Trading Frictions in Indian Village Economies

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Abstract

This paper presents evidence of trading frictions in rural Indian villages. I first introduced a new seed variety to a random subset of farmers in 82 villages. I then allowed the new variety to diffuse through farmer-to-farmer trading in a random half of villages. This mode of exchange is compared with demand that was approximated by selling the same seeds directly to farmers in the other half of villages. I find that direct trading between farmers leads to substantial under-adoption when compared to door-to-door sales — suggesting that trading frictions exist and represent a barrier to technological diffusion. Caste identity explains some, but not all, of this puzzle. Specifically, farmers sharing the same surname or belonging to the same subcaste as the original seed recipients adopt at higher rates when farmers trade amongst themselves. Overall, the trading frictions in farmer-to-farmer exchange are severe enough to make door-to-door sales cost effective.

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1 Introduction

Goods and services are often traded informally between villagers in remote parts of developing countries. In contrast to the standard marketplace — where relationships between buyers and sellers are characterized by anonymity — these trades often occur amongst connected villagers. Common examples include both reciprocal exchange of gifts and buyer-seller networks (Kranton, 1996; Kranton and Minehart, 2001). As concrete examples, informal insurance is frequently exchanged within established social networks (Mazzocco and Saini, 2012; Munshi and Rosenzweig, 2016). Or, farmers often buy irrigation water from fellow villagers (Anderson, 2011; Bubb, Kaur, and Mullainathan, 2017). As a final example, and the one considered in this paper, farmers frequently obtain new seeds directly from each other — rather than in a formal marketplace.[1]

How effective is this informal village economy in diffusing new seeds between farmers? Diffusion via social connections is an oft-cited mechanism for encouraging the spread of agricultural information (Conley and Udry, 2010; Krishnan and Patnam, 2013). Building on this, recent work has turned to understanding how network-based diffusion of information can be effectively leveraged to speed the diffusion of agricultural technology (Beaman et al., 2015). Can network relationships also be leveraged to rapidly diffuse seeds between farmers? Or, are there frictions that limit the effectiveness of farmer-to-farmer trading as an allocation mechanism? This paper seeks answers to these questions using a field experiment carried out over a three-year period in rural Odisha India.

I first provided a small amount of a profitable flood-tolerant rice seed called "Swarna-Sub1" to five random farmers in each of 82 villages.[2] These five "original recipients" then planted the seeds, producing enough to diffuse to other farmers as seeds for the following year's cultivation. Does the informal village economy effectively transmit seeds between farmers? To answer this, I generated an approximate measure of demand in half the sample by selling the same seed using door-to-door sales. This arm of the experiment provides a revealed-preference benchmark for me to compare uptake in the village economy with the demand benchmark, both for farmers that are more or less socially proximate to the original recipients.

I find a substantial gap between the adoption in door-to-door sales and the adoption that takes place in the farmer-to-farmer model of diffusion. The magnitude of this effect is striking. Compared to adoption in door-to-door sales of around 40 percent, only 7 percent of farmers adopt after one year in villages where the seed diffuses directly between farmers. This gap closes over time, but remains significant after two additional seasons. I then apply recent experimental estimates of the technology's impact (Emerick et al., 2016) to this estimated adoption gap in order to estimate the losses from trading in farmer networks. This estimate suggests that over the three-year period of

[1] Transfers of seeds between farmers have been studied for cassava in Gabon (Delêtre, McKey, and Hodkinson, 2011), maize in Mexico (Bellon, Hodson, and Hellin, 2011), and sorghum in Kenya (Labeyrie et al., 2016). McGuire and Sperling (2016) use primary data from 5 African countries to show that seed transfers from neighbors account for 6 percent of total seed supply in Kenya and this ranges to 22 percent in Zimbabwe.

[2] Recent experimental work has shown that Swarna-Sub1 is profitable for two reasons. First, it increases crop yield during flooding without affecting yield in normal years (Dar et al., 2013). Second, it also generates welfare gains by inducing farmers to invest more in inputs such as fertilizer and labor at planting (Emerick et al., 2016).

the study, transaction frictions in the village economy cause the average farmer to lose an amount equivalent to about 20 days of casual work, or about 8 percent of the annual rice harvest.

An immediate possible explanation of this finding is that the original recipients gained more by allocating the seed to other uses. I start by documenting that original recipients had nothing to gain — and actually lost — by not diffusing seeds to other farmers. About one third of the harvest of original recipients — an amount larger than the total amount sold in the door-to-door sales — was sold to traders at an average price of 10.3 Rupees per kilogram. The door-to-door sales experiment showed that over 30 percent of farmers in the same village were willing to pay 14 Rupees per kilogram for the same seed. These basic numbers demonstrate misallocation and rule out the explanation that alternative uses were more beneficial to original recipients.

I am not able to fully identify the source of these trading frictions. Nonetheless, the paper then turns to some exploratory analysis trying to better understand the gap in adoption between farmer networks and door-to-door sales. I start by showing that some — but not all — of this adoption gap is explained by trading occurring more frequently within (and less frequently across) caste groups. Specifically, original recipients tended to exchange with farmers that belonged to their same sub-caste or shared their same surname. The random selection of original recipients allows for estimation of these effects. In my preferred specification, having the same surname as an additional original recipient results in an approximate doubling in the one-year probability of adoption. Similarly, being part of the same sub-caste as an additional recipient leads to an approximate 53 percent increase in adoption. I observe no such peer effects in villages where demand was revealed with door-to-door sales. In contrast to recent studies where network-based transactions resolve information asymmetries or provide enforcement of bilateral contracts (Anderson, 2011; Fisman, Paravisini, and Vig, 2017), the seed markets I study involve one-off transactions that minimize these issues of moral hazard and contract enforcement. It therefore seems unlikely that within-caste trading of seeds arise as a response to one of these market frictions.

Recent work has emphasized the importance of caste for transacting in India. Nagavarapu and Sekhri (2016) show that poor households are more likely to obtain subsidized food grains when shopkeepers are part of their same caste. Similarly, Fisman, Paravisini, and Vig (2017) find that matches in caste between borrowers and lending agents increases credit uptake in Indian banks. Anderson (2011) finds that rural groundwater markets are segmented by caste. Caste relationships also guide the provision of informal insurance (Mazzocco and Saini, 2012; Munshi and Rosenzweig, 2016).[3] My finding adds to these and shows that within-caste trading *partially* explains why farmer-to-farmer exchange of seeds results in inefficiently low levels of technology adoption.

Importantly, while trading frictions are less severe within these social groups, network relationships fail to explain the entire gap in adoption between the treatments. Even the farmers that are most connected to the original recipients — in terms of subcaste and surname associations — are more likely to adopt in door-to-door sales compared to obtaining seeds from other villagers.

[3] Outside of India, ethnicity in the Democratic Republic of the Congo provides a substitute enforcement mechanism for more formal government contracts (de la Sierra, 2017).

Consequently, there must be other frictions that prevent farmer-to-farmer diffusion from achieving the same adoption as direct sales to farmers.

The data are inconsistent with two other possible explanations for the observed adoption gap between farmer-to-farmer networks and door-to-door sales. First, the seeds were no cheaper to farmers in the door-to-door sales. The prices for door-to-door sales were randomized at three levels: 10, 12, or 14 Rupees per kilogram. As mentioned above, the highest price is larger than the output price of rice. When trading amongst themselves, farmers often trade seeds for grains of another rice variety — which are valued at the output price of rice. If farmers were willing to pay 14 Rs for Swarna-Sub1 seeds in door-to-door sales, then they should have also been willing to trade rice worth less than that in order to obtain Swarna-Sub1 seeds.

Second, the lack of trading is not due to capacity constraints. The amount of seed planted in the second year of the study across the door-to-door villages averaged around 150 kilograms per village. This amounts to less than 10 percent of the amount harvested by original recipients. Put differently, original recipients had plenty of output to meet the seed demands of fellow villagers.

Taken together, the experiment uses the example of informal seed trading to document the existence of trading frictions in Indian village economies. I show some evidence that these frictions are less severe within caste groups. Yet, social identity only explains part of the puzzle. There remains a substantial adoption gap even for farmers belonging to the same social groups as other farmers possessing seeds. This experimental design doesn't pinpoint the exact mechanism underlying these frictions.

At the same time, the magnitude of the trading frictions is large enough to make the door-to-door sales a cost effective intervention. Applying impact estimates from a randomized controlled trial in the same Indian district (Emerick et al., 2016), I estimate that the average farmer in the village economy obtains cumulative three-year revenue gains from Swarna-Sub1 of around 57 dollars. The average farmer in door-to-door villages gains 108 dollars from the technology. These foregone gains of 51 dollars per farmer are larger than the costs of door-to-door sales by a factor of five — suggesting that the severity of trading frictions between farmers makes even the intensive process of selling seeds door-to-door cost effective.

The paper contributes to the literature seeking to address low levels of technology adoption in developing-country agriculture. Labor productivity in agriculture is often disappointingly low (Gollin, Lagakos, and Waugh, 2014) and recent work points to limited diffusion of improved technology as a key driver (see Jack (2011) for examples). Common explanations for low adoption include present bias, lack of profitability, failure to learn from self-experimentation, asymmetric information about quality, and uninsured risk (Duflo, Kremer, and Robinson, 2011; Suri, 2011; Karlan et al., 2014; Hanna, Mullainathan, and Schwartzstein, 2014; Emerick et al., 2016; Bold et al., 2017). These explanations suggest that demand is limited by various factors, and suggest interventions to address those factors, such as commitment devices or formal weather insurance. My findings demonstrate that some of the puzzle of low adoption can be explained simply by missing sources of supply. As consequence, making new technology directly available to farmers, therefore eliminating supply barriers, goes a long way in increasing adoption.

The rest of the paper is organized as follows. In Section 2, I give a more detailed description of the experimental design. This section also discusses previous work on the specific technology, focusing on how that work is relevant for the current experiment. Section 3 gives the main evidence of trading frictions in village economies, while Section 4 explores some possible explanations for these frictions. Section 5 concludes.

2 Background and Experimental Design

This section describes the details of the experimental design. I start by discussing background on the particular technology and relevant previous work on its' impact. The section then outlines the steps of the experiment in chronological order.

2.1 Background and previous work

The particular rice seed introduced as part of this experiment is profitable for farmers. A randomized controlled trial carried out from 2011 to 2012 demonstrated the benefits of the seed to farmers (Dar et al., 2013; Emerick et al., 2016). In particular, Swarna-Sub1 increases yield by around 50 percent during moderate to severe flash flooding of up to 2 weeks. The variety accomplishes this by suppressing the elongation response of the plant to flooding. The rice plant naturally elongates when flooded. Swarna-Sub1 suppresses this response, allowing the plant to store energy that is used as the plant regrows after floodwater recedes (Xu et al., 2006). These large benefits of the technology have also been confirmed during agronomic trials (Singh, Mackill, and Ismail, 2009).

Yet, the previous experimental work found that around 40 percent of the gains from Swarna-Sub1 are not due to this biological mechanism, but rather to how the reduction in downside risk increases investment. Most notably, the seed causes farmers to use more fertilizer, modernize planting methods, increase cultivated area, and to increase the uptake of agricultural credit. These impacts add up to increases output during "good years" when there are no floods.

This experiment builds on this previous work to measure whether trading frictions prevent this profitable seed from effectively diffusing between farmers. The established benefits to farmers indicate that adoption should be rapid in the absence of any such barriers. In addition, I use the impact estimates from this previous work to approximate the revenue gains from eliminating any trading frictions with door-to-door sales. This experiment was purposefully located in the same district as one of the districts in the previous experiment. This similarity in agronomic environments makes the impact estimates from the previous work more applicable

Despite these benefits, Swarna-Sub1 was not available to farmers when the experiment started. Farmers in the sample often obtain new seeds from local government offices. Seed supply in this channel is controlled by the state-run seed corporation and it takes them several years to multiply enough seed for all of the state's flood-prone areas. As a result, the seed remained largely unavailable during the study period. The lack of availability from outside sources allows me to compare diffusion between farmers with the approximate measure of demand from door-to-door sales.

2.2 Overview of the experiment

The experiment was carried out in 82 villages in three blocks of the Bhadrak district of Odisha.[4] This region is a coastal low-lying area where flooding is frequent. The villages selected into the study were flooded in either 2008 or 2011, based on satellite imagery. A majority of farmers in these villages grow a single rice crop during the Kharif (wet season) from June to December.[5] In addition, Swarna (the variety that is dominated by Swarna-Sub1) is widely grown. All of these characteristics are important because they combine to indicate that the innovation being studied is suitable for the sample area.

Each village was visited in May 2012 and farmers were invited to a meeting to discuss Swarna-Sub1. The meetings were open to any farmers cultivating rice and were attended by anywhere from 15 to 41 farmers, with average attendance being 22.[6] During each meeting, enumerators provided a brief overview of the characteristics of Swarna-Sub1, described its similarity to the popular variety Swarna, and pointed to flood tolerance as its only known benefit. After the information was provided, each farmer was administered a short baseline questionnaire.

The original recipients were selected at the end of the meeting via lottery. Attendees were informed that five farmers would be chosen to receive a five kilogram minikit. Minikits are a common approach to introducing a new seed variety in India (Bardhan and Mookherjee, 2011). Each minikit contained only five kilograms of Swarna-Sub1 seeds, which is enough to cultivate 10 to 20 percent of an average farmer's landholdings. Despite being a small amount of seeds, 5 kilograms multiplies to an average of just less than 350 kilograms after harvest. Each attendee then placed their name in a bucket and five names were selected. The seeds were then given to the winners immediately in front of all the meeting attendees. This approach was purposefully selected so that the identities of the five original recipients would be known to all participants. This eliminates the possibility that slow diffusion can be caused by lack of information on who was cultivating the new variety. Enumerators also informed farmers that Swarna-Sub1 would unlikely be available at local block offices where they most often buy new seeds. Therefore, any farmers that want to cultivate Swarna-Sub1 next year should purchase or exchange seeds with the original recipients.

