Casting a Wider Net: Sharing Information Beyond Social Networks

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Abstract

A key policy goal is to ensure that information about new technologies reaches as many people as possible and supports informed adoption decisions. While social networks can aid in information diffusion, identifying the most influential individuals is often costly. We test an alternative approach: randomly distributing information and encouraging communication among individuals who may not typically interact. In a randomized controlled trial in Bangladesh, we provided a randomly selected group of farmers with a new rice variety and asked them to establish demonstration plots—where the new variety is planted alongside an existing one for public viewing—to facilitate knowledge sharing. We find that demonstration plots raise awareness and learning among other farmers in the village just as effectively as the standard approach of targeting network-central individuals. Although average adoption remains unchanged, we observe significant heterogeneity: farmers update differently based on what they learn. We show that demonstration plots effectively turn ordinary farmers into information broadcasters, reaching less connected individuals and removing the need to identify key influencers within the network.

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1 Introduction

A key policy goal is to ensure that information about new technologies reaches as many people as possible, allowing them to make informed adoption decisions. This applies to the adoption of improved sanitation in developing countries (Guiteras, Levinsohn, and Mobarak, 2015), the adoption of agricultural technology (Foster and Rosenzweig, 1995; Munshi, 2004; Bandiera and Rasul, 2006; Conley and Udry, 2010) and the purchase of financial assets (Bursztyn et al., 2014), among others. To date, the literature has focused on understanding how social networks disseminate information and who should be targeted with information first. Several recent randomized controlled trials show that targeting more central people in social networks can increase the spread of information (Hinz et al., 2011; Kim et al., 2015; Banerjee et al., 2019; Beaman et al., 2021). However, prior research has shown that targeting highly connected individuals for information dissemination has limitations—it requires identifying specific farmers, which can be difficult and costly to do (Beaman and Dillon, 2018; Bandiera et al., 2022).

An alternative strategy is to randomly distribute information about new technologies and promote communication among individuals who may not typically interact. In this paper, we explore one approach that is designed to do that: demonstration plots, where a randomly selected farmer uses a new technology alongside a well-known one in side-by-side plots. The demonstration plots show other farmers that an experiment is taking place. In doing so, demonstration plots can trigger interest and induce people to seek information from other farmers, even if they are not connected in the social network. A key advantage of this method is that it eliminates the need to map out the social network and identify influential farmers, allowing everyone — not just those with influence — to participate in the experimentation process.

We investigate whether this method is effective and how it compares to the more traditional approach of seeding information with influential (more central) farmers. We do so using a multi-phase and multi-arm randomized controlled trial in 192 Bangladeshi villages. In Phase I (2016), we randomly assigned 192 villages to two groups: one that applied demonstration plots and one that did not. We provided five farmers in all villages with a small package of seeds of a new rice variety to cultivate and learn about. The new variety "BD56" matures rapidly and can be harvested earlier than other varieties. In the 96 demonstration villages these "entry-points" were instructed to plant their BD56 seeds alongside a known variety of their choosing. They were also given two wooden signs labeled with the names of the two varieties, making it easier for other farmers in the village to compare them. In the 96 villages without demonstration plots, farmers received BD56 seeds, a single display, and nothing more. Next, we varied how we selected the entry-point farmers who received the BD56 packages. Within each group of 96 villages, we selected the five entry points either 1) randomly, 2) following the selection of a local agricultural extension agent, known as the Sub-Agricultural Officer (SAO), or 3) by taking the five largest farmers (Figure 2). This step is designed to benchmark the impact of demonstration plots with random farmers against the more common approach of seeding the technology with influential (more central) farmers. We then measured awareness, learning, and adoption of BD56 over the next year.

In Phase II (June 2021), we returned to the 64 villages where we had randomly selected the entry-point farmers, and re-randomized them into demonstration and non-demonstration villages (Figure 2). We introduced a new rice variety, "BD87," to five randomly selected farmers in each village. This variety was chosen because it only differed slightly from what farmers typically grew — in this case through higher yields — making the learning problem more complex than in Phase I (where the benefits of BD56 were more visible and did not necessarily require farmers to converse). We designed this second phase to be complementary to our first phase. To do so, we collected additional outcomes on what farmers learned about the technology and elicited willingness to pay in the adoption phase. Studying the intervention in a different season also limits the chance that conclusions are specific to special circumstances during one year, as returns to agricultural technologies depend on many factors, especially weather (Rosenzweig and Udry, 2020).

Our analysis proceeds in two steps: (1) illustrating that demonstration plots can be just as effective as influential farmers in spreading information, and (2) studying the mechanism driving the effects of demonstration plots.

First, we show the impact of demonstration plots along three margins of interest: awareness, learning, and adoption. Focusing first on awareness, we find that demonstration plots increase awareness of the BD56 technology. The magnitude of this effect equates to 8.3 percentage points (p-value 0.028), or going from 59 to 67.3 percent of farmers becoming aware. We find no effects on awareness during the second phase with BD87 when baseline awareness was much higher, at around 85 percent of farmers. Interestingly, demonstration plots cultivated by random farmers increase awareness by the same amount as selecting more central entry points. These influential farmers (more central entry points) increase awareness by approximately 9 percentage points — which is statistically indistinguishable from the effect we document for demonstration plots (p-value 0.639).

Next, we show that demonstration plots get farmers talking. We find that demonstration plots encourage farmers to communicate with entry-point farmers; increasing the number of conversations with them by 19.2% (p-value = 0.146) in Phase I and 35.2% in Phase II (p-value = 0.018). To better understand the findings on conversations, we asked farmers at the end of the study about their perceptions of side-by-side demonstration plots. Farmers are more likely to tell us they view a demonstration plot as an experiment where a learning opportunity exists.[1] We show that demonstration plots generate as many, if not more, conversations than influential farmers. Entering with SAO farmers generates a 7.1% (p-value = 0.506) increase in conversations with entry-points, while using large farmers increases the number of conversations by 18.6% (p-value = 0.078), both effects that are statistically indistinguishable from the effect of demonstration plots (p-values = 0.290 and 0.957).

These additional conversations should translate into greater knowledge about the new variety. Phase I does not provide useful insights on this dimension because once people knew the variety existed, they learned about its key attributes, regardless of whether there was a demonstration plot. The shorter growing cycle was easily observable, and simply becoming aware of the technology was enough to understand this key feature. Phase II uses BD87, which has less clear differences with Swarna — the popular comparison variety in the demonstration plots. These differences were not necessarily visually apparent and required further discussion to learn about them. Here we find that the demonstration plots increase the probability of believing that BD87 has higher yields than Swarna by 5.4 percentage points (p-value = 0.027), from 35.1% to 40.5%.

We then show that neither influential farmers nor demonstration plots have a significant average impact on adoption rates in both phases. In Phase II — where we used a BDM mechanism to reveal demand — we can reject that the demonstration plots increased willingness to pay by any more than 18 percent. Although the average treatment effect is zero, this masks substantial variation, suggesting that the link between learning and adoption may not be uniform. Demonstration plots can lead some farmers to positively update their beliefs about their ability to benefit from the new variety, encouraging adoption. For others, demonstration plots may lead them to negatively update their beliefs, and discourage adoption. We examine heterogeneity along two dimensions: by location – our unit of stratification – and by predicted returns – a likely driver of adoption. We show that treatment effects vary significantly by location, and present evidence that demonstration plots lead farmers to positively update their beliefs in some locations and negatively update in others. Next, we apply machine learning methods developed by (Chernozhukov et al., 2018) to our Phase I data and show that farmers with below-median predicted benefits had more conversations that led them to adopt less. Both of these patterns suggest that farmers update their beliefs about the new rice varieties in different ways, which leads them to make different adoption

[1] Hanna, Mullainathan, and Schwartzstein (2014) show that without intervention, farmers sometimes fail to experiment with key variables in the production function. The demonstration plot is set up to encourage more experimentation. The head-to-head comparison allows farmers to learn about relative performance compared to a technology they know.

decisions.

Having documented the impacts of demonstration plots (and compared them to influential farmers), we shift to the second main objective of the paper: exploring how demonstration plots work. Using both regressions and a structural model, we show that demonstration plots help farmers broadcast information – reaching individuals they may not be directly connected to. In the 64 villages with random entry points, we show that demonstration plots increase knowledge by 11 percentage points for farmers having no baseline connections to entry points. Moreover, being connected to an entry point only helps in villages without demonstration plots: an additional connection to an entry point increases awareness by 10.5 percentage points without demonstration plots. This effect goes down to 3 percentage points with demonstration plots (p-value = 0.496). We observe a similar pattern with the number of conversations. Finally we can show that the broadcasting mechanism benefits least central farmers (who are more likely to be women, younger and less educated), likely because their network position makes them less likely to benefit from information sharing between peers (viral diffusion).

We then use the RCT to estimate a basic diffusion model that documents how these farmers receive information. This model has two parameters: a probability that information gets transmitted to a non-peer (broadcast diffusion) and viral diffusion. Using network data, we estimate the model while allowing these parameters to be different for the demonstration and non-demonstration villages. The estimated probabilities of sharing information with peers are statistically indistinguishable between demonstration and non-demonstration villages. This is not the case for broadcast transmission of information. The demonstration plots increase the probability of sharing information with a non-peer by 0.06, i.e. from 0.13 to 0.19 (p-value = 0.033).

How does this compare to the way influential farmers disseminate information? We use our structural model to show that these influential farmers also disseminate information through broadcast diffusion (p-value = 0.002). This similarity between influential farmers and demonstration plots reveals an important fact about information diffusion more broadly. The literature has focused on the role of viral diffusion by influential members of the community. Our model results show that influential farmers also broadcast information, and this method of information diffusion is critical to explaining their ability to spread information. The fact that influential farmers are more likely to engage in broadcasting helps explain why both demonstration plots and influential farmers are equally effective at spreading information. This also suggests that demonstration plots enable ordinary farmers to serve as information broadcasters — where these ordinary farmers are less likely to capture attention in the absence of demonstration plots – thereby eliminating the need to specifically identify the most influential individuals within the network.

Our paper provides new evidence on a different mechanism for triggering information dissemination and learning. Maximizing dissemination, learning, and adoption through the selection of optimal nodes in networks has received significant attention — both theoretical and empirical (Kempe, Kleinberg, and Tardos, 2005; Ballester, Calvó-Armengol, and Zenou, 2006; Hinz et al., 2011; Kim et al., 2015; Banerjee et al., 2019; Beaman et al., 2021). But there are alternatives to seeding with more influential people. For one, Akbarpour, Malladi, and Saberi (2018) show theoretically that under certain conditions, randomly seeding information with more people does as well as targeting influential nodes. BenYishay and Mobarak (2019) show empirically that seeding with a larger number of more representative "peer farmers" and paying them based on the gain in knowledge by others can improve the flow of information. We contribute to this literature by showing empirical evidence on a mechanism that is distinct from these. In particular, we provide evidence that seeding randomly, but intervening to encourage information sharing can generate similar benefits as careful seeding — the more commonly studied mechanism. We show that demonstration plots allow regular farmers to serve as broadcasters, removing the need to identify the most influential individuals within the network. In essence, demonstration plots give this "broadcasting" ability that influential farmers have to random farmers. The potential to broadly induce communication opens the door for simple, inexpensive, and policy relevant interventions — such as ours — that push people not necessarily socially connected to capitalize on an opportunity to interact with others who are informed.

