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

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Abstract

This paper studies whether trading in social networks is efficient. 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. The findings show that trading in networks results in significant under-adoption when compared to door-to-door sales. Specifically, the rate of adoption was 83% lower when trading occurred only in networks. Using variation across the sample in estimated returns of the technology, I show that the efficiency loss due to networked trade represents 63% of the expected gains from adoption that were achieved in the door-to-door sales. The costs of making links with farmers from different peer 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. The results suggest that the costs of interacting with suppliers from different social groups make exchange in social networks inefficient.

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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 the Philippines (Fafchamps and Lund, 2003; Fafchamps and Gubert, 2007), 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, where efficiency is defined as adoption by all potential buyers with positive expected returns. Despite the importance of networks as a mode of exchange, and a growing theoretical literature on network-based exchange (Kranton and Minehart, 2001; Elliott, 2013), there is little empirical evidence on how efficiently networks allocate goods. I present the first field experiment to measure whether network-based exchange is efficient. 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, buyers with high valuations of the technology may be induced to bear the costs of making links with sellers (Kranton and Minehart, 2001).

Overall, I find that trading in social networks is inefficient. This inefficiency is driven by reduced adoption combined with no improvements in targeting of buyers with high valuations of the technology. Additionally, existing social relationships between buyers and suppliers – defined by caste and surname association – have significant influence on adoption in networks. The tendency to transact with close peers, rather than with the farmers with the highest potential benefits of having the technology, limits the efficiency of networked exchange.

To measure efficiency, 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 improved 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). It is worth noting that while I rely on a particular new agricultural technology, the most important feature of the technology is that the key determinant of returns is observable. This feature is not unique to new seed varieties, but is relevant for any technology with heterogeneity in benefits.

There are three sources of experimental variation that are used in the analysis. For the first, a group of 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 of seed produces a large amount of output that can potentially be used as seeds by other farmers in the village. The

[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).

selection of the initial recipients of the technology is 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 determine adoption in networks.

Following the first year of production, the second source of variation was village-level randomization of the mode of exchange. In the first half of 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. I refer to this treatment as the "market", as it introduces anonymity and breaks down the requirement for buyers and sellers to be linked. It is however important to note that some features of a real-world market are absent in the door-to-door approach. Namely, the costs of actually going to the marketplace and finding suppliers are eliminated. I therefore consider the door-to-door approach as a method for reliably eliciting demand in an environment where transaction costs are absent. An additional important feature of this design is that 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.

My 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 fixed. Therefore, the design ensures that price differences can not explain the results.

The experiment produced four main empirical results. The first result is that the overall rate of adoption is 83% lower in networks alone. Only 7% of farmers adopted in network villages, while 40% did in market villages. While the sign of this effect is not surprising, its magnitude implies that a significant share of farmers that otherwise have positive demand for a product, do not adopt when exchange occurs in social networks.[3]

My second result speaks to how social relationships restrict trading in networks. Specifically, farmers relying on networks are much 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. These strong peer effects are eliminated when door-to-door sales are made. An equivalent interpretation of the finding is that introducing an outside buying opportunity in-

[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.

[3]One alternative explanation of this "overall access" effect is that door-to-door sales represented an effective increase in supply. I show that this explanation is unlikely because the amount of seeds available to suppliers was sufficient to meet the demand of *more* than an entire village.

creases adoption, but particularly for those that are not connected to suppliers and thus would have otherwise had high costs of 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 targeting of farmers with higher expected returns is no more effective in networks. I exploit the flood-tolerance property of Swarna-Sub1 to generate estimated returns using impact estimates from a recent randomized experiment (Dar et al., 2013b). Using these estimated returns, I use historical flood data to classify farmers according to whether they are expected to gain from the technology or not. I find that while networks exclude significantly more farmers with positive expected returns, part of this effect is offset by exclusion of farmers with negative expected returns. Overall, the average return of adopters with door-to-door sales is lower by approximately 18%, but the difference is not statistically significant, suggesting that improved targeting does not offset much of the inefficiency due to reduced adoption.

Building on the first three results, my final result quantifies the magnitude of the efficiency losses resulting from networked trade. I define efficiency losses as the percentage of the total gains in expected revenue in the door-to-door sales villages that are not achieved in networks alone. The total expected gain in revenue due to the new technology is almost three times larger in villages where farmers were offered door-to-door sales. More precisely, the efficiency loss due to missed trading opportunities in networks represents 63% of the total gains achieved by the door-to-door channel. The magnitude of the welfare effect implies substantial losses due to networked trade. The tendency for transactions to be limited to farmers sharing the same surname or belonging to the same sub-caste, suggests that costs of trading with suppliers from other social groups explain the inefficiency of networked trade.

The finding that trade in networks is inefficient adds new empirical evidence helping to distinguish between competing models of networked markets. Even considering the costs of making links, the model in Kranton and Minehart (2001) shows that networked trade can achieve efficiency by inducing buyers with high valuations to connect with suppliers. My results are more consistent with a model where costs of exchanging with socially distant peers create a key friction that limits the ability of networks to allocate goods (Elliott, 2013).

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 can 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. My results suggest that this approach will leave significant demand unmet.

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 networked trade. 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 the most likely explanation of this inefficiency result. 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 is efficient and whether social relationships with suppliers influence adoption in networks, I discuss how the these sources of variation can be used to answer these questions. Finally, I also discuss the timing of data collection.

Before discussing details of the experiment, some details on the sample area are useful. 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).[4] 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 rain season from June-October. Most recently, heavy flooding occurred in 2008, 2009, and 2011.

Suppliers were randomly selected at a village meeting carried out during May 2012. Each village was visited and farmers were informed that there would be a meeting to discuss a new submergence-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.[5] The meetings were attended by anywhere from 15 to 41 farmers, with average attendance being 22. 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. 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.

The 25 kg of seed provided to suppliers produced enough output to eliminate any concern that demand could not be met with this amount. The minikits were planted by suppliers upon the arrival

[4] 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.

[5] 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).

of the southwest monsoon, which occurred around the second week of June. Crops were harvested in late November to early December. Enumerators returned to all villages during harvesting to collect information about production. A total of 396 of the 410 suppliers were contacted and surveyed. Of the farmers surveyed, 346 indicated that the minikit had been planted.[6] The average amount of land allocated to Swarna-Sub1 amongst those cultivating it was 0.13 hectares. The average harvest at the village level was approximately 1.8 tons. Since most farmers use approximately 5-10 kg of seed during their first year of cultivation, the amount of seeds available to suppliers was sufficient to meet demand. As I discuss in further detail in Section 5, alternative uses of output were less profitable to suppliers, indicating that when ignoring any transaction costs, the most profitable use of output was trading with other farmers.

By randomly selecting suppliers, I can compare adoption outcomes between non-recipients (henceforth "buyers") that are more or less connected to suppliers. If costs of exchange with farmers from other social groups is important, then farmers should be more likely to trade with close peers.

Prior to randomization of the mode of exchange, a survey was administered to 1,151 randomly selected potential buyers during February-April 2013.[7] There were three 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 Swarna-Sub1 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, 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 means of spread of the technology. Take-up in this network treatment obviously requires informal transactions between connected farmers. The transactions could include sales, exchanges, or outright gifts - the latter likely occuring with some expectation of future reciprocity.[8] This randomization was stratified by block – an administrate unit two levels above villages – and the relative importance of suppliers to buyers. Relative importance of suppliers was measured using an indicator variable for whether the ratio of the average sharing degree of suppliers to that of buyers is greater than the sample median.[9]

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

[7]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.

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

[9]The sharing degree is simply the number of links of the farmer where a link between two farmers is defined as either farmer stating that they would go to the other farmer for seeds, fertilizers, or other inputs.

In the remaining half of villages, farmers were also given the opportunity to purchase the technology from NGO representatives in a door-to-door market. Enumerators were instructed to go 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, enumerators were instructed to give 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.

Since five suppliers were selected in all villages, network-based exchange was equally possible in all villages. Therefore, taking door-to-door markets as a near-perfect market where transaction costs are eliminated and demand is revealed, 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 markets are available.