The random selection of original recipients is important to the design because it allows for causal identification of whether trading frictions are any smaller within established networks. The tradeoff is that randomization is not amongst the real-world methods of identifying entry points for new agricultural technology. The most common approach is to use local agricultural extension agents

[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]26 percent of farmers have at least one plot that has access to lift irrigation, which is needed to cultivate dry-season crops.

[6]The households in the sample are fairly representative of the village. The average share of the population that is scheduled caste is 20 percent in both the sample and the matched 2001 census of villages. Average household size and male literacy are also similar between the sample and the census.

to identify “lead” or “contact” farmers.[7] Nonetheless, the randomization allows me to estimate the extent of diffusion when different types of farmers are selected as original recipients. I return to this in Section 4.

Survey teams then visited original recipients during the harvesting period in November of 2012. This visit had three purposes. First, enumerators verified that the crop had been planted. Most original recipients complied with the experiment by planting the minikit. Of the 396 farmers surveyed, 87 percent indicated that the minikit had been planted.[8] Second, original recipients were reminded of the potential opportunity to sell or trade Swarna-Sub1 seeds after the harvest. Third, enumerators collected a number of characteristics of original recipients to be used in heterogeneity analysis.

I then identified 15 non-recipients in each village by taking a random sample amongst the farmers that attended the meetings, but were not selected as original recipients.[9] This group of farmers serves as my main estimation sample. The sample was drawn from the meeting attendees for two reasons. First, the meeting attendees witnessed the selection of original recipients and therefore focusing on attendees eases the concern that information about identities of original recipients can drive adoption patterns. Second, the benefits of Swarna-Sub1 were explained to meeting attendees. Focusing on attendees therefore reduces the likelihood that non-adoption could be caused by lack of information.

Enumerators then surveyed each of these 1,151 non-recipients during February-April 2013. There were three purposes of this survey. First, a plot-level record of flooding during the previous five years was collected in order to estimate the expected returns of the new technology. I return to the estimation of expected returns using these data below. Second, farmers were also reminded about the new variety and the potential to obtain it from other farmers in the village. These reminders limit the possibility that farmers chose not to adopt simply because they had forgotten or did not know about the technology. Third, all respondents were again informed about the flood tolerance benefits of Swarna-Sub1.

41 of the villages were randomly assigned to receive a door-to-door treatment where enumerators went to each of the 15 non-recipients and asked them if they were interested in purchasing Swarna-Sub1 seeds.[10] The door-to-door sales took place in late May and early June of 2013. Except for

[7] Beaman et al. (2015) show that using the structure of the social network to identify optimal injection points can increase adoption relative to this approach of using extension agents.

[8] 14 of the 410 original recipients could not be reached because either the household had moved from the village or household members were away for work during survey visits. 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.

[9] All non-recipients were selected into this sample in villages where fewer than 20 farmers attended the meeting.

[10] The randomization of door-to-door sales was stratified by block — an administrative unit two levels above villages — and the relative importance of original recipients to non-recipients. Original recipients were defined as being relatively more important when the ratio of average degree (number of social contacts) of original recipients to the average degree of non-recipients was larger than the sample median. The degree is simply the number of links of a farmer, where two farmers are defined to be linked if either farmer stated that they would go to the other farmer for seeds, fertilizers, or other inputs.

reminding farmers of the previous survey, enumerators gave farmers no additional details about Swarna-Sub1's benefits.

The purpose of these door-to-door sales was to approximate a revealed-preference measure of demand. A limitation of this approach is that I cannot strongly eliminate the possibility that visiting farmers and offering the seed increased demand. At the same time, the door-to-door sales allow me to estimate demand in an environment without any frictions or costs to adoption. A further limitation is that door-to-door sales do not represent an easily scalable method for diffusing technology to farmers. I return to this concern when considering cost effectiveness in Section 3.5.

Prices are another important concern because the experiment requires the door-to-door offers to be made at prices that are equivalent to the prices paid in transactions between farmers. During piloting I found that farmers often exchange seeds of one variety for output of another.[11] The price in such a transaction corresponds to the farm-gate price of rice, which is the opportunity cost of the rice that was exchanged for seed. The minimum support price set by the Indian government for the 2012-2013 season was 12.5 Rs per kilogram (1 USD $\approx$ 58 Rs).

Based on these output prices, the price for door-to-door sales was randomized at the village level to one of three values: 10, 12, or 14 Rs per kilogram. Importantly, I included the higher price of 14 Rs in order to estimate demand at a price that is *higher* than the output price of rice. The villages where demand was revealed at this price therefore allow me to establish whether there was demand at a price higher than prices for which Swarna-Sub1 was sold by original recipients.

Enumerators then revisited all 82 villages in July 2013 to track adoption — the main outcome variable of interest. Enumerators visited the sample of non-recipients in all villages, including the door-to-door villages. Farmers in door-to-door villages could have also obtained seeds from original recipients and therefore an additional survey was needed to fully track their adoption status. In addition, carrying out the survey in all 82 villages ensures that adoption is measured in a uniform way across all villages, regardless of treatment status. I use adoption from this survey as the main outcome variable in all of the analysis when uptake is the outcome variable.

In addition to this survey with non-recipients, enumerators were able to locate 394 of the original recipients. The main purpose of the survey with original recipients was to fully document the final uses of the Swarna-Sub1 output. Each original recipient was asked their harvest amount, amount sold as rice, amount sold or stored for consumption, amount saved for their own seed, and amount of seed transferred to others. Section 3.1 describes in more detail how the harvest of original recipients was allocated. Each original recipient was also asked for the identities of the farmers to which they transferred seeds.

A final survey was carried out two years later during July 2015. This second followup allows me to estimate longer term effects during both the 2014 and 2015 seasons. These effects add to the analysis because the adoption gap could dissipate over time as more farmers start cultivating and sharing seeds with each other. The survey allows me to measure the adoption gap over a

[11] This pattern was true in the data as well. As I show in Section 3.1, 70 percent of the Swarna-Sub1 transactions reported by original recipients were 1:1 exchanges for other rice varieties.

three-year period. One notable difference is that the long-term followup included all rice-farming households, including those that did not participate in the village meetings and were thus not part of the original sample.

2.3 Summary Statistics

Table 1 verifies that the non-recipient farmers are similar in the network and door-to-door villages. In addition to this test of balance, the table points out three notable features of the sample. First, Swarna is widely grown by around 70 percent of farmers. Swarna-Sub1 is superior to Swarna and therefore a maximum potential adoption rate of 70 percent is plausible. Second, the average non-recipient has 2.1 and 1.4 sub-caste and surname connections with original recipients, respectively. Third, travel costs to obtain seeds seem minor. Each respondent had just over one original recipient that lived within 50 meters from their household.

Seed sharing exists at baseline, although it is not the dominant method for obtaining seeds. 14 percent of farmers at baseline planted at least one plot with seeds that were obtained from a neighboring farmer. This figure stands at 66 percent for seeds saved from the previous harvest and 43 percent for seeds sold by local government offices. In other words, seeds from neighboring farmers account for one quarter of seed replacement, i.e. when farmers decide to plant new seeds. Most importantly, sharing seeds is not a new practice for farmers.

I also use the short survey carried out during the village meeting to verify the similarity between non-recipients and original recipients (Table A1). In addition, characteristics of recipients and non-recipients are balanced in both network and door-to-door villages.[12]

3 Results

This section starts by quantifying the harvest of original recipients and documenting the exact uses of their output. I then argue that the two alternative uses of output — consuming it as rice or selling it for consumption — were no better for original recipients in the absence of any trading frictions. Sections 3.2 then shows the main results on adoption and Section 3.3 considers targeting differences. After having established the gap between adoption in networks and door-to-door sales, Section 3.4 considers diffusion over time and shows that adoption failed to catch up to adoption in the door-to-door sales villages after two additional growing seasons. I then quantify the expected losses to farmers from this limited diffusion in Section 3.5. Finally, Section 3.6 exploits high-resolution satellite imagery to estimate productivity impacts of the new seed, further strengthening the argument that the limited diffusion between farmers reduced productivity.

[12] I regress each of 8 household characteristics in Panel A of Table A1 on village-level treatment, an indicator for original recipients, and the interaction of these two variables. The F-statistics of these regressions range from 0.29 to 1.12 and thus the three variables do not jointly explain variation in any of the household characteristics.

3.1 What did original recipients do with their harvest?

The average original recipient harvested just less than 350 kilograms of Swarna-Sub1. The left panel of Figure 1 shows this amount was allocated across four uses: transfers of seeds to other farmers, savings of seed for future cultivation, grain sold, and grain consumed or stored for future consumption. The average farmer transferred only 6 kilograms — an amount roughly equivalent to what they were given — to other farmers. There are two notable features of these transfers. First, 80 percent of the transfers reported by original recipients were with farmers from the same village. Second, trading seeds for output of another variety is the dominant contract type. 69 percent of the reported transfers were exchanges of Swarna-Sub1 for another rice variety, while 26 percent were gifts and only 4 percent were sales for cash. Interestingly, the average original recipient saved over two times as much output for their own seeds. The 16 kilograms allocated for their own cultivation amounts to enough seed for approximately 30 percent of their land, suggesting that original recipients recognized the benefits of Swarna-Sub1. Panel B shows a similar result with the extensive margin of seed allocation. 24 percent of farmers transferred seeds to others, while 70 percent saved seeds for themselves. Only 32 percent of farmers sold output as rice, while over 80 percent of farmers saved some output for their own consumption.

The implicit price of the farmer-to-farmer transactions (to the recipient farmers) is the opportunity cost of the unmilled rice that was traded for Swarna-Sub1. The government's minimum support price during this season was 12.5 Rupees per kilogram. As I note below, most farmers sell their output for lower prices to private traders — putting downward pressure on average prices. The implicit prices of the informal trades between farmers were therefore right in line with the prices in the door-to-door sales. Being able to observe the demand benchmark at 14 Rupees — a price higher than the implicit price of farmer-to-farmer trades — offers confirmation that results cannot be explained by lower prices in door-to-door sales.

Returning to Figure 1, the vast majority of the rice harvested was either sold for consumption (32 percent) or consumed directly by original recipients (62 percent). The entire experiment hinges upon these two alternative uses being no more profitable for original recipients relative to trading seeds. In other words, original recipients could not have obtained higher prices by selling for consumption, or the consumption value of Swarna-Sub1 could be no higher than the other varieties that farmers are willing to trade for Swarna-Sub1.

The first of these is directly testable in the data. I asked each original recipient that sold any Swarna-Sub1 for consumption to report the transaction price. The average price across these transactions was 10.34 rupees per kilogram and 85 percent of the transactions had prices in between 9 and 11 Rs. This amount is closest to the *lowest* price where seeds were offered during the door-to-door sales. In other words, original recipients were willing to sell their output at prices near or below the prices where demand was revealed in the door-to-door sales treatment. As a second piece of evidence, the seed varieties that farmers commonly traded for Swarna-Sub1 were no less valuable. I determined this by asking the name of the particular variety received for each trade. I then calculated the average price across these varieties (weighted by share of trades) using data on sales prices collected in the same blocks during previous work (Emerick et al., 2016). The average market price of these varieties being received by original recipients was 10.15 rupees, a value quite similar to the price original recipients received when selling Swarna-Sub1. Thus, it seems unlikely that it was more profitable for original recipients to sell their output as grain for consumption.

The observed similarity in output prices also suggests that the consumption value of Swarna-Sub1 is similar to other varieties. We would expect clear price differences if Swarna-Sub1 has superior eating quality. Direct statements from farmers in Emerick et al. (2016) also support this conclusion. The percentage of adopters in that study reporting better taste as a reason for their adoption is nearly identical for Swarna, Swarna-Sub1, and other varieties.[13] An independent survey in two Indian states also found that amongst several statements about properties of Swarna-Sub1, adopters were the least likely to agree with the statement that it tastes better than other varieties (Yamano, Malabayabas, and Panda, 2013).

Original recipients did consume a large share of their harvest. However, this was not out of necessity. The median original recipient harvested 2,300 kilograms of rice during the year before the study — an amount more than enough to feed the household for a year. This result suggests that the output of Swarna-Sub1 represents a modest share of overall production. It therefore seems unlikely that a subsistence constraint forced original recipients to consume their Swarna-Sub1 output.

Combining these descriptive data, there seems to be no evidence suggesting that original recipients would have been made worse off by transferring seeds. The profitability of alternative uses — either selling as rice or consuming directly — can't explain limited diffusion of seeds to other farmers. The rest of the paper seeks to understand whether the observed diffusion in networks is a first-best outcome and if not, attempts to quantify the magnitude of any trading frictions.

3.2 Did farmer-to-farmer trading reduce adoption relative to door-to-door sales?

The door-to-door sales experiment serves as a benchmark so that I can compare an approximate measure of demand with diffusion in farmer networks. Further, I can make this comparison at three different price levels: 10, 12, and 14 rupees per kilogram. The experiment therefore approximates demand at a price equivalent to the one received when original recipients sold output as rice for consumption. In addition, I am able to estimate whether farmers were willing to pay prices higher than those received when original recipients chose to sell output as grain. I show adoption in the door-to-door sales villages using the follow-up adoption survey with all non-recipients, which was carried out after planting for the second year of the study.

The uptake in door-to-door villages — at all three price levels — is over three times the adoption that took place when farmers shared informally amongst themselves. Figure 2 demonstrates this by showing the raw adoption rates in the network and door-to-door villages. Only 6.5 percent of non-recipient farmers adopted after the first year in network villages. At the same time, the above data showed that original recipients in the same villages were selling their output for an average of 10.34 rupees per kilogram. The striking finding is that 43.8 percent of farmers obtained seeds

[13] See Figure A1 in the online appendix of Emerick et al. (2016).

in villages where the prices was 10 rupees and this falls to 41.7 percent and 35 percent at prices of 12 and 14 rupees, respectively. Therefore, this gap in adoption can not be explained by price differences. Demand for seeds existed at a price of 14 Rs, which is 35 percent above the price that original recipients chose to sell the very same variety as rice for consumption. These findings suggest that some friction exists and impedes adoption in the village seed markets.