The rest of this paper is organized as follows. Section 2 outlines the experimental design, the technologies we introduce, and our data collection. Section 3 outlines our results on awareness, learning, adoption and mechanisms. We provide conclusions in Section 4.

2 Experimental Design and Data

2.1 Experimental Design

Seeds Every year governments and international institutions produce new seed varieties for dissemination. These seeds are bred with distinct features (drought resistance, flood resistance, short-maturation) that are suitable for different farmers depending on their local conditions. Farmers must decide each season whether or not to adopt one of these new technologies. We distribute 5kg bags (minikits) of new seed varieties that were released in Bangladesh in 2016 (BD56) and 2018 (BD87). BD56 has two potential advantages. First, it requires less water, making it more drought tolerant than other varieties. Second, it matures approximately 25 days earlier than other varieties commonly planted in the area. This makes BD56 profitable among a subset of farmers who leverage the variety's shorter duration to plant an additional crop. BD87 was released in 2018 as a high yielding variety suitable for cultivation in rainfed lowland areas.

Demonstration plots We also ask a random subset of farmers to set up demonstration plots. Demonstration plots require farmers to plant a new variety next to a known variety of their choosing, with markers (sticks) identifying each variety. Demonstration plots signal that a trial is taking place, thereby generating interest and inducing interactions. Figure 1 shows that farmers view demonstration plots as learning opportunities about an experiment. Farmers are familiar with this form of experimentation as agricultural extension agents often set up large "cluster-demonstrations" with multiple farmers, and organize information sessions for farmers in the surrounding area to attend. We adapt this model by selecting different types of farmers to showcase the new variety on smaller plots of land within their own village, and let the interactions between farmers happen organically.

Demonstration plots are less costly to implement than traditional approaches of seeding information with influential (more central) farmers. The primary cost involved is providing sticks and signs, which is minimal (less than $1 USD per stick or sign). Moreover, since any randomly selected farmer can effectively set up a demonstration plot, extension agents do not need to invest time in identifying the most central farmer for dissemination. This approach reduces the time and financial costs that traditional methods of selecting farmers with specific characteristics require, and also significantly expands the pool of eligible participants for setting up demonstration plots.

Phase I: Figure 2 summarizes the experimental design in phase I. We selected 11 subdistricts (upazilas) scattered across 3 districts of Rajshahi division for the study. We consulted with the Department of Agricultural Extension to identify upazilas that were suitable for the BD56 variety. We randomly sampled 23 or 24 villages per upazila, focusing on those with no more than 150 households.

We then distributed BD56 minikits to 5 farmers in 192 villages (the "entry-points"). We randomized whether villages were assigned to demonstration plots or not. In 96 demonstration villages, we provided two signs to the entry-points along with the seeds: one with the name of the new variety (BD56), and another with the name of the variety they had selected to plant alongside. In the remaining 96 non-demonstration villages, entry-points received a single sign for their BD56 plot. The provision of the single sign ensures that any effect we detect in the demonstration plot villages with two signs goes beyond the attention effect of placing one sign in the field (Figure 3).

In this first phase of the experiment, we further cross-randomized *which* farmers were selected as entry points. In the first group of villages, we distributed the BD56 seeds to five farmers selected at random. In the second group of villages, we ranked farmers by landholding sizes and provided seeds to the top five farmers. In the third group, we asked the Sub-Agricultural Officer (SAO) to identify five farmers in the village that would be effective in demonstrating the new variety. The improved selection of entry points – using large or SAO designated farmers – seeks to test practically feasible approaches to finding the most influential (central) farmers in the network. Importantly, the notion of optimal entry points is designed to exploit the network as it exists at baseline and does not consider that the intervention itself may change the network.[2]

Finally, we also distributed *BD51* minikits to approximately 15 farmers in an additional 64 villages.[3] BD51 is a long-duration rice variety that resembles the most commonly grown variety. By comparing agricultural outcomes between recipients of BD51 and BD56, we can measure impacts of BD56.

Phase II: In the second phase of the experiment (three calendar years later), we worked exclusively in the villages where farmers had been *randomly* selected to receive BD56 seeds in phase I (across both demonstration and non-demonstration villages). We no longer needed the benchmark of influential farmers, and excluded villages where SAO and large farmers were previously selected to receive seeds. This left us with 64 villages that we re-randomized into demonstration (N=32) and non-demonstration (N=32) villages. Within each village, we further selected 5 farmers (the "entry-points") at random to receive the new variety (BD87).

2.2 Data Collection

We collected multiple rounds of surveys for each of the two phases. Table A.1 lists the data we collected. Figure 4 presents the study timeline, which we describe in more detail below.

Phase I: In March 2016, we performed a complete census of all villages. Villages had on average 86 households, resulting in a population of 21,926 households. We captured information about social networks, including the names of up to 10 people from their village that farmers talked to about rice farming during the last Aman (rainy) season.

[2]We opted for large and SAO selected farmers because they were reported to be the most central farmers. (Banerjee et al., 2019) show that there are other ways to identify central farmers, which can be identified by asking local villagers about the characteristics of the best known farmers in the village.

[3]We selected the 5 largest farmers, 5 random, and 5 SAO-selected farmers. Due to overlap, this does not always amount to 15 farmers per village.

In June 2016, we distributed 5 kg of BD56 minikits to 5 entry-point farmers in 192 villages. We also provided farmers with signs to place in their fields as a way of demonstrating to others the varieties they were planting. In April 2017, we re-visited these villages and surveyed 10 additional farmers, selected at random, to determine if they had heard about the BD56 seeds that were introduced to entry points 10 months earlier. The survey also asked whether they knew key features of the variety.

In June 2017, we visited each treatment village to sell 5kg and 2kg bags of BD56 seeds at a 60% discount. The field team called a select sample of farmers in each village to inform them about the date and time of the seed sale. The sample included the original entry-points, and the ten randomly selected farmers who had been surveyed about their BD56 knowledge 2 months prior. The field team traveled to each village on a predetermined date, set up their truck in the middle of the village with a large sign and recorded each sale in a tablet. Although we did not record the identity of the buyer, the survey provides a measure of BD56 adoption at the village level.[4]

In addition to the main sources of data described above, we conducted a series of agricultural surveys in all villages. The goal of these surveys was to quantify the impact of BD56 on agronomic practices, cropping intensity, and crop income. A baseline survey was administered to all entry points at the time of the minikit distribution in June 2016. An agricultural year can consist of up to three crops. Therefore, we conducted three additional survey rounds to fully characterize annual production.

Phase II: Three years later, in June/July 2021, we returned to the 64 villages with random entry-points and conducted an updated census survey with all 5688 farmers. We collected information about who they talked to about rice farming, and knowledge about two rice varieties (BD87 and BD91). We conducted our updated census survey alongside the provision of minikits to five randomly selected farmers (the "entry-points") in each village. We anticipated not being able to reach all pre-selected entry points because we drew the sample from the 2016 census. As a result, we generated a replacement list (ordered randomly) that we used if the originally selected farmers were not available. We returned later in August to provide one or two signs depending on the village's treatment status. Villages assigned to "demonstration" were provided with two signs, and we collected the name of the variety farmers would be planting alongside. Villages assigned to "non-demonstration" were provided with one sign.

We returned in October/November 2021 (pre-harvest) and December/January 2021 (post-

[4]Unfortunately, we ran out of seeds before reaching all of the villages, and hence this information is only available for 168 of the 192 villages.

harvest) to ask farmers who they talked to about rice farming in the past 30 days, the number of people they talked to, what they talked about, and whether they had heard about four different rice varieties (including BD87), and their knowledge of these varieties.

Finally, we measured farmer's willingness to pay for BD87 in July 2022. Compared to phase I, we elicited individual willingess to pay so that we could trace out the entire demand cuve for BD87. We randomly selected 21 farmers per village to contact, including two entry-point farmers and 19 other farmers. We called six of these farmers ahead of time to inform them that we would be back in their village the following week to offer BD87 seeds. We elicited their willingness to pay through a Becker–DeGroot–Marschak (BDM) mechanism. Following Burchardi et al. (2021) we used multiple price lists, which present respondents with a set of prices and asks whether they would be willing to pay that price. We included a practice round, and a series of test questions to ensure comprehension.

2.3 Data Descriptives

Phase I: Table A.2 presents summary statistics from the household census and verifies randomization balance.[5] Most of our sample cultivates long-duration rice varieties in the rainy and dry season (only 1% of farmers planted short duration varieties in the 2015 crop cycle). Farms in the sample are small. The average area sown with Aman rice (the main crop) is approximately 1.33 acres.

Villages tend to have a few well-connected individuals. We define two farmers as being connected or being peers if either one names the other as somebody they talk to about rice. We use this information to create various centrality statistics including degree centrality (the number of connections a person has), eigenvector centrality, and betweenness centrality (the number of times a node acts as a bridge along the shortest path between two other nodes). Figure A.1 displays the distributions of centrality measures for the entire set of households interviewed during the census. Most farmers talk about rice with 3 to 6 of their peers, though some interact with over 25 people. The distributions of eigenvector and betweenness centrality display similar patterns: most farmers have a few connections, while some have a disproportionately high number. These long right tails suggest that farmers' information networks feature some highly central farmers that could serve as more effective entry points.

These network data also show that large and SAO-selected farmers are better connected in their villages. The top panel of Table A.4 shows that farmers have an average of 4.6 connections. This increases by 3.6 and 4.5 farmers for SAO-selected and large entry points,

[5]Table A.3 shows randomization balance for the sample of entry points receiving BD51 versus BD56 seeds.

respectively. The eigenvector centrality of the five largest farmers is almost doubled compared to other farmers.

Phase II: We called the full set of farmers living in the 64 villages in our sample. This survey was conducted over the phone, and the set of variables we collect is much smaller. Table A.5 shows summary statistics. We find that most households cultivate rice (98%), and talk to 6.5 other farmers on average about rice farming. At baseline, only a few farmers (10%) have heard about BD87.

3 Results

Our analysis exploits the random variation from both the village-level treatment assignment and the selection of entry points. All our specifications include upazila and surveyor fixed effects. While the randomizations are balanced, we include control variables to improve precision. For all tables, we use Double-Lasso to select these control variables.

3.1 Effects of demonstration plots and influential farmers

3.1.1 Awareness

We compare knowledge across the six different arms in phase I using the following regression:

$$\begin{aligned} informed_{ivse} = \beta_0 + \beta_1 RandomDemo_{vs} + \beta_2 SAONoDemo_{vs} + \beta_3 SAODemo_{vs} \\ + \beta_4 LargeNoDemo_{vs} + \beta_5 LargeDemo_{vs} + \alpha_s + \tau_e + X_{ivse}\beta + \varepsilon_{ivse}, \end{aligned} \tag{1}$$

where $informed_{ivse}$ is an indicator for whether the farmer i, surveyed by surveyor e in village v and upazila s has heard about BD56, X_{ivse} is a vector of controls selected via Lasso, and ε_{ivse} is an error term clustered at the village level. We include fixed effects for upazila α_s and surveyor τ_e. We employ a similar specification for phase II, except for we only compare demonsration to non-demonstration villages.

The results in Table 1 deliver two insights. First, demonstration plots increase awareness when awareness is modest. In phase I, where awareness in the non-demonstration group is only 60%, the rate of being informed increases by 8.3 percentage points (14.1% – p-value = 0.028) when random farmers do a demonstration plot (column 1). Column 2 shows that demonstration plots do not confer these same gains in phase II, as levels of awareness about the new variety (BD87) were high (85%) in the non-demonstration group.