Returning to prices, the prices were randomized in order to approximate the prices paid in transactions between farmers. Prices paid between farmers are commonly near the current market price of grain, which is the opportunity cost of participating in the transaction for the supplier. The minimum support price of rice 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 10-11 Rs. Using these prices as a benchmark, prices were randomly set at 3 levels: 14, 12, and 10 Rs per kg. This range of prices encompasses the prices paid in network transactions. Therefore, I can effectively hold prices constant by estimating the main treatment effects at the average price of network transactions.

A final endline survey was carried out in all villages during 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 buyers and 394 suppliers were reached. I use adoption from this survey as the main outcome variable throughout the remainder of the paper.

Summary statistics indicate that 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 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 minikits and the aggregate Swarna-Sub1 harvest are balanced across market and network villages, suggesting that any differences in adoption can not be attributed to differences in production of suppliers.[10]

3 Model of Technology Adoption in Networks

In this section I formulate a model of adoption of a new technology when network relationships create variation in costs of adopting across the population. I then use the model to build understanding on how targeting of buyers with high expected benefits varies between networks and 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 door-to-door sales. Figure 2 displays the network structure for one of my 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 blue nodes in the figure represent the five farmers that were selected as suppliers and the remaining nodes 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, efficiency requires 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 bearing the costs of trading with a supplier outside her reference group, 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 door-to-door sales are made because an outside seller is available to all buyers. Most importantly, B5 faces no transaction costs of adopting. If networks work efficiently for exchange, then B5 should adopt regardless of the mode of exchange. In contrast, if networks are inefficient, then adding door-to-door buying opportunities will crowd in those farmers that are not connected to suppliers.

3.2 Model Setup

The only 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 $R_i = \alpha_i r_i$.

[10]Another useful test is the test of whether any differences between suppliers and buyers are greater in market 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 characteristics.

I assume that a farmer knows his return due to flood exposure R_i with certainty, but that his perceived returns are $R_i + u_i$, where u_i is mean zero and independent of both R and c. The noise term u_i results from uncertain beliefs about other benefits or costs of the technology. For instance, some farmers may incorrectly perceive that the technology is less susceptible to pest damage, or more prone to drought. These mistakes can lead to targeting errors independent of the mode of exchange.

There are two sources of costs. First, the positive difference in prices between the old and new technologies is v. Second, the parameter 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. For instance, a farmer that belongs to the same sub-caste as suppliers likely has a smaller value of c than a farmer with no suppliers in his sub-caste. Additionally, it need not be the case that $c > 0$. As an example, a farmer may *benefit* from trading in networks if peers extend credit or allow for other types of flexible payments.[11]

The joint distribution of c and R is $f(c, R)$ and the correlation coefficient is ρ. The probability of adopting the new technology is $P\{R_i + u_i - v - c_i > 0\}$. Holding returns fixed, trading in networks naturally crowds out farmers with large values of c. Introducing a door-to-door market eliminates these costs and causes the adoption probability to increase to $P\{R_i + u_i - v > 0\}$.

3.3 Targeting

Since the new technology is only beneficial for farmers cultivating land in areas at risk of flooding, the most efficient allocation would result in adoption by only farmers in these areas. In terms of the model, the objective of a social planner would be to allocate the technology to all farmers with $R_i > 0$. The difference between this allocation and the allocation achieved by decentralized trade through networks depends on which farmers are screened out from the pool of adopters. If the farmers with the least connections to suppliers – and thus the highest costs of adopting in networks – are also those that have lower expected returns, then any decreases in adoption in networks are offset by more effective targeting.

There are two types of errors leading to inefficiencies. First, a farmer with positive expected returns may fail to adopt. The probability of this "exclusion error" in networks is written as,

$$p_n^{exc} = P\{R + u < c + v | R > 0\}. \tag{1}$$

Second, an inclusion error occurs if a farmer that is not expected to benefit from the technology chooses to adopt. The probability of an inclusion error is

$$p_n^{inc} = P\{R + u > c + v | R \leq 0\}. \tag{2}$$

The model generates predictions on how targeting errors are expected to vary between the two

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

treatments. Holding u fixed, going from exchange in networks to door-to-door markets naturally reduces exclusion error because farmers with moderate returns but high costs of exchange are less likely to be screened out. Similarly, exclusion errors by networks are most likely for farmers that are the least connected to suppliers. If c and R are positively correlated, the increase in exclusion error due to networks is larger. This results because the farmers that are most likely to adopt from their peers are those with the lowest returns. Similarly, If c and R are negatively correlated, then exclusion error in networks becomes less problematic because farmers with high expected returns are those that are most likely to adopt from peers.

While introducing a door-to-door market likely reduces exclusion error, this likely comes at a cost of increasing inclusion error. The door-to-door market eliminates all transaction costs, thus making it more likely that a farmer with a negative value of R and a positive value of u will adopt. Inclusion errors are also more likely for the most connected farmers. Inclusion errors by networks are reduced if c and R are positively correlated because the farmers with the most connections to suppliers will be those that benefit the least from the technology. The reverse statement is of course true for $\rho < 0$.

The important testable predictions of the model are summarized as follows. First, exclusion errors are more likely in networks, and they are particularly more likely by farmers that are the least connected to suppliers. Second, inclusion errors are more frequent in door-to-door markets, but the magnitude of this effect is smaller for the farmers that are the most connected to suppliers.

4 Results

In this section I first explain 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 no overall improvement in targeting. These results build up to an overall measure of efficiency losses discussed in Section 4.2. Finally, in Section 4.3, I estimate the demand elasticity in door-to-door sales.

4.1 Adoption, Peer Effects, and Targeting

Exchange via social networks alone results in significantly lower adoption when compared to villages where farmers also had a door-to-door buying opportunity. 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

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

where $adoption_{ij}$ is an indicator for adoption by farmer i in village j, $market_j$ is an indicator for door-to-door villages, and $price_j$ is the random offer price in door-to-door villages.[12] Since the average price of transactions between farmers is 12.4 Rs per kg, the coefficient β_1 measures the impact of adding door-to-door sales at a price equivalent to an average network transaction.

The estimates in column 1 of Table 2 show that when holding price constant, the effect of adding the door-to-door market is an increase in adoption by 33 percentage points. Using the adoption rate of 7% in networks as a baseline, this result indicates that the adoption rate increased by over 450% when adding the door-to-door treatment. Focusing on the ratio of the two estimates 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 adoption effect changes little when including control variables (column 2). Further, as shown in column 3, the door-to-door sales led to large increases in adoption at all three price levels, even at the highest price, which is larger than the prices of almost all network transactions.

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

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

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. 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 in Manski (1993).

The results in Table 3 show that while stated relationships with suppliers from the baseline social network survey have little impact on adoption in both treatments, fixed relationships with suppliers are indeed significantly more important for obtaining the technology when trading occurs in networks. A natural explanation 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. Sharing a surname with a single additional supplier has a negative effect on adoption in door-to-door sales, but the effect is positive and significantly larger in networks alone.[13] The magnitude of this difference is large. As an example, using the specification with

[12] 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. The adoption indicator is set to 1 in the case that a farmer adopted from a peer in a market village.

[13] The estimates with village fixed effects are slightly larger. 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

village fixed effects (column 6), having the same surname as a single additional supplier results in a 105% increase in the likelihood of adoption, when holding fixed the total number of farmers in the village having the same surname. Under the same baseline assumptions, 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. I obtain similar results in columns 7-9 when using sub-castes rather than common surnames.

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 the total farmers in the reference group 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, the result that being connected to suppliers influences trading opportunities in networks 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 create *inefficiencies* by limiting trading opportunities.