The regression specification corresponding to Figure 2 is

$$adoption_{ij} = \beta_0 + \beta_1 Price\ 10_j + \beta_2 Price\ 12_j + \beta_3 Price\ 14_j + \varepsilon_{ij}, \tag{1}$$

where $adoption_{ij}$ is an indicator for adoption by farmer i in village j, and β_1, β_2, and β_3 measure the gaps in adoption at the three different price levels.[14] Recall that exchanging seeds was the most frequent arrangement in direct transactions between farmers. The opportunity cost to the seller of such a transaction is the 10.34 rupees that could have been obtained by instead selling that same output to traders for consumption. The coefficient β_1 therefore represents the difference between adoption in farmer-to-farmer networks and door-to-door sales villages at comparable prices.

The estimates in column 1 of Table 2 show that the adoption at all three price levels was significantly higher than the network adoption rate. Column 2 shows my main estimate which is the average effect across all three price levels. In particular, adoption is higher in door-to-door villages by 33 percentage points. The rate of adoption of 40 percent in door-to-door villages is larger than the adoption in the network by over five times. Not surprisingly, column 3 shows that the estimated adoption gap changes little when introducing household controls.[15]

3.3 Are networks better at targeting?

This gap in adoption could be offset if farmer-to-farmer trading is more effective at targeting the seed to those with the highest returns. I test this using data on the average return of adopters. Data on flooding during the past five years are used to generate a measure of expected returns for each farmer in the sample,

$$return_{ij} = \frac{\frac{1}{5} * \sum\limits_{p=1}^{P_{ij}} \sum\limits_{t=2008}^{2012} R(d_{ijpt}) * area_{ijp}}{\sum\limits_{p=1}^{P_{ij}} area_{ijp}}. \tag{2}$$

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

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

[15] I show in Table A2 that the treatment effect of door-to-door sales is smaller for lower caste farmers and farmers that are below the poverty line. It is therefore poorer households that lose the least from network-based trading. Liquidity constraints offer one possible explanation: Poor households may hold less cash at the time of planting and therefore be unable to purchase new seeds.

of Swarna-Sub1, relative to Swarna. The units of measurement of R are kilograms per hectare cultivated. I use estimates of R that were calculated in the previous work of Dar et al. (2013). Figure A1 shows that this metric of estimated returns varies both across and within villages.

I consider the average return of adopters as the most direct measure of targeting effectiveness. Figure 3 displays the densities of estimated returns for adopters across the different treatment groups. Visually, the distribution of estimated returns in the network villages shifts to the right when compared to door-to-door villages.

OLS regression estimates also suggest that farmer networks were slightly more effective at targeting. The regression results in column 1 of Table 3 show that the average return of adopters in door-to-door sales is smaller by 38 kg per hectare, an approximate 22 percent decrease.[16] The effect is reasonably large, but not quite statistically significant (p=0.12). Column 2 shows a similar, but more precise result when using log returns as the outcome variable. Turning to column 3, similar results are obtained when using a self-reported measure of flood risk for the plot where the new variety would be planted. Farmers were asked to assess on a scale from 1-10 how prone their Swarna-Sub1 plot is to flooding. The average value amongst adopters in the network villages is 5.25. The predicted decrease with door-to-door sales is 0.81, or 15 percent. The estimated effect with this separate measure is qualitatively similar, but also not statistically significant (p=0.12).[17]

The results do suggest a slight improvement in targeting with farmer-to-farmer trading. However, the targeting effect is modest. It will therefore offset only a small amount of the losses from the large gap in adoption. This arises because the relative magnitudes of the adoption gap and targeting effect are strikingly different. The door-to-door sales increased adoption by over five times, but only reduced targeting effectiveness by around 20 percent. Therefore, the targeting differential is nowhere near large enough to offset the adoption gap.

3.4 Did the adoption gap persist over time?

There are two immediate reasons why these one-year impacts are complemented by a longer run analysis. First, it may take additional time for farmers to learn and to approach other farmers to obtain the seed. Second, the randomly selected original recipients are representative of the average farmer and not necessarily the most entrepreneurial farmer. Allowing additional growing seasons to pass would allow entrepreneurial farmers to select into adoption, multiply the seeds, and sell them widely after one year. If either of these phenomena explain the short-term adoption gap, then we should expect this gap to disappear over time.

The longer run follow-up survey allows for these ideas to be taken to the data. The survey was carried out approximately two years after the first follow-up survey. It involved a door-to-door varietal adoption census with all households in each of the 82 villages. I can therefore measure adoption for two additional years after the first survey. Attrition is not a concern. Around 99

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

[17] I show in Table A3 that the estimated returns in networks are slightly affected by two farmers that were provided free Swarna-Sub1 seeds from a local disaster management office. Dropping these farmers from the analysis makes the targeting differential slightly more precise.

percent of the households that were surveyed as part of the original survey were reached again during the second follow-up survey. I focus the analysis on the original sample of 15 farmers per village.

Figure 4 shows the differences in raw adoption rates over time.[18] There are two important observations from the figure. First, there has been some convergence. Despite this, there still remains a gap in adoption between the two types of villages. While adoption increased to 32 percent of farmers in network villages, approximately 50 percent of farmers were cultivating the technology in door-to-door villages. This translates to a 56 percent increase. This persistence of an effect over time shows that the trading frictions persist over at least a three-year period.

The longer run results also suggest that the buyers from the door-to-door sales were not effective in diffusing seeds to others. Despite creating about five additional adopters in 2013, these farmers did not cause the 2014 adoption to grow faster relative to the network villages. This suggests that the adopters from door-to-door sales diffused seeds at a rate even lower than the original recipients. One possible explanation is that encouraging the original recipients to share seeds had a modest effect, but the door-to-door adopters didn't receive this encouragement, making them less likely to transfer seeds to others.

Both this long-run survey and the one-year followup measured adoption in the same way across all villages. Each household was directly asked about their adoption of Swarna-Sub1. While adoption was directly observable from the door-to-door sales, the survey was still necessary for two reasons. First, farmers in door-to-door villages could still obtain seeds from original recipients. The survey was needed to detect adoption of this type. Second, using the survey in all villages ensures that adoption is being measured in the same way across the two treatments.

3.5 How costly is the lack of adoption?

The results establish a gap between adoption with door-to-door sales and take up when diffusion occurs informally between farmers. I next take this one step further to quantify the losses that result from farmer-to-farmer diffusion in networks. This additional exercise requires only an estimate of the causal impact of Swarna-Sub1. The experiment in Emerick et al. (2016) generated such an estimate. Specifically, the estimated impact of Swarna-Sub1 on rice yields — due solely to increased investment — is 283 kilograms per hectare cultivated.[19]

I use this value along with the estimated returns from flood tolerance (calculated above) to calculate a per-farmer measure of the revenue gains from Swarna-Sub1. I convert this measure from kilograms to rupees by multiplying by the Indian government's minimum support price for rice during each year. More specifically, the measure of estimated revenue gains is

$$\Delta revenue_i = \sum_{t=2013}^{2015} \delta^{t-2013} * price_t * adopt_{it} * (return_i * ss1_{it} + farmsize_i * 283.45), \quad (3)$$

[18]The complete regression results including strata fixed effects are given in Table A4.

[19]This value is output per hectare cultivated with rice, not output per hectare cultivated with Swarna-Sub1.

where $adopt_{it}$ is an indicator for adoption of Swarna-Sub1, $return_i$ is the return (in kg) from flood tolerance estimated in Equation 2, $ss1_{it}$ is the area planted with Swarna-Sub1, and $farmsize_i$ is the rice area of farmer i.[20] I use a discount factor of $\delta = 0.95$. I report both the difference in annual revenue gains for each of the three years and the cumulative effect as written in Equation 3.

The network-based model of diffusion reduces the expected welfare gains from new technology. This is shown graphically in Figure 5 while the complete regression results are shown in Table A5. My best estimate indicates that relative to the demand benchmark, network-based diffusion led to lower technological gains by around 21 dollars per farmer in 2013, 18 dollars in 2014, and 12 dollars in 2015. This amounts to a non-trivial magnitude of 51 dollars cumulatively over the entire three-year period. The amount is equivalent to around 20 days of casual work or around 8 percent of the annual rice harvest for an average farmer.[21]

The door-to-door sales were not meant to test a scalable intervention. Nonetheless, it is useful to benchmark these estimated revenue losses against the acutal costs of door-to-door sales. The cost of each door-to-door visit was approximately 9 dollars. The estimated losses to farmers from network-based trading are larger than the cost of door-to-door sales by a factor of five. This finding is striking and suggests that the frictions in the village seed market is large enough to make even a door-to-door sales intervention cost effective.

3.6 Did adopters benefit during the next season's flood?

I next show direct measures of the costs of non-adoption. The 2013 season (immediately following the door-to-door sales) involved variation in flooding across the sample villages. I overcome the lack of survey-based data on crop yield by using high-resolution satellite imagery that allows me to observe the greenness of fields on various days starting in April of 2013 (before planting) and continuing until March 2014 during the dry season when only irrigated fields are cultivated.[22] These data provide estimates of the Normalized Difference Vegetation Index (NDVI) — a standard measure of plant greenness that is strongly correlated with survey-based measures of rice yield (Huang et al., 2013). In addition, the spatial resolution of 30 meters allows me to generate a plot-specific measure of greenness by overlaying each image with the centroids of the farmers' plots.[23]

I combine three sources of variation to measure the impact of Swarna-Sub1 on the NDVI. First, there is variation in adoption: 59 percent of farmers for which I have plot locations did not adopt during the 2013 season. Second, there is differential exposure to flooding. Satellite images of

[20] I observe 2015 rice area and use it to estimate rice area for the other two years.

[21] The casual labor benchmark is based on the 2015-2016 Odisha wage for NREGS, the government's employment guarantee scheme. The rice output benchmark is based on the measured average output in the sample of 3.3 tons.

[22] The data are derived from the Landsat 8 8-day NDVI composites made available on Google's Earth Engine public data catalog (code.earthengine.google.com, accessed September 2016).

[23] Survey teams collected the centroids of plots that were cultivated with Swarna-Sub1 by original recipients during the 2012 season. This differed for non-recipients where survey teams collected locations for the most flood-prone plot. This implies some measurement error in identifying the plots that were actually cultivated with Swarna-Sub1 during the 2013 season when the satellite images become available. This would only affect the analysis in the unlikely event that this source of measurement error is correlated with flooding.

flooded areas identify 35 percent of plots that were flooded during the season.[24] Third and finally, I observe images during both the wet and dry seasons and flooding is non-existent during the dry season. This third source of variation therefore allows for a weaker identification assumption. I basically compare the difference between adopters and non-adopters in flooded versus non-flooded areas in both the wet and dry seasons. This triple differences approach eases concerns that adopters in flooded areas cultivated the seed on different types of land — such as irrigated fields — since these fields would appear more productive during the dry season.

Figure 6 helps visualize these data by showing the NDVI measures at four points in time: once before the 2013 wet season, twice during the season, and once after the completion of the wet season. For each of these images I basically compare the difference in greenness between adopters and non-adopters on flooded plots (the blue dots) to that on plots that were not flooded (the black dots). The flood-tolerance benefit of the technology is apparent when making this comparison. Figure 7 shows this by plotting the difference in log NDVI between adopters and non-adopters over time and separately by flood status. Visually, there is little difference between adopters and non-adopters in areas that were not flooded (the black line in the figure). In contrast, there is a noticeable increase in greenness for adopters on fields that were flooded and this increase exists only during the growing season. It is therefore not attributable to fixed differences of the land such as irrigation access, since these characteristics would be visible during the dry season.

I estimate the following triple differences regression in order to quantify this effect:

$$\begin{aligned} log(NDVI_{it}) = \beta_0 + \beta_1 flood_i * growseason_t * adopt_i + \beta_2 adopt_i + \beta_3 growseason_t + \\ \beta_4 flood_i + \beta_5 growseason_t * flood_i + \beta_6 growseason_t * adopt_i + \\ \beta_7 adopt_i * flood_i + \varepsilon_{it}. \end{aligned} \tag{4}$$

In this specification $NDVI_{it}$ is the the observed NDVI for farmer i on date t, $flood_i$ is a time-invariant indicator for farmers that were affected by flooding during the wet growing season, $adopt_i$ is an indicator for adoption, and $growseason_t$ is an indicator for observations during the wet growing season, i.e. the 7 images from August 13th to November 17th. The coefficient of interest β_1 measures the differential effect of adoption on plant greenness in areas that were flooded and for observations during the growing season. This triple differences estimate can be interpreted causally as long as there are no unobserved differences between adopters and non-adopters that both influence crop productivity and exist *only* in areas that were affected by flooding and during the rainy growing season.

Table 4 shows these results for two different measures of exposure to flooding. In column 1 flood exposure is defined as any field within 250 meters of any flooded area since this corresponds with the resolution of the flooding imagery. Using this definition, I find a 10.1 percent increase in greenness associated with adoption of Swarna-Sub1. The point estimate of β_5 shows that the average

[24] I define flooded plots using daily images of flood areas (see http://csdms.colorado.edu/pub/flood_observatory/MODISlance/080e030n/, accessed September 2016). The resolution of these images is 250 meters. I therefore consider a plot to be flooded if it is within 250 meters of the nearest area that was flooded any time during the growing season.

flooded field is 31 percent less green during the growing season and therefore the flooding imagery capture variation in flooding that is strongly associated with crop health. Access to Swarna-Sub1 eliminates around one third of this negative effect of flooding on greenness. Column 2 demonstrates that the results are similar when defining flood exposure using a 500 meter threshold. I show in the appendix that similar results are obtained when controlling for time-invariant unobservables with either village or farmer fixed effects (Table A6).

This additional analysis verifies that the new seed immediately benefitted farmers in the sample. The above cost-benefit calculation instead relied on impact estimates from a previous randomized experiment. While the impact estimates are not directly comparable because the outcomes are different, i.e. survey-based measures of crop yield vs. satellite-based measures of NDVI, these additional findings suggest that the observed trading frictions prevented farmers from benefitting from the flood tolerance of the new variety.