Second, the effect of demonstration plots with random farmers is roughly the same magnitude as the effects of entering with large and SAO farmers. As we would expect based on their network connections, entering with large and SAO-selected farmers increases the spread of information (column 1). Among non-demo villages, SAO selection increases awareness by 9.3 percentage points (15.8% – p-value = 0.006) and entering with the largest farmers increases it by 9.8 percentage points (16.6% – p-value = 0.004).[6] These effects are quite similar to the 8.3 percentage point effect of demonstration plots with random entry points (the estimate of β_1 is statistically indistinguishable from β_2 and β_4 (p-value=0.261 and 0.896, respectively). This suggests that these two approaches to information dissemination act as substitutes: interventions that get people to seek information are just as effective as selecting the more central farmers. Finally, we see that the demonstration plots have no effects when cultivated by the better-connected large and SAO farmers. The estimates of β_2 and β_3 are nearly identical (as are the estimates of β_4 and β_5), meaning that the demonstration plots did not spread awareness with SAO selection or large farmers. This suggests that these influential farmers are already known experimenters. Doing demonstration plots with these known experimenters does not trigger further learning.

3.1.2 Knowledge

Knowing that a technology exists is only a first step in deciding whether to adopt. We next turn to whether farmers communicate and what they learn from each other. The specification remains the same as in equation (1).

We find evidence that demonstration plots increase conversations about rice farming. Table 2 shows results from both phases. Column 1 shows that farmers discussed BD56 with 0.13 more farmers (p-value = 0.148) in demonstration plot villages (a 15.4% increase over non-demonstration villages where farmers have 0.84 conversations with others about BD56 on average). Column 2 shows that this is driven by talking to the entry points (p-value = 0.146) – though neither effect is statistically significant. During phase II, farmers told us all the people they had spoken to about rice farming, regardless of topic. This gives us a broader measure of discussions about farming. Column 3 shows that during the season, demonstration plots increased the number of conversations about rice farming by 0.65 per farmer (p-value = 0.096), which amounts to an 11% increase. Column 4 shows that demonstration plots lead to 0.11 additional conversations with entry-point farmers (p-value = 0.018). This amounts to a 35.2% increase when compared to 0.31 conversations in the

[6] The effectiveness of large-farmer selection should be considered as an intention-to-treat effect because large farmers were sometimes selected as entry points in random and SAO villages. At least one of the five largest farmers was selected as an entry point in 19 of the 64 random villages and 38 of the 64 SAO villages.

non-demonstration group.[7] While we also collected data on conversations after the harvest, we find no effect on conversations specifically with entry-point farmers during this period (column 6), although there is some indication of increased overall conversation (column 5). One simple explanation is that people do not communicate with the entry points once the demonstration plot has been removed after harvesting.

We can show that demonstration plots generate as many, if not more, conversations than influential farmers. Table 2, column 1, shows the impact of SAO and large farmers on the number of conversations about BD56. While the Phase I results on conversations are less precise, we find that SAO farmers generate a 7.1% ($p = 0.506$) increase in conversations with entry-points, and large farmers increase the number of conversations by 18.6% ($p = 0.078$). Both of these effects are statistically indistinguishable from the effect of demonstration plots (p-value $= 0.290$ and 0.957).

Ideally, we could capture exactly what farmers talk about to understand how these conversations translate into concrete knowledge about the new variety. While this is impossible to do in the field, our final survey in phase II asked farmers about a subset of BD87's key features.[8] We see evidence that farmers are conversing about yield. Relative to Swarna — which is the most popular comparison variety — the two most distinctive features of BD87 are that it has higher yields and it grows taller. The first row in Table 3 shows that farmers remain uncertain about yield differences, even with demonstration plots. Around 32 percent of them do not venture a guess as to the higher yielding variety. But farmers in demonstration plot villages are more likely to shift beliefs about the higher yielding seed variety from Swarna to BD87. Specifically, row 2 and 3 show that demonstrations reduce beliefs that Swarna is higher yielding by 5.6 percentage points (p-value $= 0.034$) and increase beliefs that BD87 is higher yielding by the same amount (p-value $= 0.027$). We find similar beliefs about plant height across treatments — indicating that this is not a topic of discussion between farmers.

3.1.3 Adoption

How does hearing about, and discussing, new rice varieties affect adoption? We find no clear evidence that demonstration plots increased *average* uptake in either phase. Table 4 shows that 1.7 farmers purchased BD56 in non-demonstration villages, and demonstration plots increased the number of BD56 buyers in Phase I by 0.67 farmers per village (p-value

[7] Our survey question during phase I asked about conversations specific to BD56. The phase II question asked about all conversations pertaining to rice farming. This difference explains why the mean number of conversations is larger during the phase II survey.

[8] Everyone who heard about BD56 in phase I, whether they resided in demonstration or non-demonstration villages, was aware that it was a shorter duration variety because they could see that it grew less tall.

= 0.409). This is a large increase relative to non-demonstration villages, but this effect is imprecisely estimated and only amounts to 1.95% of farmers purchasing BD56 seeds in demo villages. In sum, despite making people more aware of BD56, the demonstration plots do not guarantee that adoption will significantly increase. We also see that entering with large or SAO farmers led to similar imprecise effects, suggesting that the lack of adoption is not due to limitations of the demonstration plots.

The results in phase II confirm that the demonstration plots did not change average willingness to pay for BD87 either. Column 2 shows that the average farmer in non-demonstration villages was willing to pay about 21 BDT per kilogram for BD87 seed – less than half the market price – showing minimal demand at market prices. The estimated treatment effect of 0.775 BDT is about 3.6% of the mean and is statistically insignificant. The confidence interval ranges from -2.03 to 3.58, which allows us to rule out effect sizes on average WTP that are larger than 13%. The level of demand in demonstration villages is low as well: 6.99% of farmers purchase the seed at a market price of 40 BDT/kg. Since the average WTP can be less informative than examining the share of potential adopters at different prices, we also plot the demand curves in Figure 5. The left panel of the figure shows similar demand curves in the demo and non-demo villages. The bottom left corner shows results from a randomization inference procedure testing whether the two demand curves are identical. We cannot reject equality for the comparison between the two demand curves.

Our estimates are in line with government estimates of adoption. Figure A.2 shows that the distribution of estimated adoption rates for 73 rice varieties formally released in the country is heavily skewed toward zero. BD56 from phase I is estimated to be adopted by only 0.11% of farmers, while BD87 from phase II has an estimated adoption rate of 5.14% (BD87 was a more popular variety). We take this evidence as suggestive that our two demand elicitation exercises revealed demand that matched farmers preferences more broadly outside our experiment. While seed varieties are a key agricultural input, this is true for other technologies as well. For instance, nationally representative surveys from Ethiopia show that many promoted technologies are not widely adopted (Kosmowski et al., 2020).

But if farmers were learning positive information about the rice varieties as we show above – such as the ability to grow a second crop with BD56 or the high yields of BD87 – why do we not see higher adoption rates? Our zero average treatment effects on adoption suggest farmers may also have been learning negative features of the new varieties. While it is difficult to capture every dimension of learning, we can show that the entry-point farmers – those who tried the variety firsthand – were less likely to adopt after a year, which provides one piece of evidence that farmers may have learned something unfavorable as well. Figure

5, Panel B also compares the demand curve of the entry point farmers with that of all other farmers. The demand curve for entry points shifts in significantly, showing that farmers who cultivated BD87 had less demand for seeds the following year. This result is consistent with Column 3 Table 4, which shows that the entry points in phase II — who were randomly chosen to grow the seed the previous year — are themselves willing to pay 12% less for the seed the next year compared to other farmers (p-value = 0.002). Other farmers may have inferred negative information through interactions with these entry-point farmers. This highlights that farmers were likely learning both negative aspects (as indicated by entry-point farmers being less enthusiastic), and positive ones (such as higher yields) which could also help explain why overall adoption rates remained low.[9]

3.1.4 Connecting Learning to Adoption

How do our results on learning connect with those on adoption? Correlational evidence points to a link: farmers who believe that BD87 has higher yields are more likely to adopt it (Table A.6). We further explore this relationship by examining treatment effect heterogeneity, which demonstrates that the link between learning and adoption is not uniform across farmers. Indeed, the returns to almost all agricultural technologies vary across farmers. Some farmers may not benefit much from a new innovation, while others enjoy substantial benefits. In addition, beliefs about returns differ between farmers. The relationship between learning and adoption depends on how farmers update these beliefs. After learning, farmers could update positively and increase their propensity to adopt. Alternatively, they could update negatively and decrease adoption — which is common in practice.[10] As such, greater learning might not increase average levels of adoption due to heterogeneous effects. This has implications for the variance of adoption. As one possibility, farmers with more positive views may become more positive, and farmers who viewed technology less favorably may become even more negative. This would increase the variance of adoption. Alternatively, farmers with more pessimistic views could become more positive and those with more optimistic views could become more negative. This would decrease the variance of adoption.

We examine two dimensions of heterogeneity that indicate farmers are learning different information and, as a result, making different adoption decisions. Both these analyses suggest that the variance of adoption is reduced by more farmers learning through demonstration

[9] The fact that entry points are less willing to pay for the seed does not mean that all farmers should not adopt. Some may want to try the technology themselves as conditions on their fields may be different. We explore this in the next sections.

[10] Many agricultural technologies do not go to scale despite being well known (Figure A.2). This suggests that adoption decisions vary widely: these varieties are not profitable for all farmers, leading many to choose not to adopt

plots. We start with geographic heterogeneity, our unit of stratification. We stratified by this variable because agricultural conditions can vary widely over space and how farmers react to demonstration plots could depend on agricultural conditions. The top panel of Figure 6 shows that treatment effects vary significantly by location in both phases: demonstration plots lead to increased adoption in some upazilas and decreased adoption in others. The null hypothesis of equal treatment effects across space is rejected (p-value = 0.000 in phase II and 0.043 in phase I), suggesting the link between learning and adoption is not uniform. Next, we compare these treatment effects with the average willingness to pay in non-demo villages across the same upazilas (bottom panel of Figure 6). Upazilas with the largest treatment effects on WTP correspond to those with the lowest average willingness to pay, and upazilas with the smallest treatment effects on WTP correspond to those with the highest average willingness to pay. This suggests that demonstration plots shift farmers' willingness to pay closer to the mean, correcting overly optimistic beliefs for those with high WTP and overly pessimistic beliefs for those with low WTP. Learning from demonstration plots therefore reduces the dispersion of willingness to pay (Figure A.3).[11] The standard deviation of residualized WTP is smaller by 19% in demonstration villages.

Next, we leverage a unique feature from Phase I of our experiment to examine another important source of heterogeneity in learning and adoption decisions – farmers' predicted returns from the technology. We are able to do this because, in Phase I of the project, we randomly distributed a common seed (BD51) to five farmers in 64 villages, allowing us to measure the benefits of BD56 relative to BD51.[12] We use machine learning methods (Chernozhukov et al., 2018) to estimate the predicted benefit of growing BD56 for each farmer. More specifically, we want to estimate the conditional average treatment effect (CATE) of the BD56 variety for a particular outcome y, which we refer to as predicted benefits. This CATE is the predicted benefit of the variety conditional on a vector x of covariates.[13] We choose the outcome to be the number of crops grown because benefiting from the BD56 technology requires the farmer to increase cropping intensity. This is a better measure than BD56 adoption because adoption alone will not be beneficial without increasing the number of crops. Thus, the CATE gives us a measure of how likely any given farmer is to increase cropping intensity if they were to grow BD56. The procedure involves estimating

[11] The p-value associated with Kolmogorov–Smirnov test for equality of distributions by treatment is 0.004).

