivator in 2012 wet season. Standard errors are clustered at the village level. Asterisks indicate statistical significance at the 1% ***, 5% **, and 10% * levels.

Table A4: Heterogeneity in adoption effects by household characteristics

	(1)
Door-to-door treatment	0.409***
	(0.093)
Farmer is SC	0.016
	(0.044)
Farmer has BPL card	-0.014
	(0.033)
Land cultivated in 2012	0.007
	(0.006)
Ag. cooperative member	-0.020
	(0.027)
Swarna user in 2012	0.032
	(0.026)
Education above primary	-0.006
	(0.021)
Door-to-door treatment interacted with:	
Farmer is SC	-0.197**
	(0.076)
Farmer has BPL card	-0.103
	(0.065)
Land cultivated in 2012	-0.001
	(0.014)
Ag. cooperative member	0.009
	(0.046)
Swarna user in 2012	0.115*
	(0.068)
Education above primary	-0.114**
	(0.048)
Strata Fixed Effects	Yes
Mean of Dep Variable: Network	0.07
Number of Observations	1131
R squared	0.224

Dependent variable is 1 if farmer adopted Swarna-Sub1 for 2013 wet season. *Door-to-door Treatment* is 1 for villages where farmers could either obtain the technology from door-to-door sales or from peer suppliers. Standard errors are clustered at the village level. Asterisks indicate statistical significance at the 1% ***, 5% **, and 10% * levels.

Figure A2: Stated motivation for sharing Swarna-Sub1 by suppliers



Notes: Top panel displays distribution of stated reasons why suppliers chose not to sell, exchange or gift seeds. For instance, 45.9% of farmers that did not transfer seeds indicated it was because nobody came to them asking for seeds. Bottom panel displays distribution of how trading partners were chosen by suppliers that chose to exchange with other farmers. For instance, 86.73% of farmers that exchanged indicated that they were sought out by other farmers.

Table A5: Dyadic regressions of link formation at follow-up

	(1)	(2)	(3)	(4)	(5)
Same sub-caste	0.079^{***}				0.036^{**}
	(0.016)				(0.018)
Same surname		0.136^{***}			0.127^{***}
		(0.015)			(0.017)
Houses within 25 m			0.043^{***}		-0.002
			(0.015)		(0.017)
Plots within 100 m				0.021	0.006
				(0.014)	(0.014)
Village Fixed Effects	Yes	Yes	Yes	Yes	Yes
Mean of Dep Variable	0.380	0.380	0.380	0.384	0.385
Number of Observations	27633	27633	27427	24979	24837
R squared	0.071	0.080	0.066	0.066	0.080

Data are from follow-up social network survey of all farmers. Dependent variable is 1 if either farmer in the dyad indicated a sharing link (i.e. an undirected network). Standard errors are clustered at the village level. Asterisks indicate statistical significance at the 1% ***, 5% **, and 10% * levels.

Table A6: Heterogeneity of adoption effect according to preferences for quality seeds

	(1)	(2)
Door-to-door treatment	0.352***	0.376***
	(0.051)	(0.050)
Door-to-door treatment*Seed buyer in 2012	-0.036	
	(0.050)	
Seed buyer in 2012	-0.021	
	(0.024)	
Door-to-door treatment*Quality preference		-0.078
		(0.051)
Quality preference		-0.012
		(0.027)
Farmer is SC	-0.063	-0.054
	(0.041)	(0.039)
Farmer has BPL card	-0.055*	-0.057*
	(0.031)	(0.030)
Land cultivated in 2012	0.004	0.005
	(0.007)	(0.007)
Ag. cooperative member	-0.016	-0.007
	(0.024)	(0.023)
Swarna user in 2012	0.101***	0.091***
	(0.032)	(0.033)
Strata Fixed Effects	Yes	Yes
Mean of Dep Variable: Network	0.07	0.07
Number of Observations	1134	1134
R squared	0.206	0.209

Dependent variable is 1 if farmer adopted Swarna-Sub1 for 2013 wet season. *Door-to-door Treatment* is 1 for villages where farmers could either obtain the technology from door-to-door sales or from peer suppliers. Standard errors are clustered at the village level. Asterisks indicate statistical significance at the 1% ***, 5% **, and 10% * levels.

Table A7: Effect of door-to-door sales on sales and exchanges to farmers outside the sample

	(1)	(2)
Door-to-door treatment	-0.057	-0.047
	(0.075)	(0.073)
Swarna-Sub1 harvest (100 kg)		0.056^{***}
		(0.018)
Farmer is SC		0.268^{**}
		(0.115)
Age of farmer		-0.002
		(0.002)
Farmer has BPL card		0.034
		(0.067)
Education above primary		-0.046
		(0.075)
Strata Fixed Effects	Yes	Yes
Mean of Dep Variable: Network	0.29	0.29
Number of Observations	394	393
R squared	0.024	0.101

Data are from the final survey with suppliers. Dependent variable is the number of farmers from outside the sample that a given supplier sold or exchanged seeds with. *Door-to-door treatment* is 1 for villages where farmers (in the sample) could either obtain the technology from door-to-door sales or from peer suppliers. Standard errors are clustered at the village level. Asterisks indicate statistical significance at the 1% ***, 5% **, and 10% * levels.