4 Possible sources of trading frictions

I have shown that direct trading of seeds between farmers results in adoption that falls short of uptake when seeds are directly sold to farmers. At the same time, the technology in the experiment is profitable. What is the friction in the local seed market? This section looks at possible explanations. I start by showing that the concentration of trading within castes explains a portion of the adoption gap. At the same time, within-caste trading appears to explain no more than half of the gap in adoption. I find less evidence for four other possible explanations: capacity constraints, the random choice of recipients, unobservable seed quality, and marketing effects of door-to-door sales. Taken together, the section shows some evidence that trading frictions are smaller within caste groups. Yet, there still remains a puzzlingly large adoption gap even within networks.

4.1 Within-network trading

Is trading concentrated within established social networks? If so, then being close to an original recipient should have a positive effect on adoption and this effect should disappear when actual demand is revealed with door-to-door sales. The corresponding regression specification is

$$\begin{aligned} adoption_{ij} =& \beta_0 + \beta_1 door\ to\ door_j + \beta_2 linksOR_{ij} + \beta_3 links_{ij} + \beta_4 linksOR_{ij} * door\ to\ door_j \\ &+ \beta_5 links_{ij} * door\ to\ door_j + \varepsilon_{ij}, \end{aligned} \tag{5}$$

where $linksOR_{ij}$ is the number of peers of farmer i that were selected as original recipients and $links_{ij}$ is the total number of links of farmer i. I focus on two closely related measures of social links: sharing a common surname and belonging to the same sub-caste, or jati.[25] Surnames offer a slightly finer measure than sub-caste. While members of the same sub-caste may have several surnames,

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

sharing a common surname measures clan association or kinship. Importantly for identification of β_2 and β_4, the random selection of original recipients guarantees that the number of links with original recipients is random when conditioning on the total number of links, thus avoiding the classic reflection problem discussed in Manski (1993). A finding of $\beta_2 > 0$ and $\beta_4 < 0$ would be consistent with caste being an impediment to seed trading.

Social relationships do determine adoption. In column 1 of Table 5, sharing the same surname with an additional original recipient causes a 3.5 percentage point, or 50 percent, increase in the probability of adoption in network villages. This network effect decreases significantly by 7.5 percentage points when door-to-door sales were carried out. Turning to column 2, the effects strengthen when including village fixed effects.[26] Having the same surname as one additional original recipient results in a 106 percent increase in adoption with network-based diffusion. Again, this peer effect is eliminated with the door-to-door sales.

Direct measures of caste association deliver similar results. In column 3, having one additional original recipient from the same sub-caste leads to a 4 percentage point increase in adoption, representing a 57 percent effect. The estimated coefficient on the interaction between the door-to-door indicator and the number of original recipients in the same sub-caste is negative and of similar magnitude as the effect in the network villages. Thus, the sub-caste peer effect becomes effectively zero when door-to-door sales are made. Column 4 shows similar results when estimating the regression with village fixed effects.

These estimates are robust to two alternative estimation strategies. First, accounting for the dichotomous nature of the dependent variable by using a probit specification has little impact on the estimates (columns 3 and 4 in Table A7). Second, an alternative approach would be to use the *share* of connected farmers that were selected as recipients. As shown in Table A8, using this approach actually improves precision of the estimates.

How much of the adoption gap between treatments is accounted for by trading within these social groups? Figure 8 uses the regression results in Table 5 to plot the effect of door-to-door sales as a function of these social connections. Panel A considers a farmer that shares the same surname with five other farmers in the village and uses the regression results (column 1) to calculate predicted adoption for each of the treatment arms, while varying the number of connections with original recipients. Panel B shows results from a similar exercise for a farmer that belongs to the same subcaste as five other villagers in the sample — now using column 3 of Table 5. The adoption gap declines as a farmer becomes connected to more original recipients. Yet, such connections only explain part of the low adoption when seeds diffuse between farmers. Focusing on the left panel, farmers sharing the same surname with 4 original recipients are predicted to adopt 17.4 percent of the time in farmer-to-farmer diffusion compared to 31 percent of the time with door-to-door

[26] 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 A7 I show that the estimated peer effects are much larger in the sample of villages where there was at least one adopter (columns 1 and 2). The results are also more similar to fixed effects results when discarding the 5 percent of observations where over 15 of the farmers in the village have the same surname (not shown).

sales. Turning to the right panel, farmers belonging to the same subcaste as 4 original recipients are predicted to adopt 18.1 and 37.8 percent of the time with farmer networks and door-to-door sales, respectively. Within-network trading therefore explains some of the trading frictions in the village economy. But, there still remains a puzzlingly large adoption gap even for the farmers with the most social connections to the original recipients.

Table 6 uses the long-run survey to show that surname effects persist over the three-year period. The results in column 1 are reassuringly similar to the estimates from the initial follow-up survey.[27] That is, each additional surname connection with an original recipient causes a 5.4 percentage point increase in adoption in network villages. This peer effect is erased entirely in door-to-door villages. In fact, the peer effects in door-to-door villages are if anything negative in 2013 and 2014 and statistically insignificant in 2015.[28] Interestingly, sub-caste association is a much weaker predictor of long-run adoption in the village economy. Table A9 shows that the number of recipients in the same sub-caste is positively, but weakly related to adoption. One explanation — which is consistent with results in the online appendix — is that surnames are a stronger measure of social connections.

Table A10 considers whether farmers at followup stated they were more likely to obtain seeds or other inputs from original recipients. I find no evidence of such behavior. In contrast, there is evidence that input-sharing relationships are strongly correlated with common castes and surnames.[29]

4.2 Other possibilities

Capacity constraints

Capacity could explain the results if the output of original recipients was insufficient to meet seed demands of other villagers. The data suggest this is untrue. Original recipients harvested an average of around 1,700 kilograms in each village. The average farmer in the door-to-door sales experiment procured 2.83 kilograms.[30] Taken together, the amount produced was sufficient to meet the seed demands of 600 farmers — a number several times larger than average village size.

Figure A2 shows this across door-to-door villages by showing the distribution of the differences between the total harvest and the total amount of Swarna-Sub1 planted in each village *after* door-

[27] The 2013 adoption rate measured in the 3 year follow-up is larger in both types of villages by around 10 percentage points. One reason for the difference between the two surveys is that the original follow-up survey in 2013 was carried out after farmers had planted seedbeds but before the main rice fields had been planted. Thus, there was an additional opportunity for farmers to obtain seedlings (as opposed to seeds) from other farmers. Nonetheless, Table A4 shows that the estimated adoption gap between treatment and control villages is similar between the two surveys.

[28] The p-values for the overall effect of surname connections in door-to-door villages are 0.054, 0.029, and 0.48 for 2013, 2014, and 2015 respectively.

[29] The follow-up visits included a module where each respondent was asked whether they would go to each other respondent for sharing seeds or other inputs. I use these dyadic data to test whether links are more likely in dyads with a single original recipient. Table A10 shows that dyads with a single original recipient are about 6 percent more likely to involve a link, however this difference is not statistically significant. In contrast, original recipients are more likely to report links amongst themselves. Farmers sharing the same surnames, being part of the same sub-caste, or living close to each other are more likely to be linked (Table A11). Of these variables, sharing a common surname is the most robust predictor of link formation.

[30] This figure is unconditional, i.e. it includes farmers choosing not to purchase.

to-door sales were made. The amount harvested exceeded the amount planted during the next year by an average of 14 times. There was only one village where the harvest was particularly poor and the amount purchased exceeded the amount harvested. These straightforward calculations are inconsistent with capacity-based explanations of the findings.

Selection of original recipients

Random selection of original recipients allowed for causal identification of network effects. But, such random selection lacks policy relevance. An alternative approach — and one that is under consideration in the recent literature — would be to purposefully select the original recipients that are theoretically desirable for diffusion. Recent studies have considered the impacts of using network theory to target entry points (Beaman et al., 2015) as well as directly surveying villagers about optimal entry points (Banerjee et al., 2014).

I exploit the random selection of original recipients to test whether adoption was higher when recipients were more important in a network sense. I partition villages into two groups according to the ratio of the average degree of recipients to non-recipients. Villages where recipients are more central are defined as those where this ratio is greater than the sample median.[31] One important caveat is that the number of links is not the optimal measure of how effective a particular node in a network is as an injection point (Beaman et al., 2015). Nonetheless, the analysis helps to answer the question of whether a more targeted approach of selecting original recipients would speed diffusion.

I find no evidence that the gap in adoption is any smaller when original recipients were randomly more connected to other villagers (Table A12). If anything, the effect goes in the other direction. The effect of the door-to-door treatment is 25.6 percentage points in villages where original recipients were less important and 41 percentage points in villages where they were more important. This difference is also statistically significant at the 10 percent level. A simple explanation of this finding is that more connected original recipients are indeed better at generating additional demand. However, they are no better at actually sharing seeds with other villagers.

The random selection of original recipients allows me to further test whether adoption was faster when the recipients differed from the non-recipients on observable characteristics. Table A13 shows evidence that the relative wealth of original recipients influenced adoption. The adoption rate increased by 7.7 percentage points in villages where recipients were wealthier than non-recipients. This effect increases by 7 percentage points in door-to-door villages, yet the difference is not statistically significant. The finding suggests that targeting entry points based on wealth can increase diffusion. There are two candidate explanations. First, wealthy farmers could be less likely to store or consume their harvest and thus serve as better recipients for transmitting seeds to other farmers. Second, wealthy farmers could be better at demonstrating the technology and thus creating

[31] Randomization of village-level treatment was stratified by this degree ratio for purposes of investigating heterogeneity with respect to importance of original recipients. 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.

demand. The data seem more consistent with the latter explanation since the relative wealth of original recipients influences both adoption in networks and demand revealed in the door-to-door sales arm.

Information on returns

Are information frictions responsible for the adoption gap? All farmers were instructed on the benefits of Swarna-Sub1 during the initial village meeting. In addition, farmers were reminded of this information when surveyed before the door-to-door sales. The strong demand revealed in the door-to-door sales suggests that farmers were at least partially aware of the seed's benefits.

I test whether information constraints bind by using the flooding variation from the 2013 season. Section 3.6 showed that the returns to adopting Swarna-Sub1 were higher in villages exposed to flooding during that season. Combining these, adoption during the 2014 and 2015 seasons should therefore increase in flooded villages if this event provided new information to farmers. I estimate separate regressions for each season where adoption is regressed on an indicator for being in a flooded village and strata fixed effects.[32] Figure A3 shows that being in a flood-affected village is unrelated to adoption in 2013, suggesting that the "parallel trends" assumption needed in this approach are present in the data. Further, there is no relationship between flooding in 2013 and adoption in 2014 and 2015. This suggests that lack of information about returns did not constrain adoption decisions.

Unobservable quality

Private information about seed quality is a possible friction that would be consistent with all the results. There are two aspects of quality to consider. First, trust and counterfeiting are issues if Swarna-Sub1 is indistinguishable from other seeds. Trading within castes would in this case be a solution to the hidden-information problem, just as as lending within caste groups (Fisman, Paravisini, and Vig, 2017). Second, the adoption gap could result from failure of original recipients to take basic measures to ensure quality seed production, such as removing seeds of "off types" or varieties from the neighboring field.

A unique property of Swarna-Sub1 makes the first explanation unlikely. Swarna-Sub1 has a white husk, making it easily distinguishable from the reddish husk of Swarna. Figure A4 shows the visual comparison between the two varieties. This easy distinction makes it unlikely that this type of information asymmetry explains the findings.

Unobservable seed quality still remains as a possible explanation. The seeds that were exchanged between farmers were second generation, i.e. output from the first year's harvest, while the seeds sold in door-to-door sales were procured directly from a private seed company. If farmers fail to produce quality seeds, this could potentially explain low adoption between themselves.[33]

[32]Flooded villages are those for which at least one plot was flooded, where the definition of flooding corresponds to that in Section 3.6.

[33]As an example, if seed is stored without proper drying, then germination ability and vigor of seedlings are

I test whether the effect of door-to-door sales varies as a function of stated and revealed preference measures for new and certified seeds. I use two measures of preferences. First, approximately 42 percent of farmers purchased certified seeds from local government offices for the 2012 season.[34] Given the higher quality standards for certified seeds, this serves as a revealed preference measure of demand for seed quality. As a second measure, I use responses to a survey question where demand was elicited hypothetically for two scenarios: one where certified Swarna-Sub1 seeds were available and another where seeds were produced by another villager. I define those who indicated that a larger quantity of certified seeds would be procured as having a preference for new seeds.[35]

I find no evidence that the door-to-door sales effect varies with these two measures. Table A14 shows that the correlation between the two measures of preference for new seeds and adoption in networks is small and statistically insignificant. Further, the effect of door-to-door sales is no larger for this group of farmers. While inconsistent with the unobserved quality explanation, these findings are only suggestive since the two variables are imperfect measures of actual preferences.

Marketing effects of door-to-door sales

Simply going door-to-door to sell seeds could have increased awareness about the technology or sent a signal to farmers about its potential value. If this is true then the door-to-door sales would have created demand, rather than measured it as a benchmark. Two steps were taken to minimize this effect. First, the original recipients were selected at a village meeting to make all farmers aware of their identities. Second, farmers were reminded about the technology and its flood-tolerance property during the midline survey that occurred three months before the door-to-door sales.

To test this channel, I take advantage of the fact that while door-to-door visits were only made to a subset of villagers, it was well known that NGO staff were moving between houses to offer seeds. Houses in the sample villages are small and located in close proximity. For instance, there is an average of over two other houses in the sample within a 25 meter radius of each sample household. If the door-to-door visits themselves increased demand, then adoption rates of farmers outside the sample should be larger in door-to-door villages. In addition, original recipients would be more likely to continually adopt over time in door-to-door villages if the visits increased awareness of benefits.

Table A15 shows that the door-to-door sales had a statistically insignificant effect on the number of trades between original recipients and farmers outside the sample. Also, Figure A5 shows that the door-to-door sales had no effect on the long-run adoption of original recipients, villagers that did not receive door-to-door sales visits, or farmers that had adopted at the time of the original followup survey.