[12] Results from this comparison show that the primary advantage of planting BD56 is the ability to grow an additional crop after harvesting wet-season rice earlier (see Table A.7).

[13] The covariates are education, age, ownership of an irrigation tubewell, rice area during the wet season, other crop area during the wet season, rice area during the dry season, other crop area during the dry season, wet season nitrogen fertilizer use, wet season DAP fertilizer use, yield during the wet season, dummy variables for growing various non-rice crops, longitude, latitude, and dummy variables for five popular rice varieties at baseline.

machine learning predictions of the outcome as a function of the covariates, separately for farmers treated with BD56 and BD51. The difference between these two predictions provides an estimate of the CATE for each farmer (see Appendix B for further details on the estimation procedure).

Table 5 shows the relationship between this predicted CATE and the probability farmers heard about, and had conservations about, BD56. Columns 1 and 2 interact the treatment variables directly with the predicted CATE, while columns 3 and 4 use an indicator for observations with above-median values. The point estimates on the interaction terms between the treatments and the CATE are generally negative, meaning that the demonstration plots increased conversations more for farmers that were less likely to grow an additional crop if they were to adopt BD56. For example, column 4 shows that the demonstration plots increased the number of conversations by 0.307 for farmers with a below-median CATE and they had no effect for above-median farmers. This has implications for adoption. Figure 7 presents suggestive evidence that the demonstration plots only increased adoption in villages where the predicted benefits are expected to be greatest. The difference in effect sizes between high and low benefit villages is sizable (2.8 farmers), but not quite statistically significant (p-value = 0.123). These findings suggest that demonstration plots sparked conversations that influenced adoption outcomes differently – farmers with below-median benefits had more conversations that led them to adopt less. Finally, the heterogeneity analysis based on predicted benefits also suggests that demonstration plots reduce variability in adoption. They lead to greater adoption in areas with higher predicted returns – precisely where adoption was initially lower without demonstration plots (Figure A.4 shows a negative correlation between predicted benefits and adoption in the absence of demonstration plots).

3.2 Mechanisms of demonstration plots and influential farmers

3.2.1 Demonstration plots and broadcasting

We now explore the mechanism driving the effects of demonstration plots. We show that demonstration plots facilitate 'broadcast diffusion' where entry-point farmers spread knowledge more widely by encouraging others to seek information beyond their immediate network. This contrasts with 'viral diffusion' where information flows only between connected peers – the mechanism presented in papers of information diffusion through social networks. We show this in two ways: reduced-form regression equations and a basic diffusion model.

Reduced Form We first present evidence of the broadcasting mechanism using a regression approach in the 64 villages with random entry points. Within these villages, the number of entry points in a farmer's network is as good as randomly assigned when conditioning on their total number of connections.[14] As a result, the average effect of being connected to an additional entry point can be estimated with:

$$informed_{ivse} = \beta_0 + \beta_1 Demo_{vs} + \beta_2 Entry\ Point\ Peers_{ivs} + \beta_3 Entry\ Point\ Peers_{ivs} * Demo_{vs} + \beta_4 Total\ Peers_{ivs} + \beta_5 Total\ Peers_{ivs} * Demo_{vs} + \alpha_s + \tau_e + \varepsilon_{ivse},$$

where $Entry\ Point\ Peers_{ivs}$ is the variable measuring how many of the five entry points farmer i is connected to and $Total\ Peers_{ivs}$ is the network degree of farmer i. A coefficient estimate of $\beta_3 > 0$ would indicate that demonstration plots work better for people connected to entry points. In other words, they increase the effectiveness of viral diffusion. Coefficient estimates of $\beta_3 < 0$ and $\beta_1 > 0$ would indicate that demonstration plots inform people that are not connected to entry points, i.e. broadcasting.

Column 1 in Table 6 shows strong peer effects. Across all villages, each connection to an entry point increases the probability of hearing about BD56 by 6.8 percentage points. Column 2 shows that demonstration plots increase knowledge by 11 percentage points for farmers having no baseline connections to entry points. Moreover, being connected to an entry points *only* helps in villages without demonstration plots. An additional connection to an entry point increases awareness by 10.5 percentage points without demonstration plots, but this effect goes down to an insignificant 3 percentage points with demonstration plots (p-value=0.496). Finally, the similarity of the effects points to how demonstration plots substitute for social connections to entry points: the 11.0 percentage point effect of demonstration plots for non-connected farmers is nearly the same as the 10.5 percentage point peer effect in non-demonstration villages (p-value = 0.937).

Direct conversations with entry points are not the only way that farmers can learn about the new varieties. They could also learn through network transmission that started with entry points. We therefore perform a similar exercise with distance between farmers and entry-points. Table A.8 shows that demonstration plots increase awareness for those with longer paths to entry points. In villages without demonstration plots, an additional node between the farmer and the entry-point reduces the probability of hearing about the new variety by 9.7 percentage points. However, in the presence of demonstration plots, being further from entry points in the network has a positive effect on awareness. The associated point estimate of 0.05 (p-value = 0.389) can be derived by adding the coefficient on mean length to entry point (-0.097) and the coefficient on the interaction with demonstration village (0.147). This provides further evidence that demonstration plots have a broadcasting

[14] Miguel and Kremer (2004) use a similar strategy when estimating spillover effects from deworming.

effect where information is transmitted between unconnected farmers.

We can also run heterogeneity analysis to see which groups the demonstration plots increase awareness for most. Table A.9 shows that demonstration plots have the largest impact for farmers that are the least central in the village networks. These least central farmers are smaller farmers who are more likely to be women, younger, and less educated (Table A.10). The broadcasting mechanism appears to benefit the least central farmers because their network position makes them less likely to benefit from viral diffusion.

We find evidence of broadcasting not only in who receives the information, but also in who engages in conversations about it. If a farmer has a conversation about rice farming with an entry-point to whom they are not connected, we interpret this as evidence of broadcast diffusion.[15] Table 7 breaks down conversations by social connections. Demonstration plots increase conversations with entry points by 0.17 conversations per farmers in phase I and 0.14 conversations per farmer in phase II (columns 2 and 4), for farmers who are not directly connected to entry-points. The interaction effect between the demonstration plots and peer connections with entry points is negative in phase I (-0.17, p-value=0.212), suggesting that peer connections with entry-point are no longer relevant in the presence of demonstration plots. In phase II, the interaction is close to zero suggesting demonstration plots increase conversations with cultivating farmers during harvesting regardless of social proximity in the network. We also find suggestive evidence that mean length to entry points matters for the number of conversations with entry points (Table A.11).[16]

Structural Model Next, we develop a basic diffusion model that also provides evidence of broadast diffusion. This model considers a village with n farmers, and the village social network is described by the $n \times n$ adjacency matrix G, where $g_{ij} = 1$ indicates that farmers i and j are connected. We measure these connections with the baseline social network module. The policymaker first seeds information with five entry points. Each entry point is now "informed" and can spread the information to others. Entry points can disseminate the information to their peers (viral transmission) with probability q or beyond their social network to someone they are not connected to with probability p (broadcast transmission).

[15] We find that the average path length between a farmer and a entry-point that they spoke to is 2.3. Of the conversations involving entry-points, 76% of them are between people with no direct connection.

[16] As the average length to entry points increases by 1, the number of conversations with entry-points falls by 0.122 (17 percent) in phase I. However, the trend reverses in demonstration villages. Although these effects are not statistically significant in phase I, they suggest that demonstration plots may make the distance between the entry-point and the farmer less relevant. A similar pattern emerges in phase II where we see that an additional node between the farmer and the entry-point reduces the number of conversations they have with the entry-point by 22 percent. This negative impact is largely eliminated in demonstration villages (though the interaction effect is not statistically significant, p-value $= 0.171$). Overall, this analysis indicates that demonstration plots can mitigate the impact of being further in the network from entry points.

While we assume that broadcasting diffusion only happens in the first period, informed nodes can continue to transmit information to their connections for multiple rounds. Most of our networks have giant components, meaning that viral diffusion will inform many when the communication probability and number of rounds are high.[17] We set the number of rounds of information dissemination to four, corresponding to planting, harvesting, and two mid-season periods (weeding) to obtain the final set of informed nodes. After 4 rounds, we obtain an information matrix, a set of dummy variables indicating whether any farmer in the network is predicted to be informed or not. We simulate this model 75 times for each village, starting with actual entry points and calculate the share of times each farmer was informed across 75 simulations to obtain each farmer's probability of being informed.

To estimate the model parameters, we compute the difference between the true information signal from our BD56 knowledge survey to the average information signal we simulate. We compute this difference for all demonstration (and subsequently non-demonstration) villages in our sample. We then find the q^*, p^* that minimizes the sum of squared differences between the true and simulated information signal in all villages. Our simulation returns the q_t^*, p_t^* in demonstration and q_c^*, p_c^* in non-demonstration villages. We can take the difference $q_t^* - q_c^*$ and $p_t^* - p_c^*$ to estimate the difference in viral and broadcast transmission between demonstration and non-demonstration villages. We apply a bootstrap (N=40) to obtain standard errors.

Table 8 Panel A presents the results. The probability of broadcasting information is 6 percentage points higher in demonstration villages (p-value = 0.033), moving from 12 to 18 percent. Conversely, the probability that any informed farmer passes to their peers is not significantly different in demonstration villages relative to non-demonstration villages. This suggests that broadcasting is the primary mechanism through which demonstration plots spread information.

3.2.2 Broadcasting by more connected farmers

To what extent are influential farmers engaging in broadcast diffusion as well? We explore this by comparing estimated model parameters between large/SAO villages and random selection villages. Note that we are unable to run the same reduced form regressions as above since the number of large/SAO entry points in a farmers network is not as good a randomly assigned. Nevertheless, we re-estimate the structural model to identify the rate of

[17] A giant component exists in the network when there is a large share of farmers where a path exists between any two of them. Most of our village networks have giant components: 87 percent of farmers are inside the largest component of their village network and about 60% of our sample is in villages where the network is connected, i.e. everybody is in the giant component. These types of networks facilitate becoming aware through viral diffusion (Sadler, 2020).

viral (q^*) and broadcast (p^*) diffusion that minimize the sum of squared residuals between the true and simulated information signal – comparing the large/SAO non-demo villages with the random non-demo villages. This comparison determines whether large and SAO entry points are any more likely to spread information in either of the two ways.

Table 8 Panel B provides the results. The estimates, $q^* = 0.05$ and $p^* = 0.21$, are nearly identical to those we find when estimating the model for demonstration villages. Going from random selection (no-demo) to large/SAO selection (no-demo) has no significant effect on the probability of sharing information with peers, as the 95% confidence interval for the change in q is (-0.14,0.06). However, the probability of broad transmission to non-peers increases from 0.13 to 0.21 when going from random selection to large/SAO entry points, and this difference is statistically significant. This finding shows that large and SAO entry points broadcast information as well. Using these values of q^* and p^*, we simulate the extent of information diffusion in large and SAO villages and find that 71% of farmers hear about the technology, which is within 2% of what we find in the data.[18]

This similarity between using influential farmers and demonstration plots reveals an important fact about information diffusion more broadly. To date, the literature has focused on seeding with influential farmers to make viral diffusion more effective. Our estimates show that influential farmers are also broadcasting information, and this is critical to explaining their ability to spread information. The fact that influential farmers are indeed more likely to engage in broadcasting helps explain why both demonstration plots and influential farmers are equally effective at spreading information. Demonstration plots enable ordinary farmers to act as broadcasters, eliminating the need to specifically identify the most influential individuals within the network. In other words, demonstration plots enable ordinary farmers to serve as information broadcasters.