The results up to this point suggest that trading in social networks is highly restricted by personal relationships and that introducing an outside buying opportunity leads to large increases in adoption. 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. 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

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).

estimates of the treatment effect of Swarna-Sub1 as a function of flood duration.[14] 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.[15]

Using these values of estimated returns, I define two types of targeting errors. First, farmers that were incorrectly excluded are those with positive expected returns that failed to adopt. Second, inclusion errors are those with zero or negative returns that adopted. Combining both types of errors, the first specification is

$$error_{ij} = \beta_0 + \beta_1 market_j + \beta_2 market_j * (price_j - 12.4) + \varepsilon_{ij}. \tag{6}$$

By crowding in more farmers, door-to-door sales led to a large decrease in the rate of exclusion error. As shown in column 1 of Table 4, the probability that any targeting error was made decreases by 21.2 percentage points when door-to-door sales were offered – an approximate 28% effect. Turning to column 2, the decreased error rate is driven entirely by a lower rate of exclusion error. Given the large adoption effect, and that approximately 85% of farmers are expected to benefit from the new technology, it is not surprising that exclusion errors are reduced. Consistent with the model where door-to-door sales reduce the cost of adoption, the result in column 3 shows that inclusion errors are also much more likely in villages where door-to-door sales offers were made. This result causes the average return of adopters in column 4 to be approximately 18% lower in door-to-door villages, although the result is not statistically significant.

Exchange in networks is significantly less likely to result in exclusion errors for farmers that are better connected to suppliers. To establish this, Table 5 shows estimates of Equation 6 where the effect of introducing door-to-door markets depends on the share of a farmer's peer group that was selected as suppliers.[16] Farmers sharing the same surname with more suppliers are less likely to be incorrectly excluded from adopting from peers, as shown in column 2. The effects of connections with suppliers on inclusion error are not statistically significant, but the coefficients are imprecisely estimated (column 3). As shown in columns 4 and 5, similar results are obtained when using sub-caste as a measure of networks. The combined results indicate that exchange in networks limit adoption to farmers that are both connected to suppliers and expected to gain from the technology.

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

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

[15] One caveat is that this approach measures *agronomic* returns rather than *economic* returns. In a recent paper we show that access to Swarna-Sub1 causes farmers to change several production practices (Dar et al., 2013a), 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.

[16] I use the share of farmers that were suppliers to simplify interpretation.

values of estimated returns, the difference in adoption between networks and door-to-door markets is fairly constant. Following the literature on how people overweight recent events when making decisions, 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 lack of information 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 6 confirm that adoption is indeed positively correlated with expected returns. The correlation between adoption and expected returns in networks alone is positive, but not statistically significant (column 1). 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.[17] Both sets of standard errors account for clustering at the village level. Returning to the magnitude of the estimates, 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 results do rule out that the correlation between adoption and returns is larger in networks. Finally, column 2 verifies that the quadratic relationship between adoption and 2011 flood severity is highly statistically significant in door-to-door sales, but not in networks alone.

Taken together, the results on targeting suggest that there is no evidence that targeting was more effective in networks. Decreases in inclusion errors were offset by increases in exclusion errors, and the correlation between adoption and returns was no larger in networks. These results are consistent with the model where returns are uncorrelated with costs of adopting through networks.

4.2 Efficiency Loss

The absence of direct buying opportunities, and thus having to rely on networks to obtain a new technology, is inefficient. As a first step in quantifying the magnitude of this inefficiency, I define

[17] 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.

the gain in expected 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. Panel A of Figure 5 shows the aggregate gain in expected revenue achieved in both the treatments as well as the most efficient scenario where every farmer with positive expected returns adopts.[18] The total gain in expected revenue in the network villages is 23,000 Rs, while the corresponding gain when adding door-to-door sales is 61,700 Rs. Therefore, the efficiency loss due to trading in networks represents approximately 63% of the aggregate expected returns generated by door-to-door sales. While the allocation achieved by adding door-to-door sales is more efficient, it is still far from the fully efficient allocation. This is driven by the fact that only 40% of farmers adopt in markets even though almost 86% 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.

Due to the large adoption gap, productivity under heavy flooding is expected to be significantly larger in villages where door-to-door offers were made. I use the regression estimates of yield as a function of flood duration in Dar et al. (2013b) to calculate expected yields under two scenarios. In the first scenario all varieties are fixed at those cultivated by farmers in 2012, while in the second, the farmers that actually adopted Swarna-Sub1 are assumed to cultivate it on all of their land. In both scenarios, flood duration is assumed to be equal to the duration of flooding during the most recent large flood in 2011. Panel B in Figure 5 shows that introducing Swarna-Sub1 is expected to lead to a 30% increase in average yield in villages with door-to-door buying opportunities and only a 5% increase when peer networks were the mode of exchange.

4.3 Demand Curve

I next use the random variation in prices across door-to-door villages to more carefully characterize the demand curve.[19] Table 7 displays regression estimates. 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.[20]. 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

[18]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.

[19]4.5% farmers surveyed in market villages adopted from their peers rather than from the NGO representatives. I treat these farmers as non-adopters when estimating demand.

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

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. The intuition of this finding is that if returns are sufficiently low, then decreasing price does little to induce adoption because there are few farmers that were close to adopting at the higher price. If returns are higher, then decreasing price crowds in more farmers because there are more farmers for which adoption was nearly profitable at the higher price.[21]

The policy implication of this finding is that small subsidies of this technology may not induce sharp increases in demand by farmers with low benefits. One argument against using subsidies to induce adoption of a technology is that low prices will induce adoption by people with low benefits. Antimalarial drugs are an example where *heavy* subsidies result in high adoption by people with low benefits and therefore potentially reduce the overall effect of the drugs due to resistance and learning externalities (Cohen, Dupas, and Schaner, 2013). My results indicate that a small change from a high to more moderate price will achieve the desirable policy outcome of increasing adoption significantly more for farmers with higher expected returns.

5 Why is exchange in networks inefficient?

Trading in social networks is inefficient. I next show additional analysis consistent with this being explained by trading links not being made across peer groups. I also present results that rule out several alternative explanations of the findings.

5.1 Failed Network Adjustment

Evidence from the endline survey with suppliers points to failure of buyers to effectively link with suppliers as an explanation of the inefficiency of networked trade. As displayed in Figure A2, the most popular reason given by suppliers for not selling or exchanging seeds is that nobody asked. Two candidate explanations are (1) networks failed to disseminate information on who suppliers were and (2) farmers knew the identities of suppliers, but chose not to incur the costs of establishing links. The first explanation is unlikely because suppliers were publicly identified at the beginning of the experiment when minikits were disseminated via lottery.

Amongst suppliers that traded seeds, most suppliers identified trading partners as being close family and friends. 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 trading in networks is strongly limited to pairs of farmers that have strong connections. Interestingly, suppliers clearly expected buyers to initiate trades: only 8% of suppliers reported actively seeking buyers.

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

In addition to the survey evidence from suppliers, followup social network data indicate that 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 degree 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 8. 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 sharing 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.

While the increases in degree of suppliers suggest that there was at least some change in stated network relationships, this alone is not enough to create opportunities for trade. The new links must be between buyers and suppliers in order to facilitate trade. To investigate whether new links were concentrated between buyers and suppliers, I use a dyadic regression model of network formation. The baseline specification is

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

where $onesupplier_{ikj}$ and $twosupplier_{ikj}$ are indicators for buyer-supplier and supplier-supplier dyads, respectively.[22] If new connections between buyers and suppliers are driving the increased degree of suppliers, then β_1 should be positive and large. Column 1 of Table 9 shows 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 and not statistically significant. The effect is however slightly larger in the subset of farmers where plot coordinates were taken (column 2), likely because coordinates were not taken for suppliers that did not cultivate the new variety.

Homophily – the tendency of farmers to interact with other farmers having similar characteristics – is present in the data. An implication of homophily in this context is that it limits trading to farmers in the same peer group. Turning to the coefficient estimates, farmers belonging to the same

[22] 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). 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.

sub-caste are 3.5 percentage points – or 9% – more likely to be linked. Similarly, farmers sharing the same surname are 12.2 percentage points – or 32% – more likely to be linked.[23] As shown in Table A4, there is significant correlation between common surnames, sub-caste association, and geographic proximity. Overall, networks in the sample are formed according to all of these characteristics.