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.

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

[35]These two measures are not strongly correlated. A regression of one characteristic on the other produces a point estimate that is small and statistically insignificant.

Adoption in the door-to-door treatment is an overestimate of demand if the door-to-door sales led to a marketing effect and therefore created demand. While the sales staff were instructed to only remind farmers of their previously received information, the inability to firmly rule out that the door-to-door sales had zero marketing effect is a limitation of the experiment.

5 Conclusions

I have shown evidence that trading frictions exist amongst Indian villagers. Injecting a new agricultural seed variety into villages and relying on farmer-to-farmer trading of the seeds leads to less than one fifth of the uptake observed when an outside NGO representative sells seeds directly to farmers at their homes. This lack of trading is costly. Applying an impact estimate of the seeds benefits, the average farmer gained 51 dollars — or about 8 percent of an annual rice harvest — from being offered the door-to-door sales visit. Importantly, these gains are over five times the cost of sending a sales agent to a farmer's home.

There doesn't appear to be a single unique friction explaining why informal trading in the village economy leads to such low uptake. The paper has shown some evidence that trading frictions are smaller within caste groups. Farmers in the village economy were more likely to adopt if more members of their caste group were randomly endowed with seeds. Trading within these tight-knit social groups doesn't seem to be a response to hidden information about seed type. The new seed is visually distinguishable from other types, eliminating this type of information asymmetry. However, large trading frictions remain even for farmers that are the most socially proximate to those initially endowed with seeds. Therefore, social proximity cannot be the only explanation for the puzzling amount of adoption when farmers exchange seeds between themselves.

Turning to policy, diffusion via social networks is a popular mechanism for disseminating new agricultural innovations. Given this, and the ability of farmers to reproduce and trade large amounts of seeds, diffusion of new seeds between farmers seems like a practical and inexpensive approach for dissemination. This paper has shown that this network-based approach is limited by significant trading frictions in village economies. As a result, even an intensive door-to-door sales intervention is cost effective.

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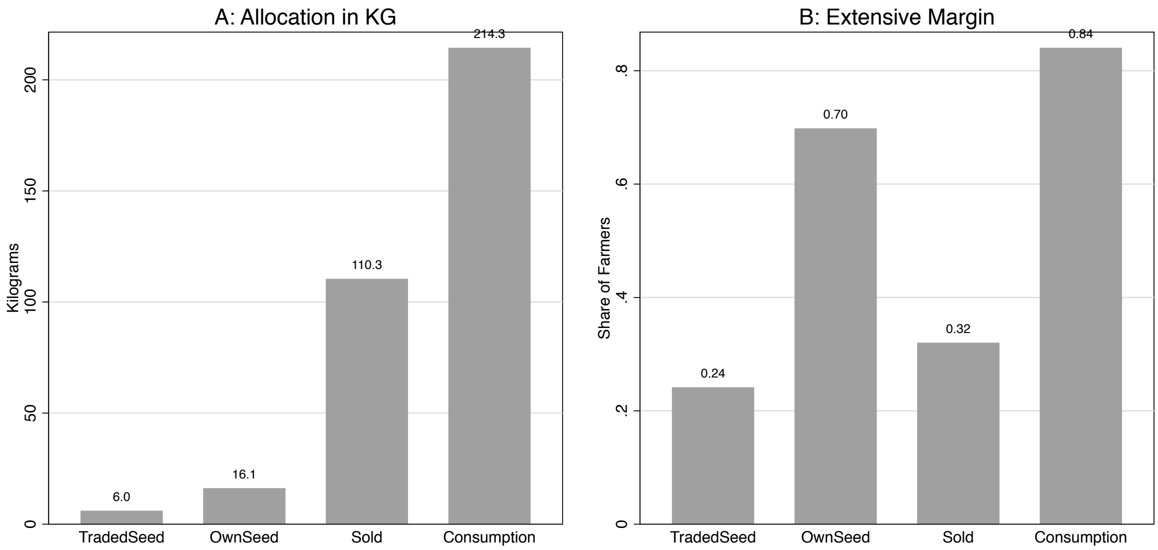
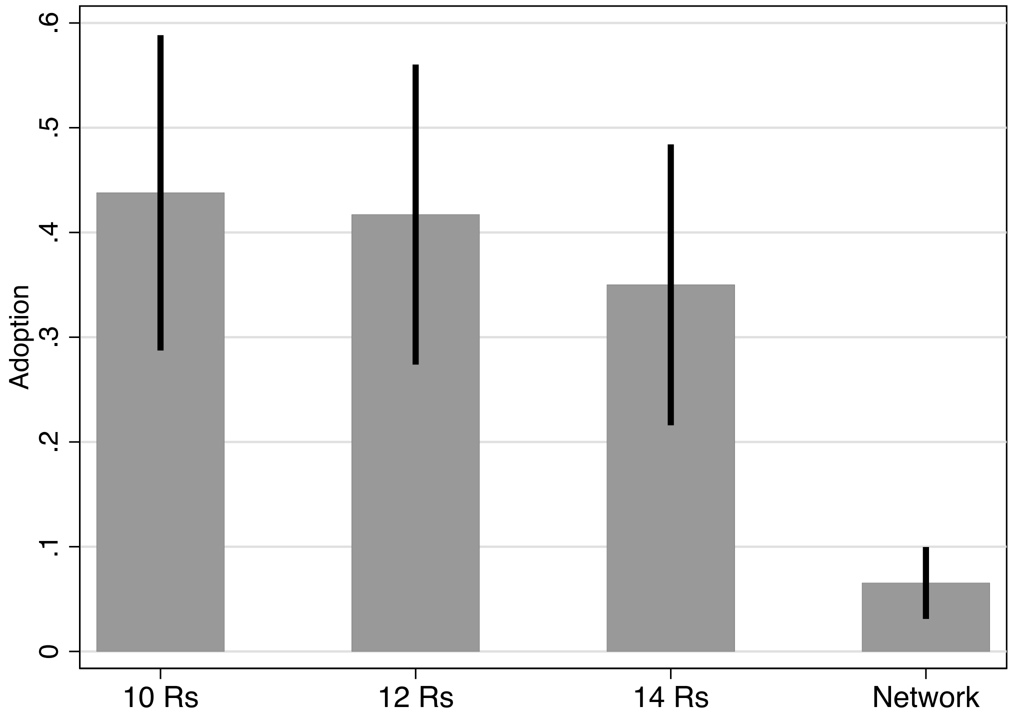
Figures

Figure 1: Allocation of Swarna-Sub1 output across different uses by original recipients



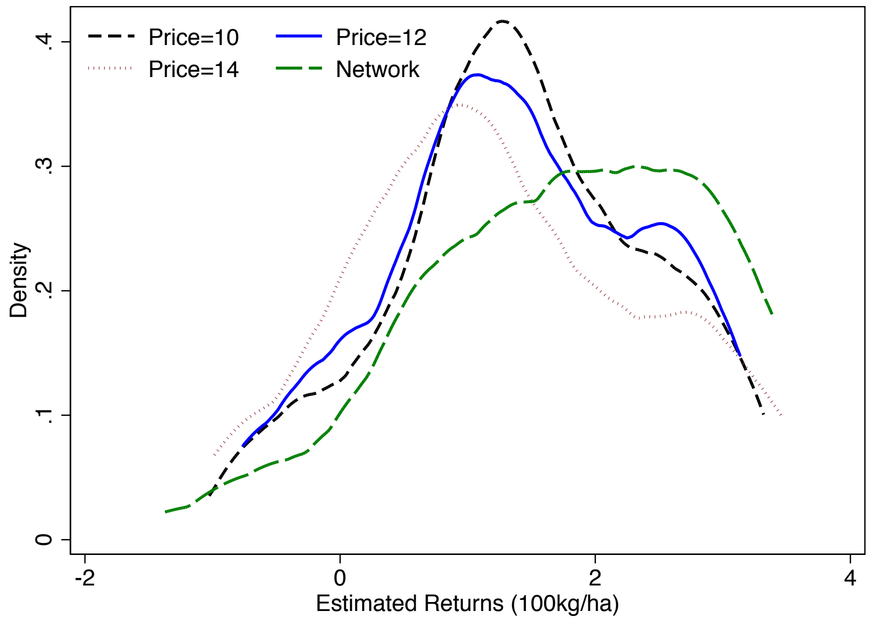
Notes: Data are from July 2013 follow-up survey where each original recipient was asked about their total Swarna-Sub1 harvest and its allocation across uses. Bar heights in Panel A are average values in kilograms across all farmers. “Traded seed” is the output that was either sold, traded, or given to other farmers to be used as seed. “Own seed” is the output for use as seed in the upcoming season. “Sold” is output that had been sold as grain for consumption while “Consumption” is the output that the farmer’s household had already consumed or set aside for their own consumption. Bar heights in Panel B represent that share of farmers that allocated a non-zero amount of their harvest to the various uses.

Figure 2: Adoption in door-to-door sales and farmer-to-farmer networks



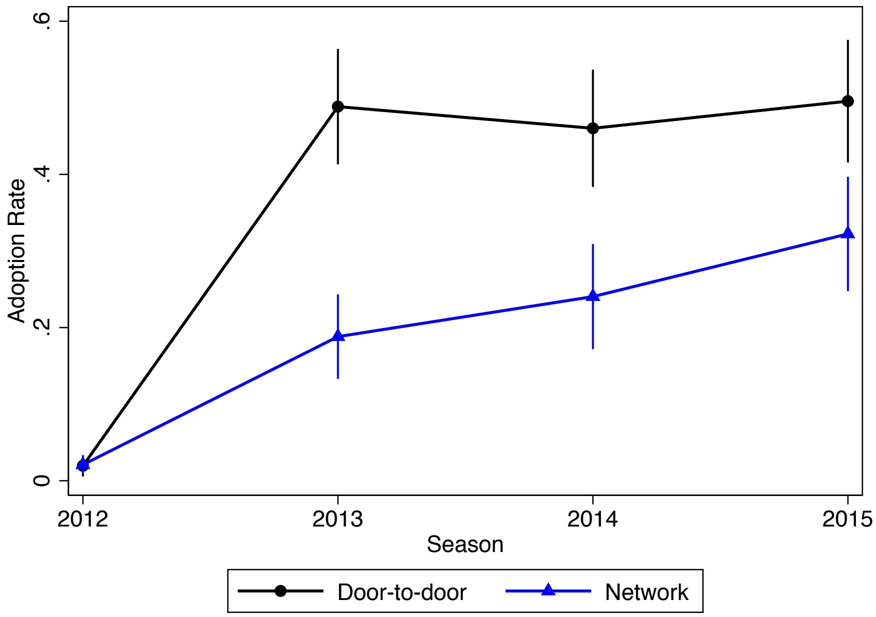
Notes: Figure displays the raw adoption rates for the sample of non-recipients during the 2013 agricultural season. The bands represent 95 percent confidence intervals where standard errors are clustered at the village level.

Figure 3: Densities of estimated returns of adopters, by treatment



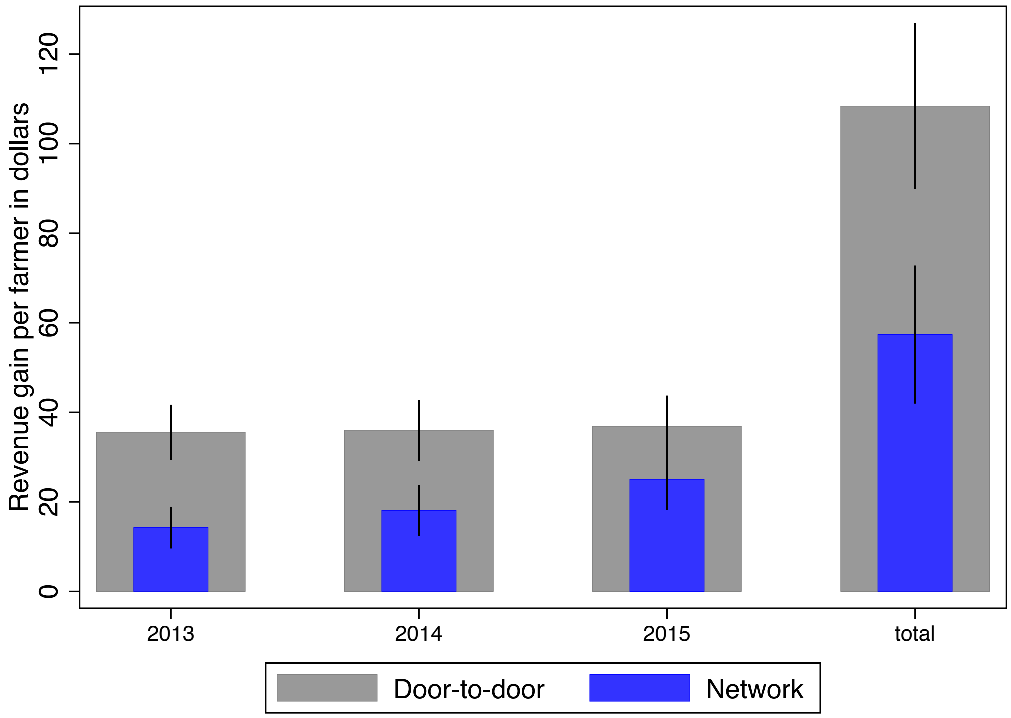
Notes: Figure displays kernel densities of estimated returns, by treatment group. Densities are estimated only for the group of farmers that adopted Swarna-Sub1 for the 2013 wet season.