We show the relevance of the broadcasting mechanism in two other ways. First, we re-estimate the model assuming no broadcast diffusion. This produces values of $q^* = 0.41$ for randomly selected farmers and $q^* = 0.57$ for large/SAO farmers (Table 8 Panel C). Yet, when we simulate the extent of diffusion under this model, the model fit decreases by 40%. This suggests that a model based solely on viral diffusion does not accurately capture how information spreads in large or SAO villages. Second, we apply the broadcast and viral probabilities estimated from random villages to the large and SAO villages, and find that this increases diffusion by only a small amount relative to seeding with random

[18]We also run heterogeneity analysis and show that the large/SAO treatments have the largest impacts for farmers that are the least central in the village networks (A.9). These least central farmers are smaller farmers who are more likely to be women, younger, and less educated (Table A.10). This finding implies that influential farmers broadcast to a wide audience and are capable of reaching groups that were unlikely to learn from viral diffusion alone.

farmers. This suggests that entering with the centrally positioned farmers within the network doesn't significantly enhance diffusion – likely because, after a few rounds, central farmers are reached anyways and the information spreads similarly throughout the village. These findings underscore the critical role of broadcast diffusion in understanding how influential farmers spread information.

3.2.3 What facilitates broadcasting?

We argue that demonstration plots and influential farmers trigger a broadcasting effect by capturing farmers' attention. Demonstration plots do so by signaling that an experiment is underway (Figure 1), which we document triggers conversations and knowledge exchange (Table 2 and 3). Analogously, the broadcasting effect of larger/SAO farmers is likely driven by their greater visibility.

Could part of the broadcasting effect also be explained by demonstration farmers and influential farmers gaining a better understanding of the varieties themselves, thereby improving their ability to share information with others? Perhaps demonstration plots help randomly selected entry-point farmers better recognize the main features of the new variety, enabling them to effectively share that information with others. Similarly, large or SAO farmers may be better equipped to learn the varieties' key features, and communicate them more broadly.

We explore this by using data on farmers' cropping patterns from Phase I.[19] Table A.12 shows that, compared to those growing BD51, farmers who were treated with BD56 harvest earlier and are significantly more likely to cultivate the rabi crop that fits between the two rice-growing seasons (columns 1 and 2). Randomly selected farmers with demonstration plots are no more likely to grow this rabi crop (column 1 and 2), and do not increase overall cropping intensity (column 4). However, we see that the effect on growing the rabi crop is prevalent for large and SAO selected farmers. This suggests that SAO and large farmers are effective at demonstrating the benefits of the technology, which may explain how they can broadcast.[20] This is not the case for demonstration farmers. We can further demonstrate this using mediation analysis. Table A.13 shows that the greater likelihood of visibly demonstrating benefits explains why awareness spreads more with large and SAO

[19]As Figure 2 shows, we have 64 pure control villages where farmers received BD51 (longer duration) seeds. 15 farmers were selected in these villages, using the same three selection mechanisms as for the BD56 seeds. This allows us to measure the impact of introducing short duration BD56 relative to longer duration BD51. Moreover, we can estimate heterogeneity by the type of entry point. The specification is similar to equation 1, with the only modification being the inclusion of indicator variables for large and SAO farmers.

[20]It is important to note that this does not necessarily lead to higher adoption rates, because some farmers may learn that the technology is not suitable for them, while others learn that it is—leading to mixed adoption responses.

entry points. Controlling for whether the farmer grows a rabi crop eliminates 16-20% of the effect of large/SAO selection.

While randomly selected farmers with demonstration plots are not gaining sufficient knowledge to capitalize on the primary benefit of BD56, they do something else to facilitate broadcasting that influential farmers cannot do. By showing a head-to-head comparison of seed varieties, the demonstration is designed to make it easier to separate possible returns from farmer characteristics. Without demonstrations, part of the reason farmers rely on their peers for learning is that peers tend to be similar. Demonstration plots can help farmer learn different things by making adoption decisions less dependent on how relatable the entry point is to individual farmers. Farmers can then assess whether the technology suits them without needing to resemble the entry-point. This mechanism is unlikely to apply to large/SAO farmers, as they are, by definition, different from the average farmer in the village.

We investigate this by analyzing how the difference in willingness to pay between farmers and entry-points varies with their level of similarity. For each farmer and entry point in our sample, we have baseline data from the Phase I census, which allows us to construct a dataset to compare each farmer with entry points in their village.[21] We calculate the differences in baseline characteristics between each farmer in our sample and each entry point within their village, then compute the Euclidean distance between them. A greater Euclidean distance indicates that the farmer and the entry point are more dissimilar. Table 9 shows that a one standard deviation increase in the Euclidean distance from entry points, increases the difference in farmers' willingness to pay compared to the entry point by 5.2%. However, in villages with demonstration plots, this difference is nearly eliminated (p-value = 0.031), suggesting that demonstration plots make similarity to the entry point less critical. Farmers who are different from the entry-point can still learn from the demonstration plot and make informed decisions about whether or not to adopt based on what they believe works best for their own circumstances.

4 Conclusion

People commonly hear about new technologies from peers. This makes it valuable to uncover the structure of social networks. Knowing the structure of the network can help increase

[21] These variables include the amount of land cultivated with rice and other crops during the previous Aman season, the quantity of fertilizer (Urea and DAP) applied during the last Aman season, the number of rice varieties grown last Aman, the total amount of rice harvested, the amount of land devoted to rice and other crops during the last Boro Season, the number of farmers they communicate with about farming, and whether or not they own a tubewell.

dissemination by seeding information with the most influential people. Indeed, many studies on information dissemination have highlighted the importance of who gets informed first. But not all interactions happen between agents that are linked in a network. An alternative method to boost awareness and learning is to create a reason for people to communicate with others irrespective of their existing networks.

We show that a simple intervention can trigger information exchange. In the context of agricultural seed varieties, demonstration plots publicly signal the existence of a more formal experiment. We find that such plots increase the share of people in the village becoming aware of the technology, and the number of conversations that people have with the farmers who received the initial seeds. We also find that demonstration plots increase the share of farmers who learn about the variety's key features.

While demonstration plots led to more farmer interactions, they had no average effect on adoption or willingness to pay. However, this average masks substantial variation. In some areas, demonstration plots increased willingness to pay, while in others, they reduced it. We also find suggestive evidence that adoption increases only among farmers who are predicted to have the highest returns. These differing adoption patterns likely reflect the fact that farmers are learning different things from the demonstration plots.

Further evidence shows that demonstration plots increase awareness by enabling broad information transmission, even to individuals who are not socially connected. In doing so, demonstration plots allow ordinary farmers — who might otherwise go unnoticed — to act as effective information broadcasters. This reduces the need to identify and target the most influential individuals in the network. Interestingly, we also find that influential farmers are more likely to engage in this kind of broadcasting, which helps explain why both demonstration plots and seeding information through influential individuals are similarly effective. While existing literature emphasizes the role of influential farmers in viral diffusion, our findings suggest they also contribute by actively broadcasting information——an overlooked but important mechanism.

The broader implication of our findings is that learning can be induced with simple interventions that spark people's interest in communicating. This suggests a broader class of interventions than those that optimize where to seed information in social networks. We see value in future work that identifies new ways of sparking communication between people.

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Tables

Table 1: Demonstration Plots and influential farmers increase awareness

	Phase I Post	Phase II During
	(1)	(2)
	Heard About	Heard About
Random w/ demo	0.083**	-0.011
(β_1)	(0.038)	(0.017)
SAO no demo	0.093***	
(β_2)	(0.034)	
SAO w/ demo	0.090**	
(β_3)	(0.036)	
Large no demo	0.098***	
(β_4)	(0.034)	
Large w/ demo	0.093**	
(β_5)	(0.041)	
Mean in Random No Demo	0.589	0.855
p-value: $\beta_1 = \beta_5 - \beta_4$	0.091	
p-value: $\beta_1 = \beta_3 - \beta_2$	0.075	
p-value: $\beta_1 = \beta_4$	0.639	
p-value: $\beta_1 = \beta_2$	0.765	
Number of Observations	1767	4632

The table presents rates of awareness of new seed varieties: awareness of BD56 from phase I (columnn 1) and awareness of BD87 from phase II (column 2). In Phase I (column 1), the data are for the 10 random farmers per village that were selected for the information survey in the 192 villages (96 demo villages and 96 non-demo) – excluding the minikit recipients. In Phase II, the data are for the full sample of farmers that we were able to reach in each village. The dependent variable in column 1 is an indicator for having knowledge of BD56. The dependent variable in column 2 is an indicator for having knowledge of BD87. Standard errors are clustered at the village level. Asterisks indicate statistical significance at the 1% ***, 5% **, and 10% * levels.

Table 2: Demonstration plots increase conversations

	Phase I Post		Phase II During		Phase II Post	
	(1) Convos	(2) Convos w/ Entry	(3) Convos	(4) Convos w/ Entry	(5) Convos	(6) Convos w/ Entry
Random w/ demo	0.133	0.136	0.645*	0.109**	0.536	-0.002
(β_1)	(0.092)	(0.094)	(0.388)	(0.046)	(0.378)	(0.043)
SAO no demo	0.049	0.051				
(β_2)	(0.074)	(0.077)				
SAO w/ demo	0.096	0.125				
(β_3)	(0.094)	(0.091)				
Large no demo	0.149*	0.132*				
(β_4)	(0.078)	(0.075)				
Large w/ demo	0.118	0.138				
(β_5)	(0.083)	(0.086)				
Mean in Random No Demo	0.836	0.712	5.803	0.310	3.454	0.298
p-value: $\beta_1 = \beta_5 - \beta_4$	0.149	0.259				
p-value: $\beta_1 = \beta_3 - \beta_2$	0.460	0.593				
p-value: $\beta_1 = \beta_4$	0.840	0.957				
p-value: $\beta_1 = \beta_2$	0.261	0.290				
Number of Observations	1768	1768	4632	4632	3141	3141

The table presents the number of conversations that farmers have. In Phase I (column 1,2), the data are for the 10 random farmers per village that were selected for the information survey in the 192 villages (96 demo villages and 96 non-demo) – excluding minikit recipients. In Phase II (column 3,4,5,6), the data are for the full sample of farmers that we were able to reach in each village. The dependent variables are the number of conversations farmers have (columns 1,3,5) and the number of conversations they have with entry-points specifically (columns 2,4,6). In phase II we ask farmers these questions twice, once during the growing season (column 3,4) and once post-harvest (column 5,6). Standard errors are clustered at the village level. Asterisks indicate statistical significance at the 1% ***, 5% **, and 10% * levels.