Taken together, the results suggest that network structure did not adjust in a way that facilitated exchange. Rather, farmers tended to exchange with close family and friends, preventing spread of the technology outside of these groups.

5.2 Supply effects and prices

One different interpretation of the increased adoption in door-to-door sales 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 6 shows the distribution of the differences between the harvest of suppliers during the first year and the total amount 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 harvest of suppliers in 40 of the 41 villages where door-to-door sales were made. In other words, the door-to-door sales did not increase supply above an amount that could have been met by suppliers. On average, the excess amount was far greater than zero, demonstrating that seed availability can not explain the results.

The value of output to suppliers under alternative uses was lower than prices where farmers were shown to be willing to purchase seeds. 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, the most efficient use of output would be use as seed by other farmers. Given that significant demand exists at prices above 10.4, and that suppliers had more than enough output to meet this demand, the most efficient allocation would involve transfers to other farmers. 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 sales and exchanges was 12.4 Rs. Since this value falls in the middle of the range of prices charged in door-to-door sales, the analysis was structured to hold prices fixed at the average price of exchanges in networks. Further, there is still significant demand at prices *above* this average value, suggesting

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

that welfare could have been improved if these transactions were made.

5.3 Selection of Suppliers

A possible explanation of the results is that adoption is low in network villages because randomization was a poor strategy for selecting suppliers. 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 diffusion 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.

Importantly, I can 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 greater than the sample median.[24] The regression specification is

$$adoption_{ij} = \beta_0 + \beta_1 market_j + \beta_2 important_j + \beta_3 market_j * important_j + x_{ij}\delta + \varepsilon_{ij}, \tag{9}$$

where $important_j$ is an indicator for villages where suppliers were relatively more important than buyers.[25]

The data rule out that networks were more effective at diffusing the technology when suppliers were more central. Focusing on column 1 of Table 10, 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 inefficiency of networked trade is not due to the nonstrategic way in which suppliers were selected.[26] 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.

Adding the door-to-door buying opportunity, however, led to larger increases in adoption when suppliers were 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. One plausible explanation is that farmers do learn effectively from the most central farmers in the village, but that costs of exchanging with

[24] 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.

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

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

other farmers prevent physical transactions from taking place.

5.4 Quality Differences

Seed quality is the only potential product attribute that could have varied between the two treatments. 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 purchased for the purposes of the experiment from a private seed company in a neighboring state. If farmers fail to produce quality seeds, this could potentially explain low adoption in peer-to-peer networks.[27] Descriptively, 16% of suppliers reported that seed quality was the reason they chose not to exchange with others (Figure A2).[28]

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.[29] Farmers that bought certified seeds likely value seed quality more than those using output from their own harvests. 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 with 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.

5.5 Risk preferences

My approach to measuring efficiency uses gains in expected revenue rather than gains in expected utility. This could complicate interpretation if farmers in flood-prone areas are less risk averse. In this case, the most efficient allocation in terms of utility could vary from the that using expected gains in revenue.

There is no evidence that the least risk averse are those with the highest expected returns. To establish this, I use risk preferences that were elicited by asking farmers to select from a set of

[27]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.

[28]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.

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

hypothetical lotteries, where the expected value of each lottery was positively correlated with its variance.[30] I use the responses to this question to define the highly risk averse as the farmers that chose the sure option over any lottery with a positive variance. Regression results (not shown) indicate that high risk aversion is *positively* correlated with the measure of expected returns. Expected returns are on average larger by 30% for the highly risk averse and the estimated difference is highly statistically significant ($p<0.001$). This result goes against the argument that the least risk averse select into cultivation of flood-prone plots.

5.6 Heterogeneity

Are there some groups that benefit more from having a door-to-door buying opportunity, or is the increase in adoption similar across the population of farmers? Table A5 investigates heterogeneity according to several household characteristics.

The increase 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 the variety that is otherwise identical to Swarna-Sub1. While the differential effect for SC farmers is difficult to interpret because caste status is assuredly correlated with other factors, one plausible explanation is that liquidity constraints are more binding for lower caste farmers, making cash transactions less feasible. 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 rely less on formal cash transactions. An affirmative action policy that introduces more formal markets at the same time as favoring SC's in seed distribution could limit the negative effects on equity because the SC's would benefit more from peer-to-peer exchange if more of the initial adopters came from their caste group.

Combining all results on possible explanations of the inefficiency of trading in networks, the lack of strong evidence for any of the alternative explanations, combined with the strong peer effects in networks, suggest that large costs of exchanging with farmers from other social groups drive the inefficiency of networked trade. An equivalent interpretation is that homophily – the concentration of links amongst similar individuals – leads to exchange being limited to these groups, and thus has negative implications for efficiency of trade via networks.

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 equally efficient to an approach where demand was revealed via door-to-door sales. The theoretical motivation for the question is transaction costs. Links between buyers and sellers

[30]This question was administered as part of the pre-intervention survey with buyers during February 2013. The lotteries were coin flips with the following results: 30-30, 25-50, 20-70, 15-90, 10-110, 5-130, 0-150.

are needed for transactions to take place in networks. If transacting with people from other social groups is costly, then it is theoretically ambiguous as to whether buyers and sellers will 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 strong peer effects when exchange occurred in networks. A farmer with a single additional supplier belonging to her sub-caste was approximately 50% more likely to adopt the technology when trading occurred in networks. Similarly, a farmer with one additional supplier having her 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 in door-to-door markets. Targeting was also no more effective in social networks. That is, any gains from excluding farmers with zero returns were offset by exclusion of farmers with positive returns. In summary, the large decrease in adoption, combined with the lack of improved targeting, cause the efficiency loss of networked trade to represent over 60% of the gains from exchange when door-to-door sales were made.

An important policy implication of the results is that the network approach 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 new technology. If the allocation achieved by exchange in networks is efficient, then networks could be relied upon as a highly 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 of South Asia where formal markets for seeds are absent. Introducing more formal buying opportunities can increase access and thus lead to increases in efficiency.

The paper also makes a broader contribution to the empirical literature on networked markets. Past theoretical work on transactions in networks has considered numerous topics such as bargaining between connected agents, the importance of intermediaries in facilitating transactions, the effects of network structure on outcomes, and whether agents can make the connections needed for exchange to occur. This large theoretical literature has generally not been accompanied by experimental tests, especially outside of the lab environment (Jackson and Zenou, 2013). The results presented here make a contribution in this direction by being one of the first to use a field experiment to test the efficiency of an extremely common mode of exchange. In doing so, the experiment serves as a test of competing theories of networked markets. The results are most consistent with a model where costs of exchange create frictions that prevent efficiency (Elliott, 2013).

One caveat of the results is that the experiment was carried out only over a single year, and thus the results have little to say about the ability of social networks to allocate 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, meeting the Indian government's goal of achieving widespread adoption of Swarna-Sub1 in a short time period requires rapid early take-up. My results suggest that taking a hands off approach by relying on trading in networks will result in a far less efficient initial allocation of this promising new technology.