Figure 4: Adoption rates over time as a function of treatment status



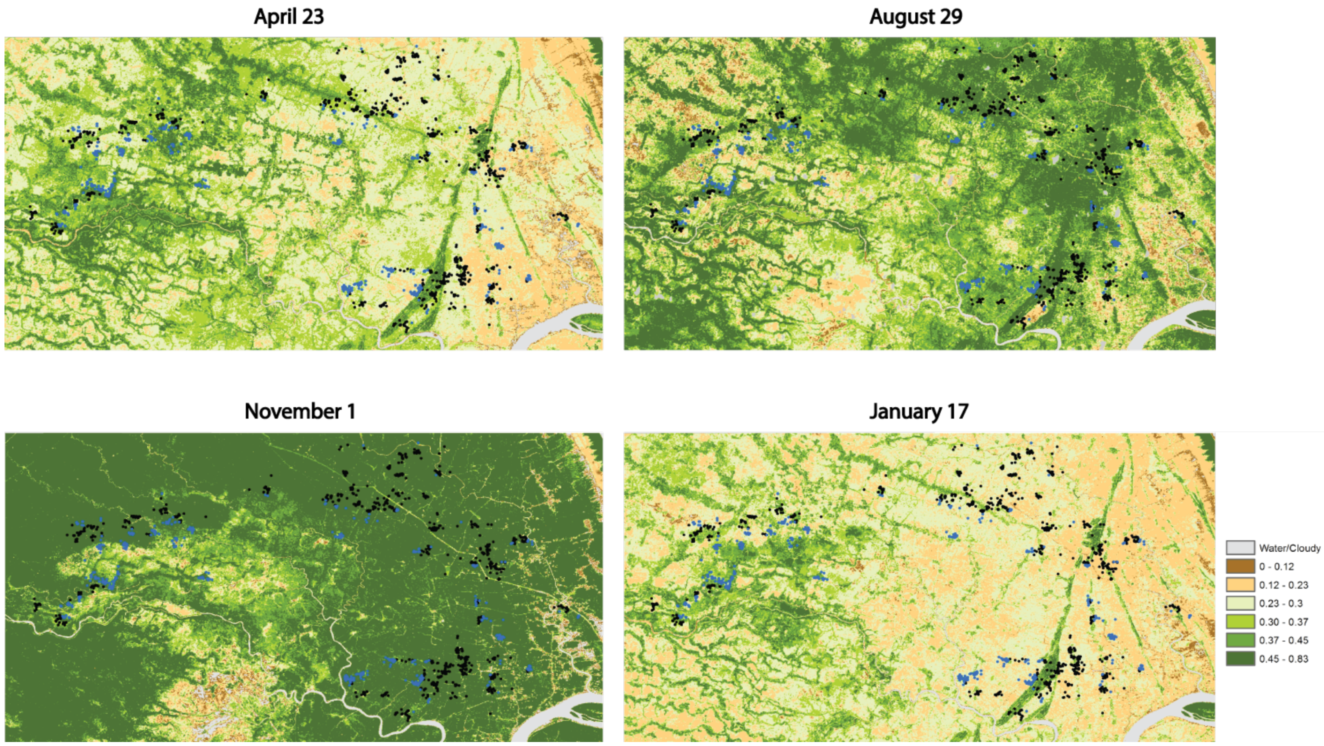
Notes: Figure displays the adoption rate as a function of time for door-to-door and network villages. Adoption was estimated using the long-term folllowup survey in July 2015. The sample consists of 1,139 farmers from the original sample of non-recipients that were reached again during this survey.

Figure 5: Estimated losses from slow diffusion in farmer-to-farmer networks



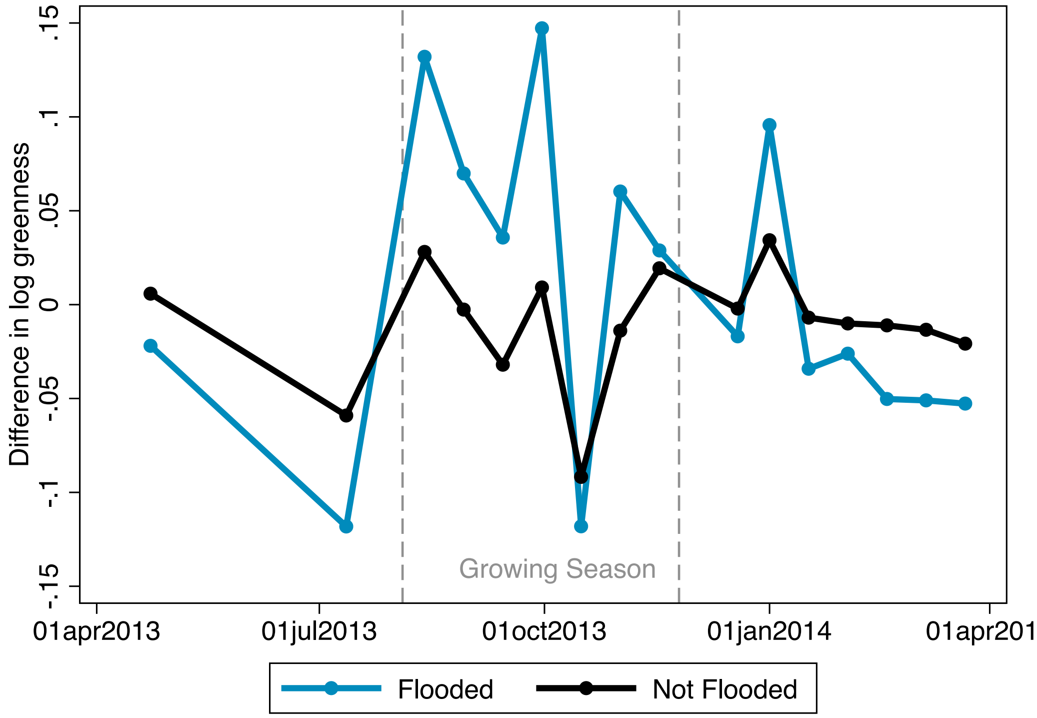
Notes: The height of each bar is the per-farmer estimated revenue gain from Swarna-Sub1. The grey bars are for door-to-door villages and the blue bars are for network villages. The differences between the two bars represent the per-farmer losses from slow diffusion in networks. The black bands represent 95 percent confidence intervals. The total revenue gain (fourth bar) is the sum of the revenue gains from 2013-2015.

Figure 6: Evolution of satellite-based greenness on fields cultivated by sample farmers



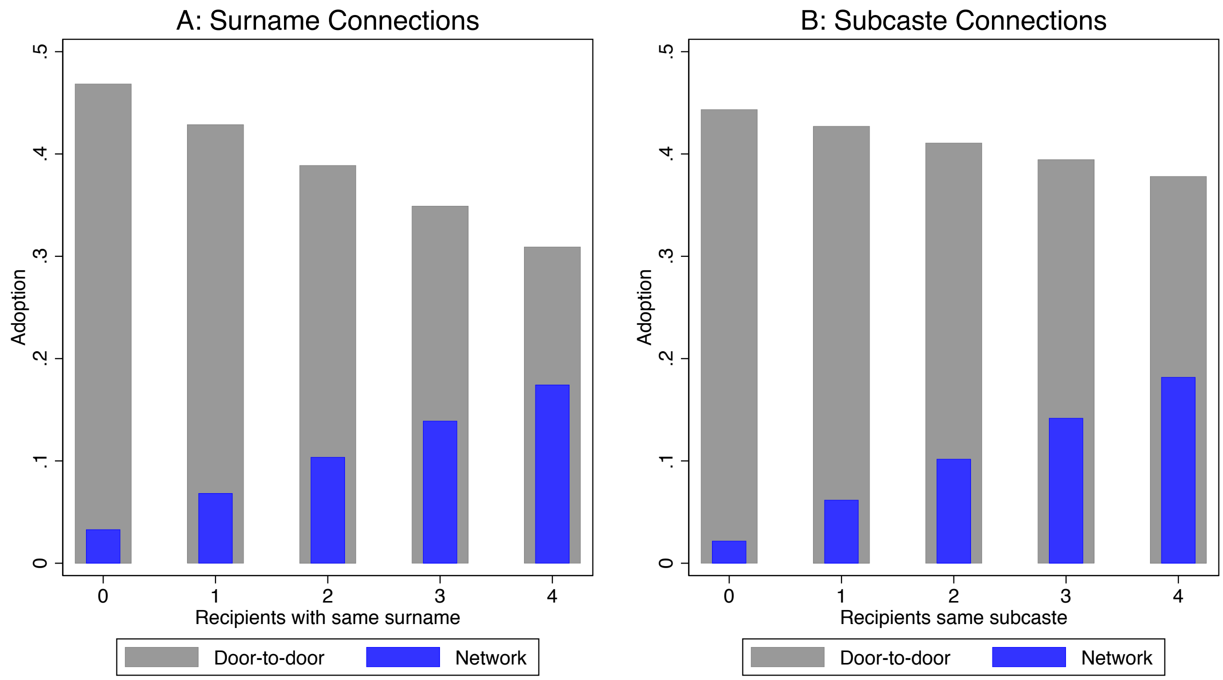
Notes: Figure shows satellite measures of NDVI before the growing season (April 23) during the growing season (August 29th and November 1) and after the growing season (January 17th). The images are from the 2013-2014 agricultural season, i.e. the first season after the door-to-door sales. The spatial resolution is 30 meters, implying that each pixel is around 0.09 hectares, or slightly less than the amount of area that can be cultivated with 5 kg of seed. The dots are fields cultivated by farmers in the sample, where black dots represent fields that were not affected by flooding and blue dots represent flooded fields.

Figure 7: Visualization of the effect of adoption on satellite-based measure of greenness



Notes: The figure shows the difference in vegetation greenness (log NDVI) between adopters and non-adopters. The light blue line are these gains from adoption in areas that were flooded and the black line is the gains from adoption in areas that were not flooded.

Figure 8: Adoption gaps and social connections



Notes: The figure shows the impact of door-to-door sales on adoption for farmers with varying numbers of surname connections (left panel) and subcaste connections (right panel) to the original seed recipients. The number of total surname and subcaste connections is held constant at 5 in both cases. The figure uses regression estimates from column 1 (left panel) and column 3 (right panel) of Table 5.

Tables

Table 1: Summary statistics of non-recipient sample

	Means		
	Network	Door-to-door	p-value
Area cultivated in 2012 (acres)	2.714	3.055	0.075
Land owned (acres)	1.674	1.835	0.326
Swarna user in 2012	0.723	0.695	0.624
Rice yield in 2012 (kg per acre)	1146.918	1188.065	0.448
Ag cooperative member	0.448	0.457	0.820
Monthly income of highest earning member (Rs)	3492.811	3685.515	0.450
Farmer is SC	0.240	0.168	0.266
Household head at least primary education	0.667	0.693	0.520
Thatched roof	0.689	0.775	0.016
Owns private tubewell	0.231	0.148	0.124
Access to electricity	0.893	0.894	0.962
Below the poverty line card	0.610	0.649	0.368
Villagers in sample same subcaste	8.176	8.890	0.492
Villagers in sample same surname	5.476	5.586	0.895
Original recipients same subcaste	2.121	2.133	0.970
Original recipients same surname	1.417	1.485	0.770
Original recipient houses w/in 50 meters	1.176	1.048	0.523
Bought seeds from government	0.441	0.419	0.624
Used seeds from previous harvest	0.652	0.675	0.526
Obtained seeds from neighboring farmer	0.126	0.159	0.305

The data are from the February 2013 survey with non-recipients. The survey took place 3 months before the door-to-door sales. Columns 1 and 2 show mean values of each characteristic in network and door-to-door villages, respectively. Column 3 gives the p-value for the joint test of equality where standard errors are adjusted for clustering at the village level.

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

	(1)	(2)	(3)
Door-to-door and Price=10	0.380***		
	(0.077)		
Door-to-door and Price=12	0.357***		
	(0.066)		
Door-to-door and Price=14	0.275***		
	(0.061)		
Door-to-door treatment		0.336***	0.337***
		(0.043)	(0.043)
Farmer is SC			-0.060
			(0.040)
Farmer has BPL card			-0.054*
			(0.030)
Land cultivated in 2012			0.004
			(0.007)
Ag. cooperative member			-0.019
			(0.023)
Swarna user in 2012			0.090***
			(0.033)
Strata Fixed Effects	Yes	Yes	Yes
Mean of Dep Variable: Network	0.07	0.07	0.07
Number of Observations	1150	1150	1134
R squared	0.190	0.185	0.203

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

Table 3: Relative targeting effectiveness

	All adopters		
	(1) Return	(2) Log Return	(3) Flood severity (1-10)
Door-to-door treatment	-0.384	-0.281***	-0.813
	(0.241)	(0.098)	(0.518)
Constant	1.742***	0.581***	5.250***
	(0.219)	(0.063)	(0.463)
Mean of Dep Variable: Network	1.742	0.581	5.250
Number of Observations	266	233	267
R squared	0.016	0.022	0.026

The data are limited to the sample of farmers that cultivated Swarna-Sub1 for the 2013 wet season. The dependent variable in column 1 is the expected return of Swarna-Sub1, measured in quintiles (1 quintile = 100 kg) per hectare. The dependent variable in column 2 is log of the expected return. The dependent variable in column 3 is a subjective measure of the flood severity of the plot where Swarna-Sub1 was being planted. This variable ranges from 1-10 and was collected during the final follow-up survey with all non-recipients. *Door-to-door treatment* is 1 for villages where farmers had the opportunity to obtain the technology from a door-to-door salesperson. Standard errors are clustered at the village level. Asterisks indicate statistical significance at the 1 percent ***, 5 percent **, and 10 percent * levels.

Table 4: Effects of adoption on satellite-based measures of plant greenness

	Flooding threshold:	
	(1)	(2)
	250 m	500 m
Adopter * Flooded * Growing Season	0.101**	0.091**
	(0.049)	(0.043)
Adopter * Flooded	-0.025	-0.018
	(0.035)	(0.029)
Adopter * Growing Season	-0.009	-0.014
	(0.024)	(0.027)
Growing Season * Flooded	-0.314***	-0.231***
	(0.057)	(0.056)
Growing Season	0.427***	0.432***
	(0.029)	(0.029)
Adopter	-0.012	-0.013
	(0.019)	(0.017)
Flooded	0.087**	0.054*
	(0.035)	(0.032)
Mean of Dep. Variable	-1.18	-1.18
Number of Observations	18689	18689
R squared	0.125	0.117

The dependent variable in both columns is the log of the NDVI value of the field. The data consist of the 8 day NDVI composites from the Landsat 8 satellite (available via Google Earth Engine API). The coordinates of each plot were matched to Landsat images from 4/23/2013, 7/12/2013, 8/13/2013, 8/29/2013, 9/14/2013, 9/30/2013, 10/16/2013 11/1/2013, 11/17/2013, 12/19/2013, 1/1/2014, 1/17/2014, 2/2/2014, 2/18/2014, 3/6/2014, and 3/22/2014. The growing season extends from late July (transplanting) to mid November (harvesting). Flooded plots were identified using daily flood layers generated from NASA's Modis satellite. Standard errors are clustered at the village level. Asterisks indicate statistical significance at the 1 percent ***, 5 percent **, and 10 percent * levels.