Table 3: Demonstration plots increase learning about harder-to-see attributes

	Control Mean	Estimate
Unknown	0.323	-0.013 (0.032)
BD87 yield is higher	0.352	0.054** (0.024)
Swarna yield is higher	0.157	-0.056** (0.026)
Same yield	0.063	0.024 (0.016)
Unknown	0.274	-0.004 (0.031)
BD87 duration is shorter	0.504	-0.008 (0.037)
Swarna duration is shorter	0.044	0.007 (0.009)
Same duration	0.070	0.004 (0.011)
Unknown	0.299	-0.016 (0.033)
BD87 is taller	0.253	-0.004 (0.037)
Swarna is taller	0.239	0.015 (0.028)
Same height	0.138	-0.004 (0.014)

The table presents farmers' knowledge of BD87 in phase II relative to a commonly grown rice variety (Swarna). The data are for the set of farmers we were able to reach in our post-harvest survey in phase II who said they heard about BD87. We ask respondents "how does the yield of BD87 compare with the yield of Swarna" and "how does the height of BD87 height compare to the height of Swarna?", to which farmers can answer one is higher than the other, they are the same, or they do not know. The dependent variable in all regressions is listed in each row, and we regress the dependent variable on an indicator for being in a village assigned to demonstration, and the standard set of controls. Standard errors are clustered at the village level. Asterisks indicate statistical significance at the 1% ***, 5% **, and 10% * levels.

Table 4: Demonstration plots do not affect average levels of adoption

	Phase 1	Phase 2	
	(1) Number Farmers	(2) WTP	(3) WTP
Random w/ demo	0.673	0.775	
(β_1)	(0.813)	(1.434)	
SAO no demo	0.697		
(β_2)	(0.694)		
SAO w/ demo	0.116		
(β_3)	(0.615)		
Large no demo	0.272		
(β_4)	(0.535)		
Large w/ demo	0.866		
(β_5)	(0.641)		
Entry Point			-2.499**
			(0.798)
Mean in Random No Demo	1.68	21.30	20.44
p-value: $\beta_1 = \beta_5 - \beta_4$	0.937		
p-value: $\beta_1 = \beta_3 - \beta_2$	0.245		
p-value: $\beta_1 = \beta_4$	0.602		
p-value: $\beta_1 = \beta_2$	0.979		
Number of Observations	168	1099	1218

The table presents farmers adoption of the new seed varieties. The data from phase I are from seed sales that were carried out for each village prior to the 2017 rainy season. We are missing data for 24 of the 192 villages because the seed supply ran out before those villages could be completed. The data from phase II are the results of a willingness to pay experiment that we conducted with approximately 21 farmers per village. The dependent variables are the number of farmers purchasing BD56 seeds in phase I (column 1) and farmers' willingness to pay in phase II (columns 2 and 3). The regression in column 1 uses robust standard errors while standard errors are clustered at the village level in columns 2 and 3. Asterisks indicate statistical significance at the 1% ***, 5% **, and 10% * levels.

Table 5: Heterogeneous effects on knowledge and conversations by predicted impact of BD56 on number of crops grown

	Predicted Benefit Heterogeneity		Index Above Median	
	(1)	(2)	(3)	(4)
	Heard About	Conversation	Heard About	Conversations
Random w/ demo	0.091	0.271**	0.127**	0.307***
	(0.067)	(0.119)	(0.057)	(0.116)
SAO no demo	0.106*	0.136	0.118**	0.147
	(0.064)	(0.102)	(0.055)	(0.091)
SAO w/ demo	0.125**	0.277***	0.134**	0.321***
	(0.062)	(0.103)	(0.053)	(0.096)
Large no demo	0.155***	0.251**	0.152***	0.282***
	(0.060)	(0.098)	(0.053)	(0.097)
Large w/ demo	0.138*	0.233**	0.153**	0.287***
	(0.079)	(0.111)	(0.064)	(0.091)
Heterogeneity	0.026	0.382*	0.100*	0.306***
	(0.129)	(0.207)	(0.052)	(0.091)
Random w/ demo *	-0.033	-0.467**	-0.079	-0.320**
Heterogeneity	(0.141)	(0.224)	(0.066)	(0.128)
SAO no demo *	-0.050	-0.272	-0.034	-0.153
Heterogeneity	(0.141)	(0.249)	(0.065)	(0.103)
SAO w/ demo *	-0.126	-0.617***	-0.073	-0.442***
Heterogeneity	(0.144)	(0.223)	(0.069)	(0.130)
Large no demo *	-0.198	-0.339	-0.097	-0.240*
Heterogeneity	(0.140)	(0.251)	(0.068)	(0.123)
Large w/ demo *	-0.162	-0.398*	-0.110	-0.321***
Heterogeneity	(0.175)	(0.234)	(0.070)	(0.104)
Mean in Random No Demo	0.59	0.84	0.59	0.84
Number of Observations	1767	1768	1767	1768

The table presents whether the different treatments increase awareness and conversations more (or less) for farmers that are predicted to have the largest impact of BD56 on the number of crops grown. The data are for the 10 random farmers per village that were selected for the information survey in phase I – excluding minikit recipients. For each farmer we calculate $\hat{s_0}(z_i)$ as the median value across the 100 sample divisions. Columns 1 and 2 show linear heterogeneity where the treatment indicators are interacted with $\hat{s_0}(z_i) = E(y_i|D_i = 1, z_i) - E(y_i|D_i = 0, z_i)$ and columns 3 and 4 partition the sample into farmers that are above and below the median in the distribution of $\hat{s_0}(z_i)$. The dependent variable in columns 1 and 3 is an indicator for having heard of BD56. The dependent variable in columns 2 and 4 is the number of conversations the farmer had with 15 other farmers about BD56. Standard errors are clustered at the village level. Asterisks indicate statistical significance at the 1% ***, 5% **, and 10% * levels.

Table 6: Demonstration plots increase awareness for farmers that are not connected to entry points

	(1)	(2)
Demonstration Village (β_1)		0.110***
		(0.041)
Peer connections w/ entry points (β_2)	0.068**	0.105**
	(0.032)	(0.041)
Peer connections w/ entry points * Demonstration Village (β_3)		-0.075
		(0.058)
Total peer connections (β_4)	-0.004	-0.002
	(0.003)	(0.006)
Total peer connections * Demonstration Village (β_5)		-0.002
		(0.006)
Mean in Random No Demo	0.589	0.589
p-value: $\beta_2 + \beta_3$		0.496
p-value: $\beta_1 = \beta_2$		0.937
Number of Observations	593	593

The table presents rates of awareness for farmers with and without connections to entry-points. The data are for the 10 random farmers per village that were selected for the information survey in phase I – excluding minikit recipients. The data are limited to the 64 villages where entry points where chosen randomly and peer effects can therefore be causally identified. The dependent variable in all regressions is an indicator for having heard of BD56. The variable *Peer connections w/ entry points* is the number of entry points (from 0 to 5) that the farmer is connected to, and the variable *Total peer connections* is the total number of people the farmer is connected to. Standard errors are clustered at the village level. Asterisks indicate statistical significance at the 1% ***, 5% **, and 10% * levels.

Table 7: Demonstration plots and conversations

	Phase I		Phase II	
	(1)	(2)	(3)	(4)
	Convos w/ Entry	Convos w/ Entry	Convos w/ Entry During	Convos w/ Entry During
Demonstration Village (β_1)		0.173*		0.142*
		(0.100)		(0.073)
Peer connections w/ entry points (β_2)	0.041	0.128	0.047***	0.048**
	(0.060)	(0.096)	(0.016)	(0.020)
Peer connections w/ entry points * Demonstration Village (β_3)		-0.171		-0.000
		(0.137)		(0.034)
Total peer connections (β_4)	0.001	0.001	-0.004*	-0.003
	(0.006)	(0.010)	(0.002)	(0.002)
Total peer connections * Demonstration Village (β_5)		-0.000		-0.003
		(0.011)		(0.005)
Mean in Random No Demo	0.589	0.712	0.310	0.310
p-value: $\beta_2 + \beta_3$		0.593		0.077
p-value: $\beta_1 = \beta_2$		0.776		0.217
Number of Observations	594	594	4632	4632

The table presents the number of conversations that farmers had (for farmers with and without connections to entry-points). In Phase I (column 1,2), the data are for the 10 random farmers per village that were selected for the information survey in the 192 villages (96 demo villages and 96 non-demo) – excluding minikit recipients. In Phase II (column 3,4), the data are for the full sample of farmers that we were able to reach in each village during the growing season. The dependent variables are the number of conversations farmers had with entry-points in phase I (column 1,2), and the number of conversations farmers had with entry-points during the growing season in phase II (column 3,4). The variable *Peer connections w/ entry points* is the number of entry points (from 0 to 5) that the farmer is connected, and the variable *Total peer connections* is the total number of people the farmer speaks to about farming. Standard errors are clustered at the village level. Asterisks indicate statistical significance at the 1% ***, 5% **, and 10% * levels.

Table 8: Model Estimates: Transmission Effects under Different Strategies

Panel A: Effects of Demonstration Plots

Var	Desc	Avg	CI
q_c^*	Viral Transmission (C)	0.10**	(0.01, 0.19)
		(0.05)	
q_t^*	Viral Transmission (T)	0.06***	(0.03, 0.08)
		(0.01)	
$q_t^* - q_c^*$	Viral Transmission (diff)	-0.05	(-0.14, 0.04)
		(0.05)	
p_c^*	Broad Transmission (C)	0.13***	(0.09, 0.17)
		(0.02)	
p_t^*	Broad Transmission (T)	0.19***	(0.15, 0.23)
		(0.02)	
$p_t^* - p_c^*$	Broad Transmission (diff)	0.06**	(0.00, 0.13)
		(0.03)	

Panel B: Effects of Entering with Influential Farmers

Var	Desc	Avg	CI
q_c^*	Viral Transmission (C)	0.09*	(-0.00, 0.19)
		(0.05)	
q_t^*	Viral Transmission (T)	0.05***	(0.04, 0.07)
		(0.01)	
$q_t^* - q_c^*$	Viral Transmission (diff)	-0.04	(-0.14, 0.06)
		(0.05)	
p_c^*	Broad Transmission (C)	0.13***	(0.08, 0.18)
		(0.02)	
p_t^*	Broad Transmission (T)	0.21***	(0.18, 0.25)
		(0.02)	
$p_t^* - p_c^*$	Broad Transmission (diff)	0.08***	(0.03, 0.14)
		(0.03)	

Panel C: Effects of Entering with Influential Farmers (No Broadcasting)

Var	Desc	Avg	CI
q_c^*	Viral Transmission (C)	0.41***	(0.24, 0.58)
		(0.09)	
q_t^*	Viral Transmission (T)	0.57***	(0.39, 0.75)
		(0.09)	
$q_t^* - q_c^*$	Viral Transmission (diff)	0.15	(-0.06, 0.37)
		(0.11)	

The table presents the results from estimating the structural model. Panel A presents the q^* and p^* that minimizes the sum of squared differences between the true and simulated information signal in random demo (t) and random non-demo (c) villages. Panel B presents the q^* and p^* that minimizes the sum of squared differences between the true and simulated information signal in SAO/Large non-demo (t) and random non-demo (c) villages. Panel C presents the q^* that minimizes the sum of squared differences between the true and simulated information signal in SAO/Large non-demo (t) and random non-demo (c) villages. It assumes no broadcasting. The numbers in parentheses below each point estimate are standard errors. Asterisks indicate statistical significance (1% ***, 5% **, and 10% *).