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Tables and Figures

Figure 1: Location of villages in Bhadrak district

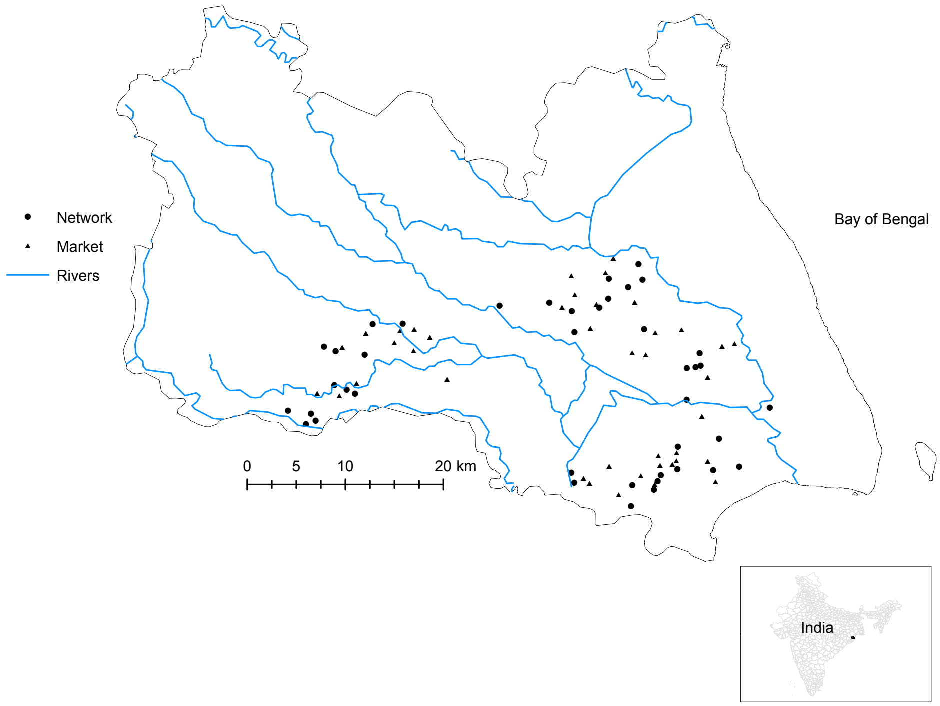
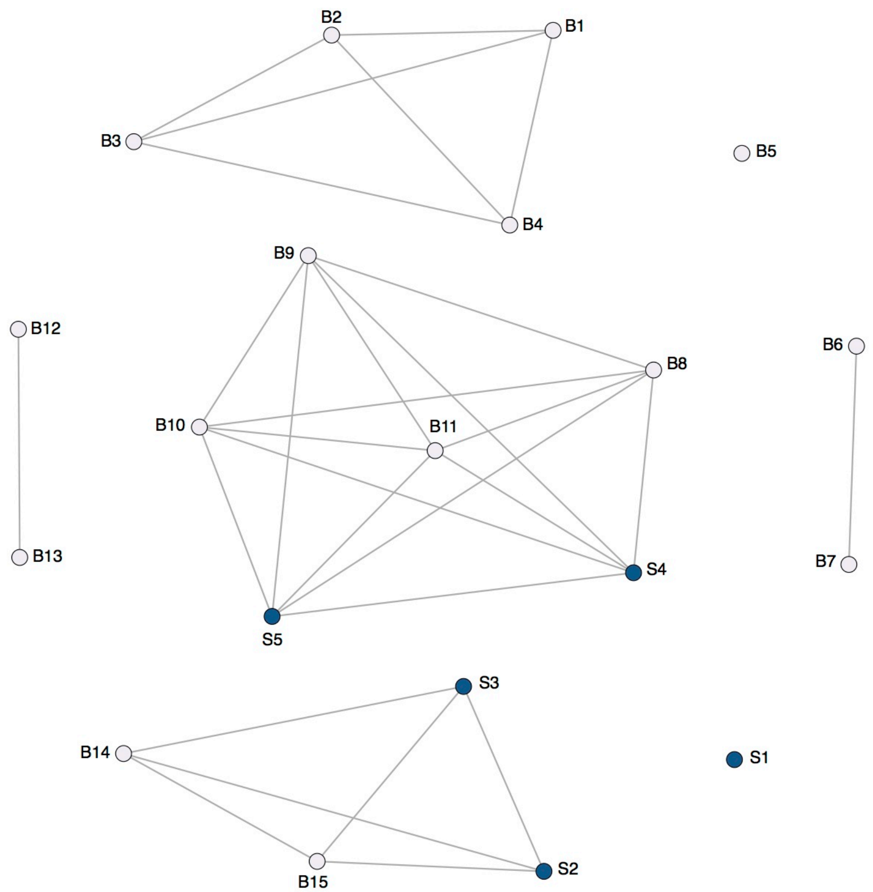


Table 1: Summary Statistics

	(1) Buyer/Network	(2) Supplier/Market	(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 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)			
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 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.

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. Nodes shaded in blue are farmers that were randomly selected as suppliers.

Table 2: Effect of adding door-to-door buying opportunity on technology adoption

	(1)	(2)	(3)
Market Treatment	0.327***	0.328***	
	(0.042)	(0.041)	
Market Treatment*(Price-12.4)	-0.026	-0.026	
	(0.024)	(0.024)	
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)
Market and Price=10			0.385***
			(0.078)
Market and Price=12			0.351***
			(0.067)
Market and Price=14			0.280***
			(0.059)
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

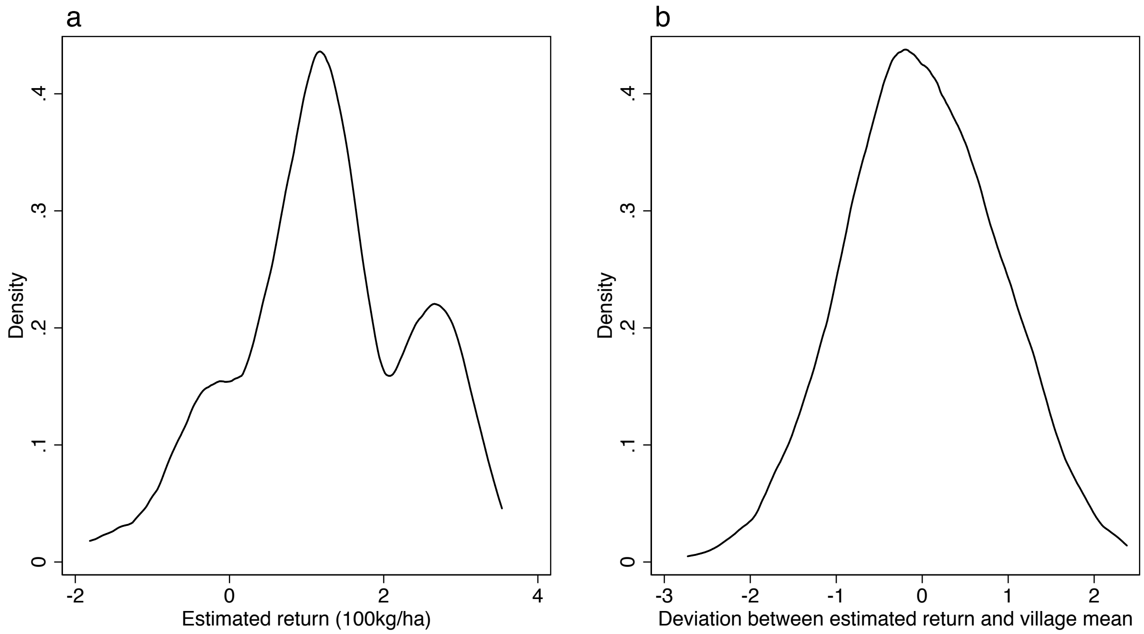
Dependent variable is 1 if farmer adopted Swarna-Sub1 for 2013 wet season. *Market Treatment* is 1 for villages where farmers could either obtain the technology from door-to-door sales or from peer suppliers. Standard errors are clustered at the village level. Asterisks indicate statistical significance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

Table 3: Effects of social relationships with suppliers on technology adoption

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Market Treatment	0.346***	0.341***		0.332***	0.327***		0.367***	0.362***	
	(0.068)	(0.067)		(0.056)	(0.055)		(0.065)	(0.062)	
Market Treatment * Baseline links with suppliers	0.002	-0.000	-0.026						
	(0.033)	(0.033)	(0.031)						
Market Treatment * Baseline degree	-0.003	-0.001	-0.002						
	(0.016)	(0.016)	(0.013)						
Baseline links with suppliers	-0.007	-0.006	-0.004						
	(0.011)	(0.012)	(0.013)						
Baseline degree	0.005	0.003	0.003						
	(0.008)	(0.008)	(0.007)						
Market Treatment * Number suppliers w/ same surname				-0.075*	-0.072*	-0.109**			
				(0.043)	(0.042)	(0.045)			
Market Treatment * Total number w/ same surname				0.021	0.020	0.035**			
				(0.014)	(0.014)	(0.014)			
Number suppliers w/ same surname				0.035	0.027	0.074**			
				(0.026)	(0.027)	(0.032)			
Total number w/ same surname				-0.008	-0.004	-0.023**			
				(0.008)	(0.009)	(0.009)			
Market Treatment * Number suppliers same sub-caste							-0.056*	-0.058*	-0.053
							(0.030)	(0.030)	(0.036)
Market Treatment * Total number same sub-caste							0.011	0.011	0.014
							(0.009)	(0.010)	(0.010)
Number suppliers same sub-caste							0.040*	0.024	0.037*
							(0.021)	(0.023)	(0.021)
Total number same sub-caste							-0.010	-0.007	-0.011
							(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. *Market 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.