Table 5: Estimated peer effects in network and door-to-door villages

	(1)	(2)	(3)	(4)
Door-to-door Treatment	0.332*** (0.056)		0.367*** (0.065)	
Door-to-door Treatment * Original recipients w/ same surname	-0.075* (0.043)	-0.111** (0.045)		
Original recipients w/ same surname	0.035 (0.026)	0.081** (0.031)		
Total number w/ same surname	-0.008 (0.008)	-0.025*** (0.009)		
Door-to-door Treatment * Total number w/ same surname	0.021 (0.014)	0.035** (0.014)		
Door-to-door Treatment * Original recipients same sub-caste			-0.056* (0.030)	-0.051 (0.035)
Original recipients same sub-caste			0.040* (0.021)	0.044** (0.020)
Total number same sub-caste			-0.010 (0.007)	-0.011 (0.007)
Door-to-door Treatment * Total number same sub-caste			0.011 (0.009)	0.015 (0.010)
Strata Fixed Effects	Yes	No	Yes	No
Village Fixed Effects	No	Yes	No	Yes
Mean of Dep Variable: Network	0.07	0.07	0.07	0.07
Mean Original recipients w/ same surname	1.45	1.45		
Mean Total number w/ same surname	5.53	5.53		
Mean Original recipients same sub-caste			2.12	2.12
Mean Total number same sub-caste			8.53	8.53
Number of Observations	1135	1135	1135	1135
R squared	0.191	0.410	0.192	0.404

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

Table 6: Long run peer effects

	(1) 2013	(2) 2014	(3) 2015
Door-to-door Treatment	0.259***	0.176**	0.090
	(0.064)	(0.071)	(0.071)
Door-to-door Treatment * Original recipients w/ same surname	-0.108***	-0.141***	-0.081**
	(0.034)	(0.038)	(0.040)
Original recipients w/ same surname	0.054**	0.072***	0.058***
	(0.021)	(0.022)	(0.022)
Total number w/ same surname	-0.020***	-0.027***	-0.027***
	(0.007)	(0.007)	(0.007)
Door-to-door Treatment * Total number w/ same surname	0.036***	0.045***	0.037***
	(0.011)	(0.012)	(0.013)
Strata Fixed Effects	Yes	Yes	Yes
Mean of Dep Variable: Network	0.19	0.24	0.32
Number of Observations	1137	1137	1137
R squared	0.112	0.081	0.081

Dependent variable in all columns is 1 if the farmer adopted Swarna-Sub1 in the given year. Standard errors are clustered at the village level. Asterisks indicate statistical significance at the 1 percent ***, 5 percent **, and 10 percent * levels.

Appendix: Additional Figures and Tables

Table A1: Baseline characteristics for original recipients and non-recipients

	(1) Non-recipient	(2) Original recipient	(3) p-value: (1)-(2)
Rice acres in Kharif 2011	3.88	3.80	0.53
Acres flooded 4 days or less in Kharif 2011	1.25	1.25	0.94
Acres flooded 5 days or more in Kharif 2011	2.63	2.56	0.52
Acres grown with Swarna in Kharif 2011	1.95	1.88	0.34
Farmer is Scheduled Caste (SC)	0.20	0.18	0.46
Age of farmer	48.96	49.07	0.86
Farmer is lead farmer	0.09	0.11	0.29
Network degree	4.19	4.37	0.21

Data are from the short baseline survey that took place during the village meeting in May or June 2012. Column 1 gives mean values for farmers that were not selected as original recipients. Column 2 gives mean values for farmers that were randomly selected as original recipients. Column 3 gives the p-value for the test of equality of means. Network degree is defined as the number of links of a farmer from the baseline survey (undirected).

Table A2: Heterogeneity in adoption effects by household characteristics

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

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

Table A3: Relative targeting effectiveness when dropping two farmers that obtained Swarna-Sub1 from local government office

	Adopters from peers or door-to-door		
	(1)	(2)	(3)
	Return	Log Return	Flood severity (1-10)
Door-to-door	-0.524***	-0.281***	-0.945*
treatment	(0.155)	(0.098)	(0.499)
Constant	1.882***	0.581***	5.382***
	(0.117)	(0.063)	(0.441)
Mean of Dep Variable: Network	1.882	0.581	5.382
Number of Observations	264	233	265
R squared	0.029	0.022	0.033

The data are limited to the sample of farmers that cultivated Swarna-Sub1 for the 2013 wet season and either obtained it from the door-to-door sales experiment or directly from a peer. The dependent variable in column 1 is the expected return of Swarna-Sub1, measured in quintiles (1 quintile = 100 kg) per hectare. The dependent variable in column 2 is log of the expected return. The dependent variable in column 3 is a subjective measure of the flood severity of the plot where Swarna-Sub1 was being planted. This variable ranges from 1-10 and was collected during the final follow-up survey with all non-recipients. *Door-to-door treatment* is 1 for villages where farmers had the opportunity to obtain the technology from a door-to-door salesperson. Standard errors are clustered at the village level. Asterisks indicate statistical significance at the 1 percent ***, 5 percent **, and 10 percent * levels.

Table A4: Long run effects of door-to-door treatment on adoption

	(1) 2013	(2) 2014	(3) 2015
Door-to-door	0.301***	0.222***	0.175***
Treatment	(0.048)	(0.051)	(0.051)
Strata Fixed Effects	Yes	Yes	Yes
Mean of Dep Variable: Network	0.19	0.24	0.32
Number of Observations	1139	1139	1139
R squared	0.102	0.064	0.069

Dependent variable in all columns is 1 if the farmer adopted Swarna-Sub1 in the year corresponding to the column label. Standard errors are clustered at the village level. Asterisks indicate statistical significance at the 1 percent ***, 5 percent **, and 10 percent * levels.

Table A5: Effects of door-to-door treatment on estimated revenue gains from the new technology

	(1) 2013	(2) 2014	(3) 2015	(4) Total
Door-to-door Treatment	21.389*** (3.933)	18.119*** (4.366)	11.883*** (4.440)	51.391*** (11.799)
Strata Fixed Effects	Yes	Yes	Yes	Yes
Mean of Dep Variable: Network	14.25	18.09	25.02	57.36
Number of Observations	1137	1137	1137	1137
R squared	0.065	0.050	0.053	0.058

Dependent variable in columns 1-3 is the estimated revenue gain from Swarna-Sub1 in the year corresponding to the column label. The dependent variable in column 4 is the sum of columns 1 to 3. The unit of the dependent variable is dollars in all regressions. Standard errors are clustered at the village level. Asterisks indicate statistical significance at the 1 percent ***, 5 percent **, and 10 percent * levels.

Table A6: Robustness of productivity effects to village and farmer fixed effects

	(1) Village FE	(2) Farmer FE
Adopter * Flooded * Growing Season	0.103**	0.098*
	(0.049)	(0.053)
Adopter * Flooded	-0.032	
	(0.030)	
Adopter * Growing Season	-0.010	-0.007
	(0.025)	(0.026)
Growing Season * Flooded	-0.321***	-0.324***
	(0.058)	(0.061)
Growing Season	0.421***	0.425***
	(0.029)	(0.031)
Adopter	-0.002	
	(0.020)	
Flooded	0.034	
	(0.029)	
Mean of Dep. Variable	-1.18	-1.18
Number of Observations	18689	18689
R squared	0.176	0.280

The dependent variable in both columns is the log of the NDVI value of the field. The data consist of the 8 day NDVI composites from the Landsat 8 satellite (available via Google Earth Engine API). The coordinates of each plot were matched to Landsat images from 4/23/2013, 7/12/2013, 8/13/2013, 8/29/2013, 9/14/2013, 9/30/2013, 10/16/2013 11/1/2013, 11/17/2013, 12/19/2013, 1/1/2014, 1/17/2014, 2/2/2014, 2/18/2014, 3/6/2014, and 3/22/2014. The growing season extends from late July (transplanting) to mid November (harvesting). Flooded plots were identified using daily flood layers generated from NASA's Modis satellite. Standard errors are clustered at the village level. Asterisks indicate statistical significance at the 1 percent ***, 5 percent **, and 10 percent * levels.

Table A7: Robustness of estimated peer effects to different subsamples and nonlinear model

	Variation in adoption		Full sample	
	(1) OLS	(2) OLS	(3) Probit	(4) Probit
Door-to-door Treatment	0.268*** (0.080)	0.206** (0.095)	0.349*** (0.055)	0.357*** (0.059)
Door-to-door Treatment * Original recipients w/ same surname	-0.159** (0.061)		-0.076** (0.036)	
Original recipients w/ same surname	0.110** (0.053)		0.027* (0.016)	
Total number w/ same surname	-0.015 (0.011)		-0.010 (0.013)	
Door-to-door Treatment * Total number w/ same surname	0.034** (0.016)		0.021 (0.014)	
Door-to-door Treatment * Original recipients same sub-caste		-0.120** (0.045)		-0.063** (0.027)
Original recipients same sub-caste		0.075* (0.041)		0.024* (0.013)
Total number same sub-caste		-0.024 (0.017)		-0.014 (0.012)
Door-to-door Treatment * Total number same sub-caste		0.031* (0.017)		0.017 (0.012)
Strata Fixed Effects	Yes	Yes	Yes	Yes
HH controls	Yes	Yes	Yes	Yes
Mean of Dep Variable: Network	0.18	0.18	0.07	0.07
Number of Observations	744	744	1134	1134
R squared	0.120	0.118		

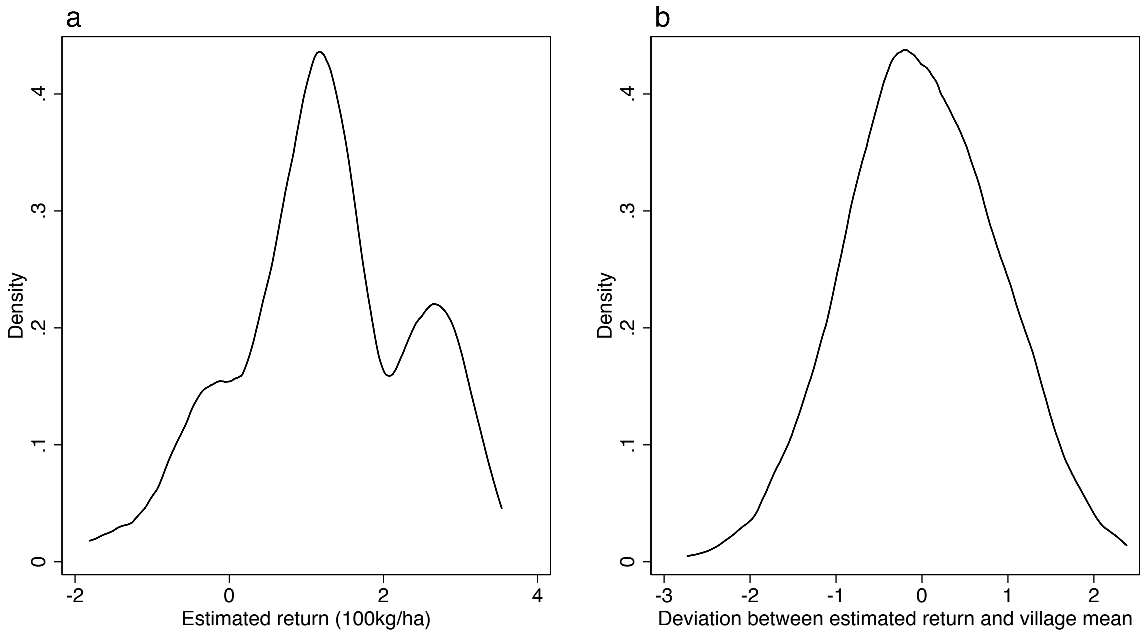
Data in columns 1 and 2 are limited to villages where at least one farmer adopted Swarna-Sub1 for 2013 wet season. Dependent variable in all columns is 1 if farmer adopted Swarna-Sub1 for 2013 wet season. Columns 3 and 4 present marginal effects calculated from probit coefficients, along with standard errors calculated from the delta method. 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 percent ***, 5 percent **, and 10 percent * levels.

Table A8: Robustness of estimated peer effects to measurement of peer influence in shares rather than levels

	(1)	(2)	(3)	(4)
Door-to-door	0.439^{***}		0.439^{***}	
Treatment	(0.047)		(0.054)	
Door-to-door	-0.373^{***}	-0.346^{***}		
Treatment * Share of same surname that are recipients	(0.112)	(0.130)		
Share of same	0.206^{**}	0.202^{**}		
surname that are recipients	(0.080)	(0.095)		
Door-to-door			-0.398^{**}	-0.411^{**}
Treatment * Share of same sub-caste that are recipients			(0.167)	(0.184)
Share of same			0.125	0.174^{*}
sub-caste that are recipients			(0.090)	(0.099)
Strata Fixed Effects	Yes	No	Yes	No
Village Fixed Effects	No	Yes	No	Yes
Household controls	Yes	Yes	Yes	Yes
Mean of Dep Variable: Network	0.07	0.07	0.07	0.07
Number of Observations	1008	1008	1055	1055
R squared	0.220	0.435	0.218	0.434

Dependent variable in all columns is 1 if farmer adopted Swarna-Sub1 for 2013 wet season. 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 percent ***, 5 percent **, and 10 percent * levels.