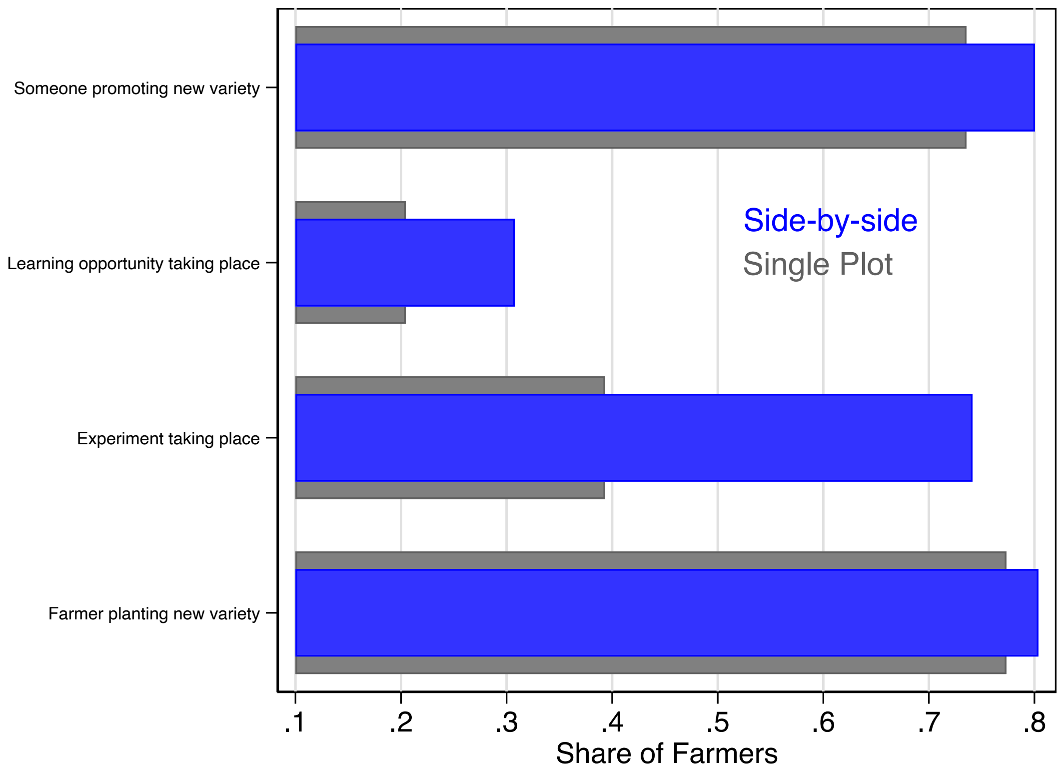
Table 9: Similarity with entry points and willingness to pay

	(1) Differential WTP Geography	(2) Differential WTP Euclidean
Demonstration Village	-0.758	0.243
	(1.159)	(1.118)
Geography Distance * Demonstration Village	0.525	
	(2.086)	
Geography Distance	-1.207	
	(1.240)	
Euclidean Distance * Demonstration Village		-0.376**
		(0.171)
Euclidean Distance		0.400***
		(0.112)
Mean in Random No Demo	8.75	8.75
Number of Observations	2058	2058

The table presents the link between farmers' willingness to pay for BD87 and their distance to the entry point. Each observation in the regression is a farmer-by-entry point combination. The dependent variable in both regression is the difference in WTP between the farmer and the entry point. Column 1 uses a similarity measure equal to the geographic distance between the house of the farmer and the house of the entry point. Column 2 uses a euclidean distance between vectors of household covariates for the farmer and the entry points. Standard errors that are clustered at the village level are included in parentheses. Asterisks indicate statistical significance at the 1% ***, 5% **, and 10% * levels.

Figures

Figure 1: Demonstration Plots Signal an Experiment



Notes: This figure presents what farmers infer when they see a demonstration plot. In phase II, we ask farmers what they infer when they see two sticks side by side in a field, versus only one. We provide four answers to choose from: someone is promoting a new variety, a learning opportunity is taking palace, an experiment is taking place, and a new variety is being planted. The x-axis presents the share of farmers who selected the response options presented in the y-axis. Farmers are more likely to believe an experiment or learning opportunity is taking place when they see two sticks.

Figure 2: Experimental Design

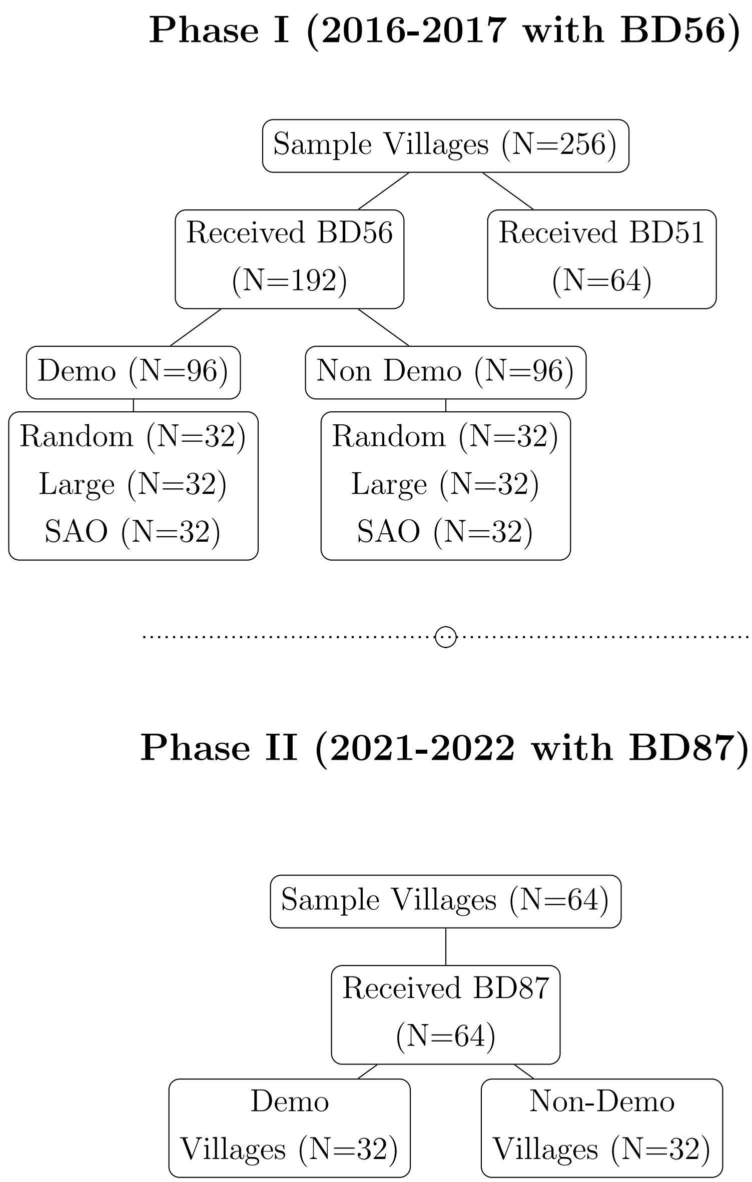


Figure 3: Visualization of the demonstration plot in comparison to the non-demonstration group

A: Demonstration Plot B: Control Plot

Notes: This figure shows an example of a demonstration plot. In Panel A, we see the plot on the left side is the BD56 plot while the plot on the right is the popular longer duration variety Swarna. Panel B on the right shows an example from the comparison villages where farmers were only given one marker to denote the BD56 plot.

Figure 4: Timeline of the experiment and data collection

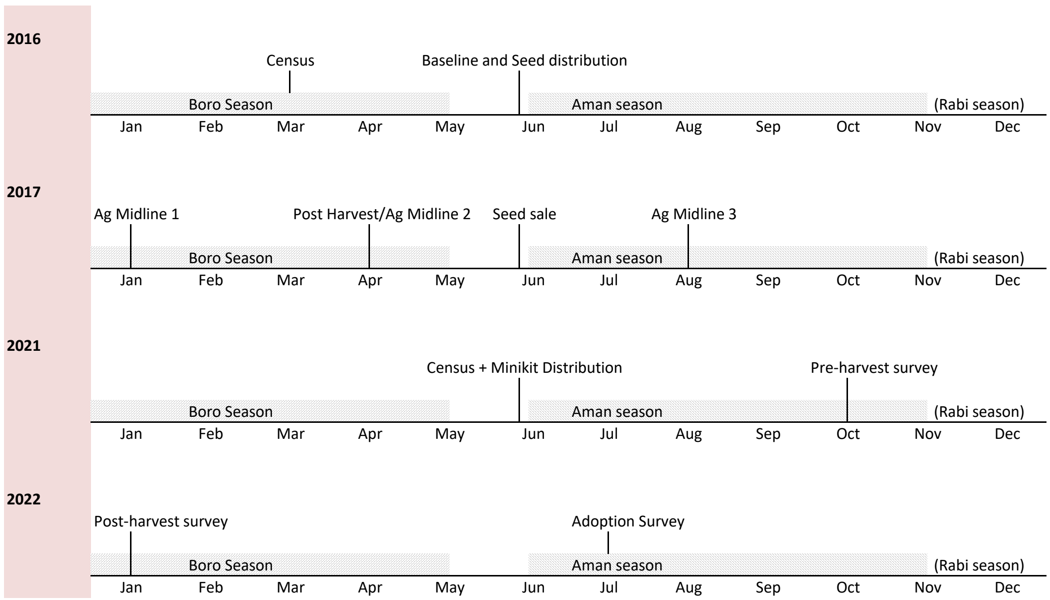
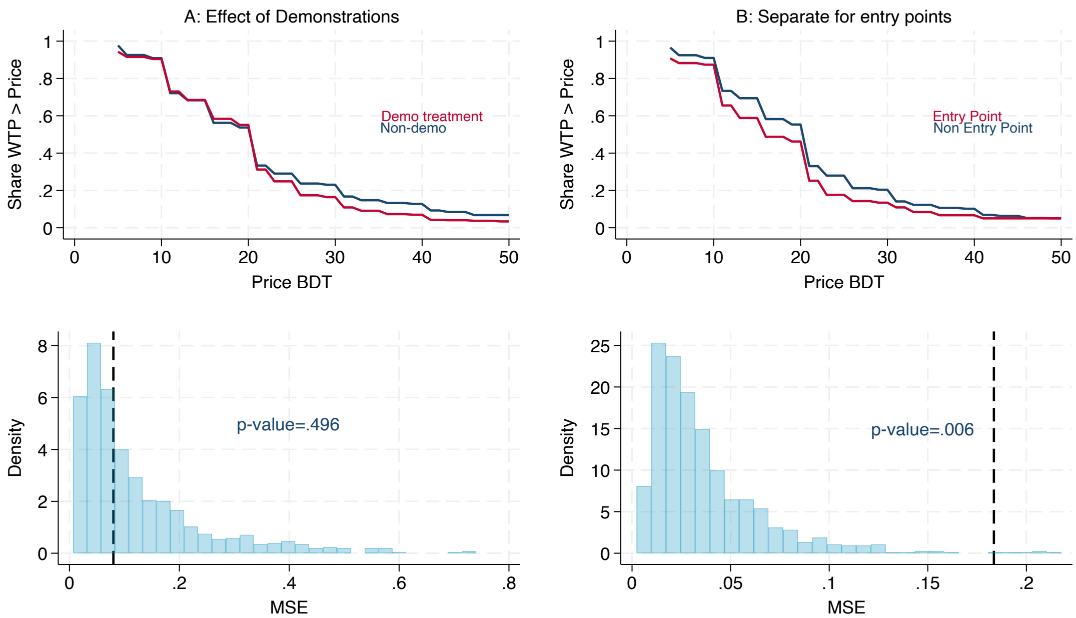
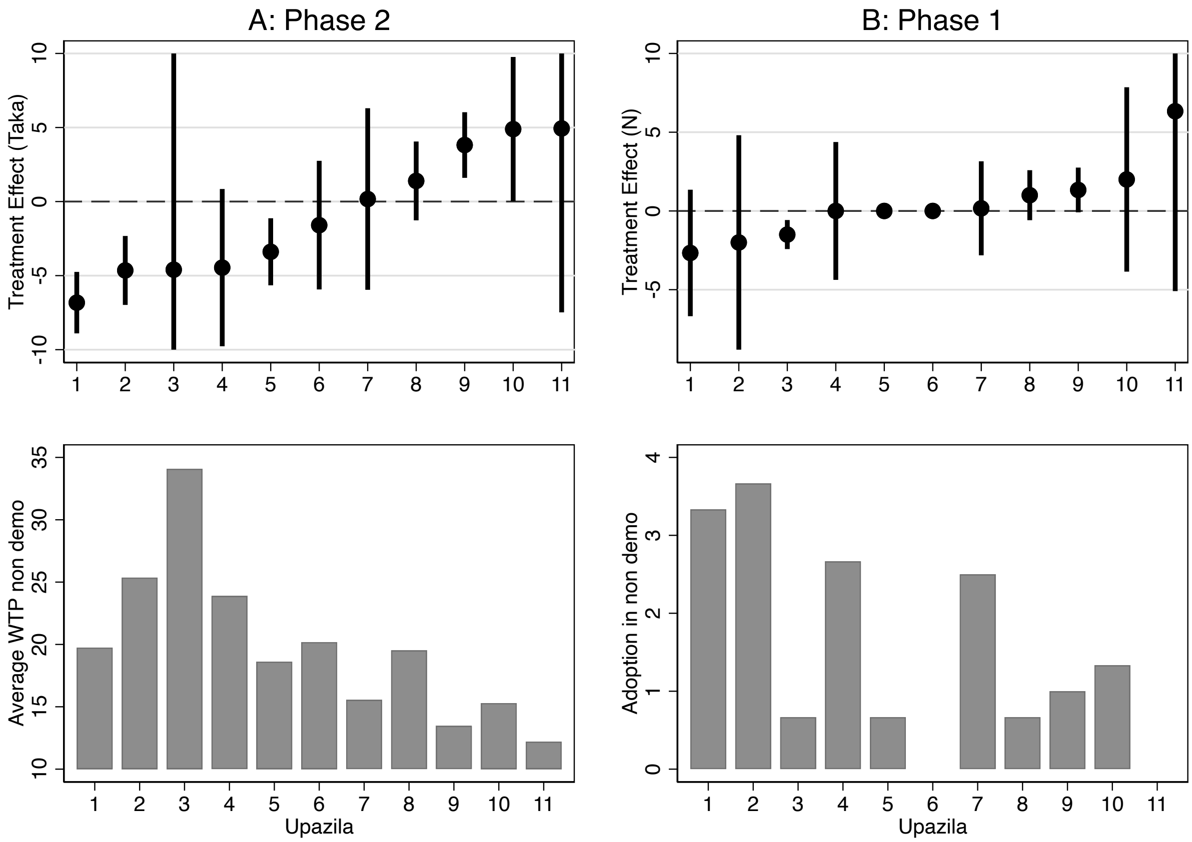