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.

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

	(1) Any error	(2) Exclusion	(3) Inclusion	(4) Average Return
Market Treatment	-0.212***	-0.317***	0.292***	-0.313
	(0.047)	(0.044)	(0.089)	(0.257)
Market Treatment*(Price-12.4)	0.019	0.026	-0.026	-0.062
	(0.019)	(0.023)	(0.056)	(0.067)
Strata Fixed Effects	Yes	Yes	Yes	Yes
Mean of Dep Variable: Network	0.766	0.916	0.040	1.742
Number of Observations	1145	961	184	266
R squared	0.094	0.182	0.195	0.096

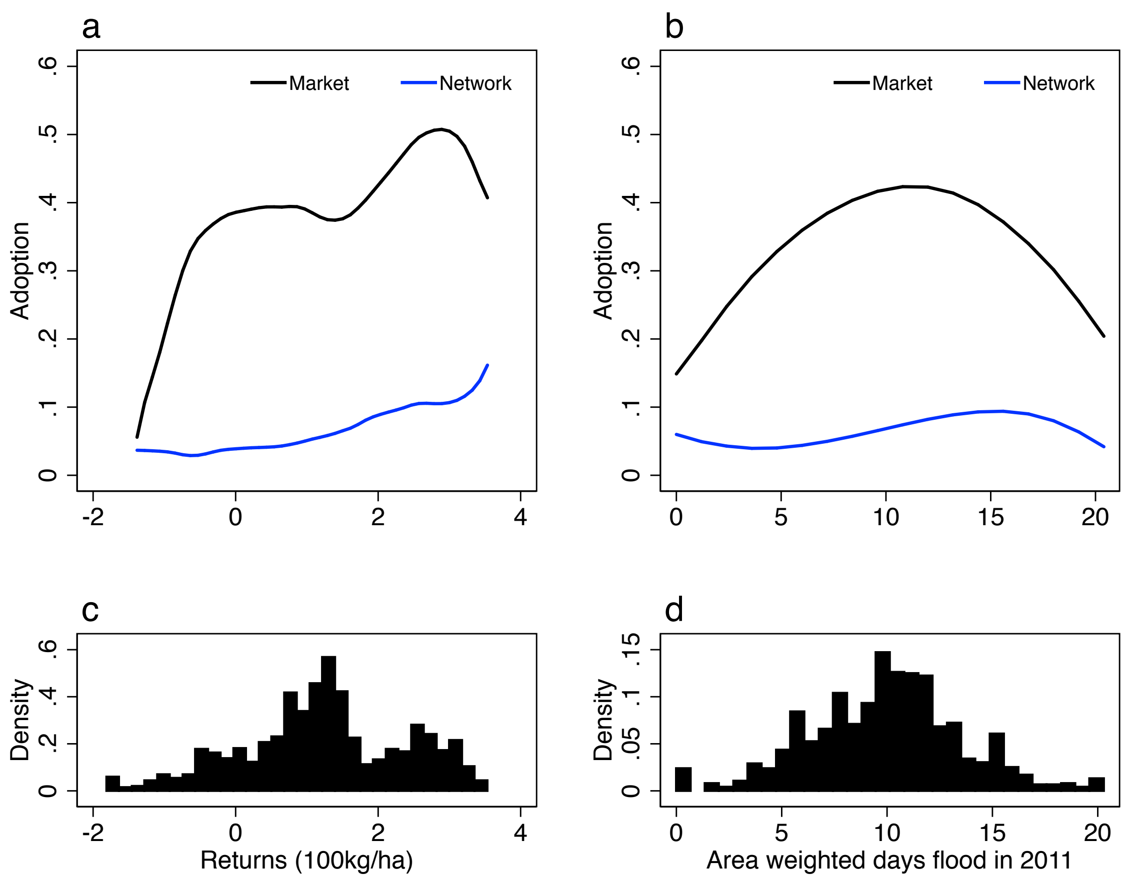
Dependent variable in column 1 is equal to 1 if any error in targeting was made (either exclusion of farmers with positive expected returns or inclusion of farmers with negative expected returns). Column 2 limits to the sample of farmers with positive expected returns and looks at exclusion error. Column 3 limits to farmers with negative expected returns and considers inclusion error. The dependent variable in column 4 is average expected returns. *Market 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 5: Heterogeneity in differential targeting effectiveness of social networks and door-to-door sales

	(1)	(2)	(3)	(4)	(5)	(6)
	Any error	Exclusion	Inclusion	Any error	Exclusion	Inclusion
Market Treatment	-0.284***	-0.423***	0.332***	-0.289***	-0.428***	0.385***
	(0.064)	(0.053)	(0.094)	(0.064)	(0.060)	(0.117)
Share of same surname that are suppliers	-0.143	-0.227**	0.071			
	(0.120)	(0.094)	(0.123)			
Market Treatment*Share of same surname that are suppliers	0.300*	0.410***	-0.116			
	(0.154)	(0.132)	(0.264)			
Share of same sub-caste that are suppliers				-0.122	-0.191**	-0.068
				(0.096)	(0.086)	(0.137)
Market Treatment*Share of same sub-caste that are suppliers				0.290*	0.429**	-0.355
				(0.171)	(0.177)	(0.405)
Strata Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Mean of Dep Variable: Network	0.766	0.914	0.046	0.768	0.915	0.044
Number of Observations	1019	856	163	1066	893	173
R squared	0.103	0.198	0.213	0.104	0.198	0.240

All effects reported in the table are at a price of 12.4 Rs per kg. That is, regressions in columns 1-3 include $MarketTreatment * (Price - 12.4)$ and $Market\ Treatment * (Price - 12.4)$**Share of same surname that are suppliers*. Similarly defined variables for sub-caste are included in columns 4-6.Dependent variable in columns 1 and 4 is equal to 1 if any error in targeting was made (either exclusion of farmers with positive expected returns or inclusion of farmers with negative expected returns). Columns 2 and 5 limit to the sample of farmers with positive expected returns and consider exclusion error. Columns 3 and 6 limit to farmers with negative expected returns and consider inclusion error. *Market 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 4: Relationship between estimated returns and adoption, by treatment