Figure A1: 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. (2013) 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 A9: Long run peer effects when measuring connectivity using sub-caste association

	(1) 2013	(2) 2014	(3) 2015
Door-to-door Treatment	0.336^{***} (0.072)	0.275^{***} (0.075)	0.169^{**} (0.081)
Door-to-door Treatment * Original recipients same sub-caste	-0.045 (0.038)	-0.049 (0.040)	-0.006 (0.040)
Original recipients same sub-caste	0.012 (0.030)	0.024 (0.032)	0.010 (0.032)
Total number same sub-caste	-0.005 (0.010)	-0.003 (0.011)	-0.000 (0.012)
Door-to-door Treatment * Total number same sub-caste	0.007 (0.012)	0.006 (0.014)	0.002 (0.014)
Strata Fixed Effects	Yes	Yes	Yes
Mean of Dep Variable: Network	0.19	0.24	0.32
Number of Observations	1137	1137	1137
R squared	0.109	0.070	0.070

Dependent variable in all columns is 1 if the farmer adopted Swarna-Sub1 in the year corresponding to the column label. Standard errors are clustered at the village level. Asterisks indicate statistical significance at the 1 percent ***, 5 percent **, and 10 percent * levels.

Table A10: Dyadic regressions of network formation

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

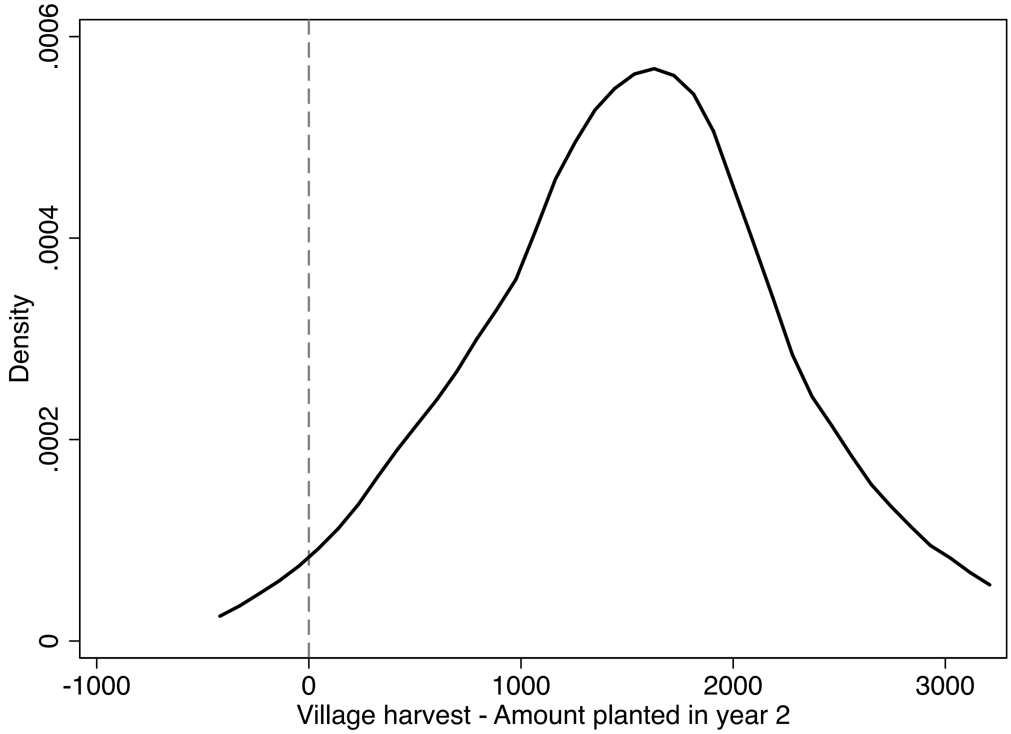
Data are from follow-up social network survey of all farmers. Dependent variable is 1 if either farmer in the dyad indicated a sharing link (i.e. an undirected network). Standard errors are clustered at the village level. Asterisks indicate statistical significance at the 1 percent ***, 5 percent **,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

Table A11: Effects of different household characteristics on the probability of link formation

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

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

Figure A2: Distribution of difference between total harvest of Swarna-Sub1 in year 1 and amount planted in year 2 in door-to-door villages



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

Table A12: Heterogeneous effects according to network connectivity of original recipients

	(1)	(2)
Door-to-door treatment	0.256^{***}	0.256^{***}
	(0.063)	(0.063)
1 if recipient degree / non-recipient degree > median	-0.054	-0.047
	(0.035)	(0.038)
Door-to-door treatment*1 if recipient degree / non-recipient degree > median	0.159^{*}	0.157^{*}
	(0.088)	(0.088)
Farmer is SC		-0.071^{*}
		(0.041)
Farmer has BPL card		-0.061^{*}
		(0.032)
Land cultivated in 2012		0.004
		(0.007)
Ag. cooperative member		-0.025
		(0.024)
Swarna user in 2012		0.074^{**}
		(0.032)
Block Fixed Effects	Yes	Yes
Mean of Dep Variable: Network	0.07	0.07
Number of Observations	1135	1134
R squared	0.182	0.199

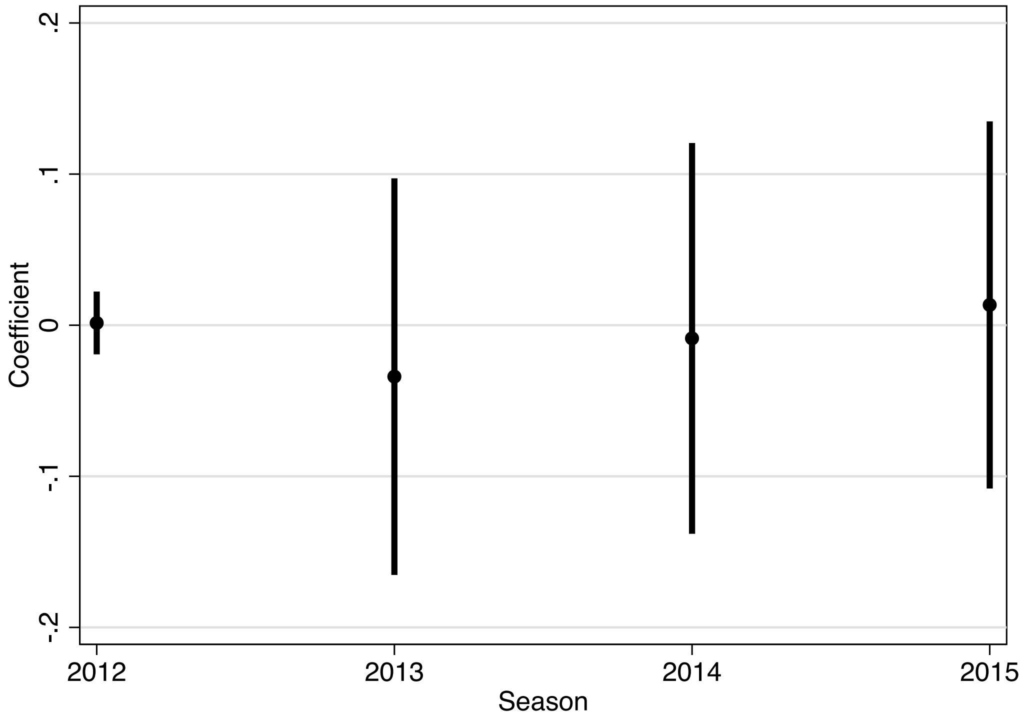
Dependent variable is 1 if farmer adopted Swarna-Sub1 for 2013 wet season. 1 if recipient / non-recipient degree > median is a village-level indicator for ratio of average degree of recipients to average degree of non-recipients being larger than the median. *Door-to-door treatment* is 1 for villages where farmers had the opportunity to obtain the technology from a door-to-door salesperson. Land cultivated in 2012 is measured in acres. Standard errors are clustered at the village level. Asterisks indicate statistical significance at the 1 percent ***, 5 percent **, and 10 percent * levels.

Table A13: Heterogeneous effects according to relative wealth of original recipients

	(1)	(2)
Door-to-door treatment	0.309***	0.317***
	(0.056)	(0.056)
Recipients realtively wealthy	0.077**	0.100**
	(0.036)	(0.038)
Door-to-door treatment * Recipients relatively wealthy	0.070	0.052
	(0.088)	(0.085)
Block Fixed Effects	Yes	Yes
Household controls	No	Yes
Mean of Dep Variable: Network	0.07	0.07
Number of Observations	1120	1119
R squared	0.194	0.213

Dependent variable is 1 if farmer adopted Swarna-Sub1 for 2013 wet season. *Recipients relatively wealthy* is an indicator for villages where the average wealth of original recipients divided by the average wealth of non-recipients is larger than the median. Wealth is defined as monthly average income for the highest earning household member. *Door-to-door treatment* is 1 for villages where farmers had the opportunity to obtain the technology from a door-to-door salesperson. Standard errors are clustered at the village level. Asterisks indicate statistical significance at the 1 percent ***, 5 percent **, and 10 percent * levels.

Figure A3: Relationship between village-level flooding in 2013 and adoption of Swarna-Sub1



Notes: The figure shows estimates from separate regressions of adoption on an indicator for flood-affected villages and strata fixed effects. Flood-affected villages are defined as those where at least one field was flooded during the 2013 floods. Each point in the figure is the point estimate on the indicator for flood-affected villages and the bands denote 95 percent confidence intervals. Standard errors are clustered at the village level in each regression.

Figure A4: Color distinction between Swarna and Swarna-Sub1 seeds

Notes: The image shows unmilled rice seeds of Swarna (on the left) and Swarna-Sub1 (on the right). The color distinction between Swarna and Swarna-Sub1 eliminates the possibility that farmers fail to trade because of a lack of trust on the type of variety being exchanged.

Table A14: Heterogeneity of adoption effect according to preferences for quality seeds

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

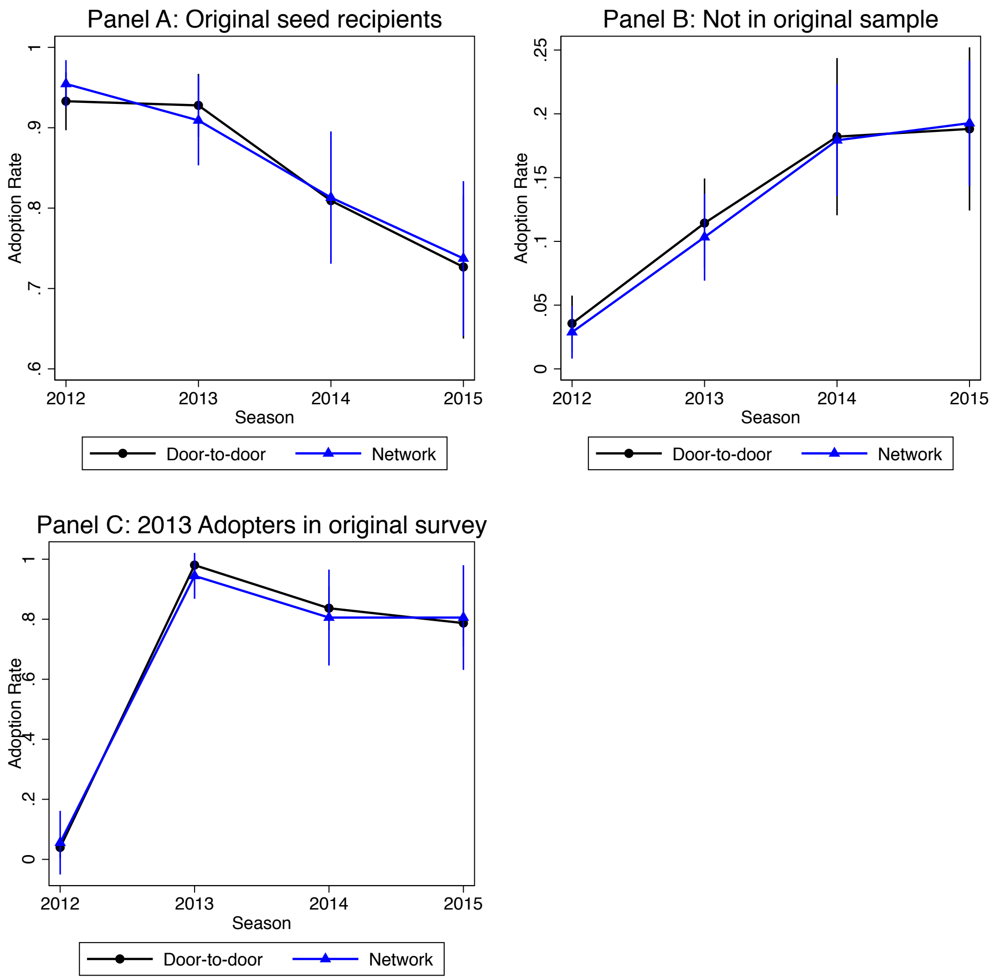
Dependent variable is 1 if farmer adopted Swarna-Sub1 for 2013 wet season. *Door-to-door treatment* is 1 for villages where farmers had the opportunity to obtain the technology from a door-to-door salesperson. Standard errors are clustered at the village level. Asterisks indicate statistical significance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

Table A15: Effect of door-to-door sales on sales and exchanges to farmers outside the sample

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

Data are from the final survey with original recipients. Dependent variable is the number of farmers from outside the sample that a given original recipient sold or exchanged seeds with. *Door-to-door treatment* is 1 for villages where farmers had the opportunity to obtain the technology from a door-to-door salesperson. Standard errors are clustered at the village level. Asterisks indicate statistical significance at the 1 percent ***, 5 percent **, and 10 percent * levels.

Figure A5: Adoption rates over time as a function of treatment status



Notes: Figure displays the adoption rate as a function of time for door-to-door and network villages. Adoption was estimated using the long-term folllowup survey in July 2015. Panel A includes the 392 farmers that received seed minikits in 2012. Panel B includes the 4,738 farmers that did not receive minikits and were not part of the original sample that was surveyed in 2013. Panel C includes the 238 farmers that adopted Swarna-Sub1 at the time of the original 2013 follow-up survey.