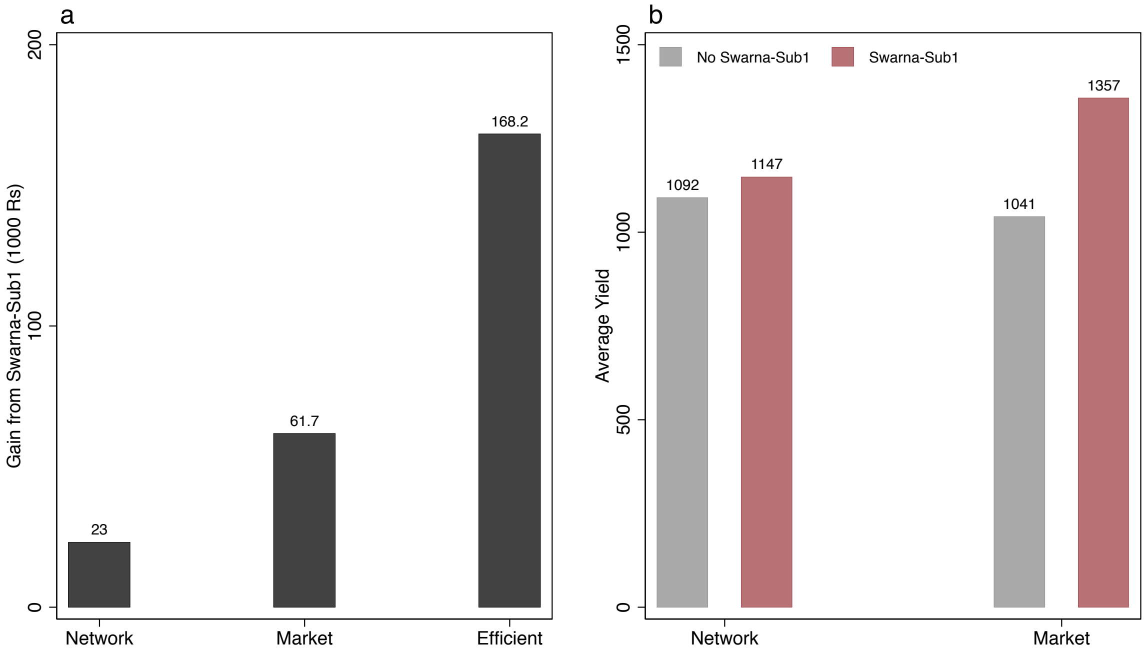
Notes: **(a)** Nonparametric fan regression of adoption on estimated returns. **(b)** Nonparametric fan regression of adoption on area weighted duration of flooding during 2011 floods. **(c)** Density of estimated returns. **(d)** Density of area weighted flood duration in 2011.

Table 6: Estimated correlation between expected returns and adoption

	(1)	(2)
Market Treatment	0.300***	0.130
	(0.049)	(0.126)
	[0.065]	
Market 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)
Market Treatment*2011 Area weighted days flood		0.044**
		(0.018)
Market 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	1.24	1.24
Number of Observations	1134	1126
R squared	0.212	0.213

Dependent variable is 1 if farmer adopted Swarna-Sub1 for 2013 wet season. *Market Treatment* is 1 for villages where farmers could either obtain the technology from door-to-door sales or from peer suppliers. 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.

Figure 5: Efficiency loss of exchange in social networks



Notes: **(a)** Figure shows total gain in expected revenue due to Swarna-Sub1, where expected gain is set to 0 for farmers that did not adopt. The efficient network is one where every farmer with positive expected returns adopts. 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 average expected yield under flood conditions identical to those experienced during 2011 floods. Height of gray bars is average expected yield when varieties grown are fixed at those chosen during 2012. Height of red bars is average expected yield when all plots are cultivated with Swarna-Sub1 *only for those* that either adopted from a peer or from the market. Varieties are fixed at 2012 choices if farmer did not adopt Swarna-Sub1. Expected yields are calculated using regression results in Dar et al. (2013b).

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: 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

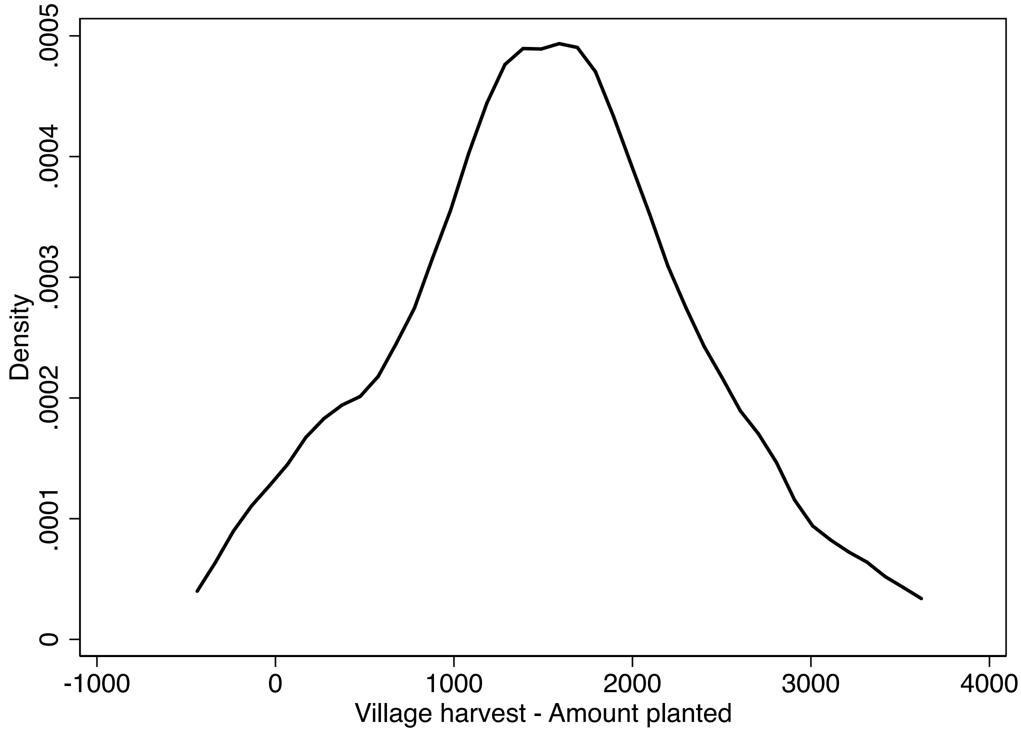
Asterisks indicate statistical significance at the 1% ***, 5% **, and 10% * levels. Standard errors are clustered at the village level. Degree is the total number of links reported by either the surveyed farmer or other farmers in her village. The in-degree is the total number of *other* farmers in the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

Table 9: Dyadic regressions of network formation at follow-up

	(1)	(2)
One farmer is seller	0.013	0.025*
	(0.014)	(0.015)
Both farmers are sellers	0.182***	0.210***
	(0.030)	(0.035)
Same sub-caste		0.035*
		(0.018)
Same surname		0.122***
		(0.018)
Houses within 25 m		0.007
		(0.014)
Plots within 100 m		0.023*
		(0.013)
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.

Figure 6: Distribution of difference between total harvest 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 by suppliers and aggregate amount 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.

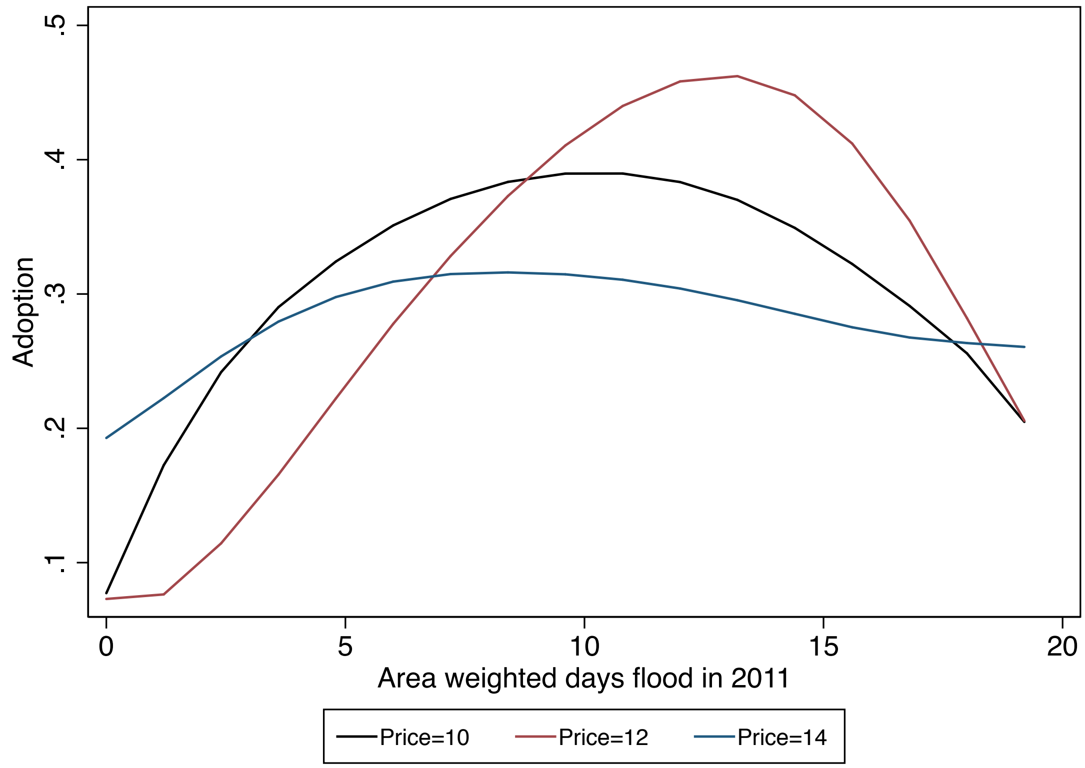
Table 10: Heterogeneous effects according to baseline importance of suppliers

	(1)	(2)
Market Treatment	0.256***	0.309***
	(0.063)	(0.065)
1 if supplier degree / buyer degree > median	-0.047	
	(0.038)	
Market Treatment*1 if seller degree / buyer degree > median	0.157*	
	(0.088)	
1 if supplier size / buyer size > median		-0.057
		(0.036)
Market 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.*Market 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.

Appendix

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 market 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
Market Treatment	0.268***	0.206**	0.316***	0.328***	0.349***	0.357***
	(0.080)	(0.095)	(0.069)	(0.085)	(0.055)	(0.059)
Market Treatment * Number suppliers w/ same surname	-0.159**		-0.155***		-0.076**	
	(0.061)		(0.052)		(0.036)	
Market Treatment * Total number w/ same surname	0.034**		0.048***		0.021	
	(0.016)		(0.016)		(0.014)	
Number suppliers w/ same surname	0.110**		0.061		0.027*	
	(0.053)		(0.038)		(0.016)	
Total number w/ same surname	-0.015		-0.017		-0.010	
	(0.011)		(0.011)		(0.013)	
Market Treatment * Number suppliers same sub-caste		-0.120**		-0.092**		-0.063**
		(0.045)		(0.035)		(0.027)
Market Treatment * Total number same sub-caste		0.031*		0.026***		0.017
		(0.017)		(0.010)		(0.012)
Number suppliers same sub-caste		0.075*		0.053**		0.024*
		(0.041)		(0.023)		(0.013)
Total number same sub-caste		-0.024		-0.018**		-0.014
		(0.017)		(0.007)		(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. *Market 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)
Market Treatment	0.435***	0.439***		0.435***	0.439***	
	(0.049)	(0.047)		(0.057)	(0.054)	
Market Treatment *	-0.364***	-0.373***	-0.346***			
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)			
Market Treatment *				-0.384**	-0.398**	-0.411**
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

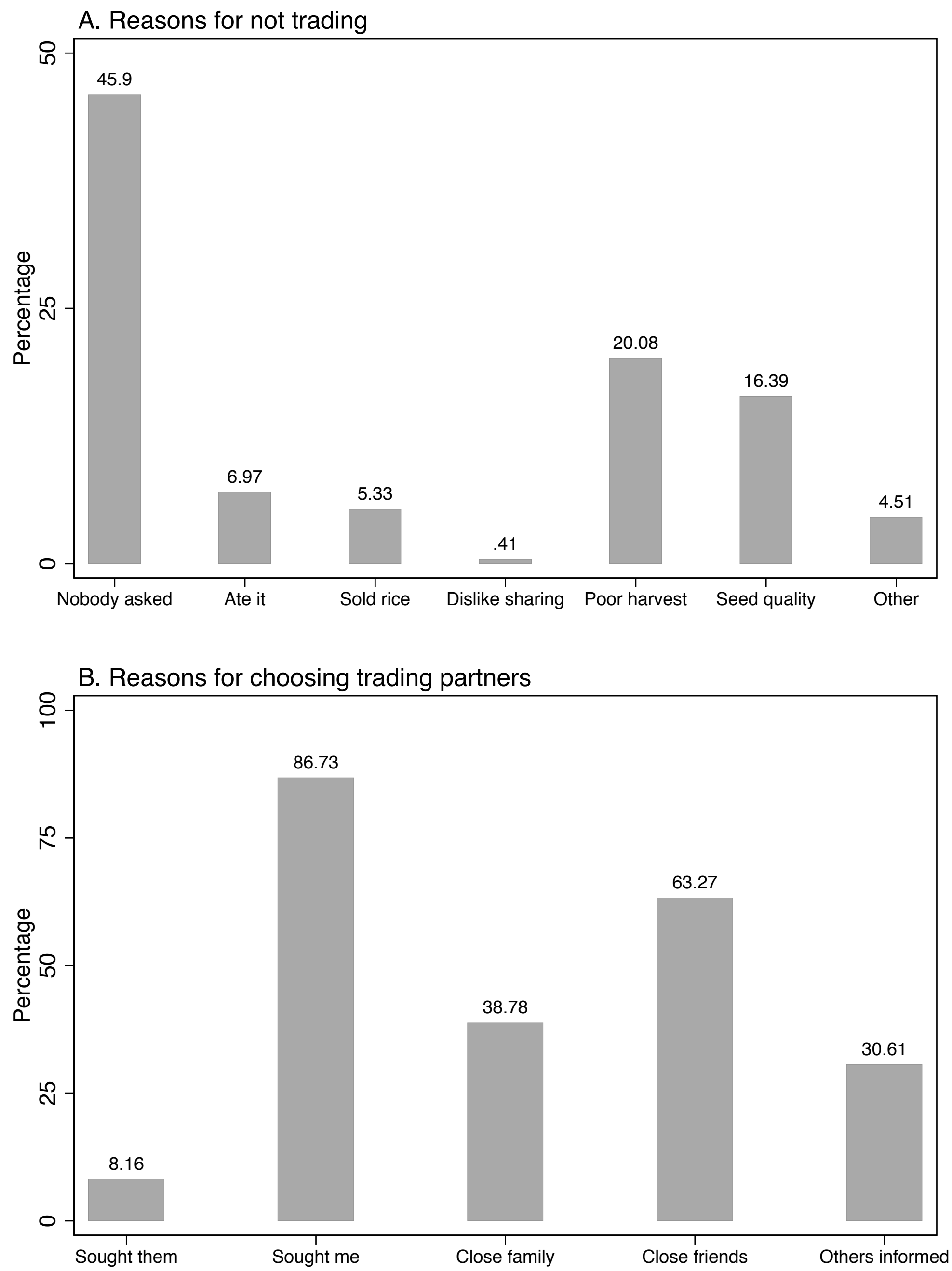
Dependent variable in all columns is 1 if farmer adopted Swarna-Sub1 for 2013 wet season. *Market Treatment* is 1 for villages where farmers could either obtain the technology from door-to-door sales or from peer suppliers. Control variables are indicator for SC, indicator for holding BPL card, land 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)
Market Treatment	0.316***	
	(0.066)	
Market Treatment *	0.009	-0.019
Followup links with suppliers	(0.027)	(0.021)
Market Treatment *	0.001	0.004
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. *Market 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.

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 A4: Dyadic regressions of link formation at follow-up

	(1)	(2)	(3)	(4)	(5)
Same sub-caste	0.079***				0.035*
	(0.016)				(0.018)
Same surname		0.136***			0.126***
		(0.015)			(0.017)
Houses within 25 m			0.042***		-0.000
			(0.012)		(0.014)
Plots within 100 m				0.028**	0.017
				(0.013)	(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	0.067	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 A5: Heterogeneous effects of trading in social networks

	(1)
Market 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)
Market 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. *Market 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 A6: Heterogeneous effect of trading in networks according to proxy measures of preference for quality seeds

	(1)	(2)
Market Treatment	0.352***	0.376***
	(0.051)	(0.050)
Market Treatment*Seed buyer in 2012	-0.036	
	(0.050)	
Seed buyer in 2012	-0.021	
	(0.024)	
Market 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. *Market 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.