Figure 5: Inverse demand curves for BD87 in Phase II



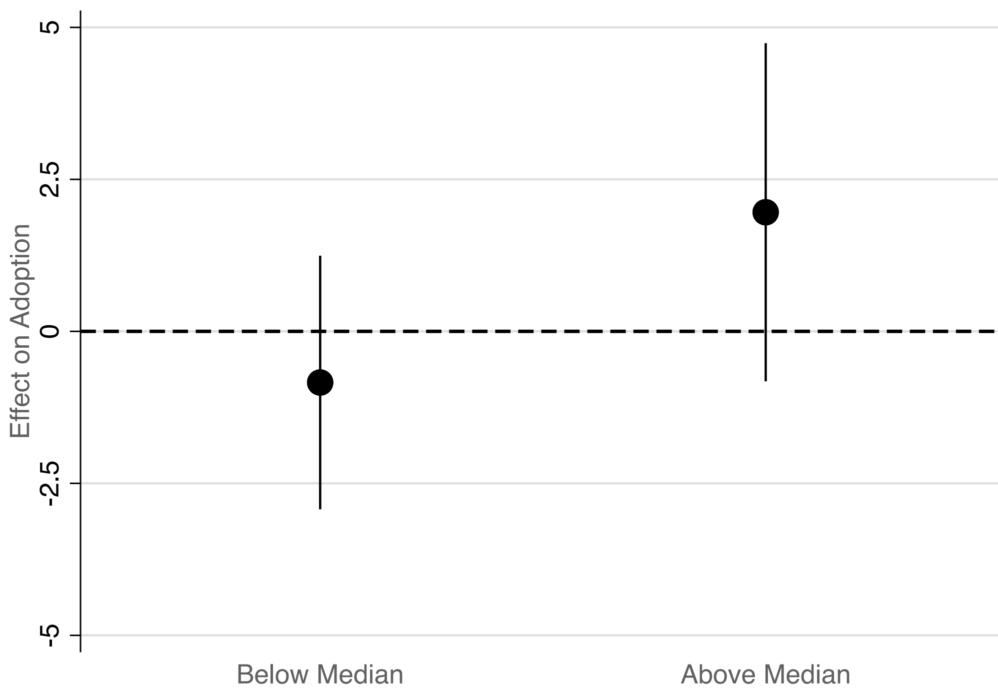
Notes: This figure uses individual-level WTP from the BDM survey in Phase II. Each curve shows the share of farmers that have WTP greater than or equal to each of the prices on the horizontal axis. Panel A uses all farmer where we elicited WTP and compares demonstration to non-demonstration villages. The BDM also included 118 randomly selected entry points (approx. 2 per village). The right panel compares these farmers to the non-entry point farmers and shows that cultivating BD87 one year before decreased demand for seeds the following year. The bottom two panels show results from a randomization inference procedure testing whether demand curves are identical in the two groups. The dashed vertical lines show the mean squared difference between the two demand curves across all prices from the top panels. The histograms show the distributions of the same statistic, but across 1,000 fake random assignments to demo/non-demo (left panel) or entry point / non-entry point (right panel). The p-values are the share of the 1,000 replications for which the mean squared difference is larger than for the actual assignment.

Figure 6: Differential effects on adoption across geographic areas



Notes: This figure shows the treatment effects of demonstration plots on willingness to pay and adoption for the 11 upazilas in the study. The top-left panel shows treatment effects on WTP elicited by BDM during the second phase. The top right panel shows treatment effects on the number of adopters at the village level in phase I. The bottom panels show the average WTP and adoption in the group without demonstration plots. All treatment effects are computed from a fully interacted model where upazila indicators are interacted with treatment. The interaction effects between demo plots and the upazila indicators are jointly significant in both cases (p=0.043 in phase I and p=0.000 in phase II). Standard errors are clustered at the village level. The bands in the top panel show 95% confidence intervals.

Figure 7: Differential effects on adoption by predicted benefits



Notes: This figure estimates the treatment effects of demonstration plots on the number of farmers adopting BD56 at the village level separately for villages where the predicted benefit index for adoption was below the median (low predicted benefits to adoption) and above the median (high predicted benefits to adoption). The point estimate on 'below median' suggests that the demonstration plots did not increase adoption in villages where predicted benefits are below the median. The point estimate on 'above median' suggests that the demonstration plots had an imprecise positive effect. The difference in effect sizes between high and low benefit villages is sizable, but not statistically significant.

Casting a Wider Net:
Sharing Information Beyond Social Networks
Online appendix

Erin Kelley, Manzoor Dar, Alain De Janvry, Kyle Emerick, Elisabeth Sadoulet

Contents

A Appendix tables and figures

A.1 Tables

Table A.1: Data Collected in Phase II and Phase II

Round	Feature	Phase I	Phase II
Diffusion Surveys			
Census	Time	March 2016	June 2021
	Sample	Full sample	Full sample
	Key Data	Social Networks	Social Networks
Minikit Distribution	Time	June 2016	June/August 2021
	Sample	Entry-points	Entry-points
	Key Data	Delivery of seed/stick	Delivery of seed/stick
Pre-Harvest	Time	X	October 2021
	Sample	X	Full Sample
	Key Data	X	Awareness, Knowledge
Post-Harvest	Time	April 2017	January 2022
	Sample	10 random farmers	Full sample
	Key Data	Awareness, Knowledge	Awareness, Knowledge
Seed Sale	Time	April 2017	July/August 2022
	Sample	Village	19 farmers
	Key Data	Seed Sale	WTP and planting
Agricultural Surveys (BD56)			
Baseline	Time	June 2016	X
	Sample	Entry-points	X
	Key Data	Plots/Crops	X
Midline 1	Time	January 2017	X
	Sample	Entry-points	X
	Key Data	Aman production	X
Midline 2	Time	April 2017	X
	Sample	Entry-points	X
	Key Data	Additional crop production	X
Midline 3	Time	August 2017	X
	Sample	Entry-points	X
	Key Data	Boro production	X

Table A.2: Balance of household characteristics across treatment arms

	Control	Large	SAO	Random	Large + Demo	SAO + Demo	Random + Demo	Joint p-value
		Treatment Arm:						
Education	4.235	3.951	4.663	4.604	4.216	4.368	4.768	0.381
	(4.314)	(4.202)	(4.521)	(4.293)	(4.125)	(4.466)	(4.235)	
Age	41.356	41.908	41.660	41.650	41.820	40.938	41.261	0.829
	(12.407)	(11.926)	(12.348)	(12.300)	(12.143)	(12.023)	(12.039)	
Owns Shallow Tubewell	0.103	0.149	0.160	0.085	0.072	0.086	0.115	0.356
	(0.304)	(0.356)	(0.367)	(0.278)	(0.259)	(0.280)	(0.319)	
Aman Rice Area (Bigah)	4.071	4.293	5.029	4.221	4.678	4.775	4.265	0.770
	(5.656)	(5.550)	(12.429)	(6.027)	(5.530)	(5.983)	(5.152)	
Aman Other Crop Area (Bigah)	0.348	0.375	0.319	0.462	0.300	0.236	0.395	0.682
	(1.567)	(1.893)	(1.478)	(9.638)	(1.676)	(0.794)	(1.412)	
Boro Rice Area (Bigah)	3.328	3.002	3.812	3.344	2.515	3.289	2.889	0.383
	(4.264)	(4.296)	(5.847)	(5.312)	(4.171)	(4.699)	(4.060)	
Boro Other Crop Area (Bigah)	1.125	1.252	1.332	1.140	1.478	1.100	1.346	0.840
	(2.454)	(2.513)	(3.325)	(2.362)	(3.043)	(2.219)	(2.358)	
Aman Urea Fertilizer (KG per Bigah)	21.427	21.953	21.260	22.161	20.644	21.313	20.588	0.843
	(15.109)	(15.459)	(21.673)	(21.759)	(17.417)	(25.641)	(14.648)	
Aman DAP Fertilizer (KG per Bigah)	15.834	16.110	15.519	16.435	14.889	15.813	15.157	0.326
	(11.660)	(15.169)	(20.073)	(13.662)	(6.739)	(15.346)	(10.332)	
Aman Rice Yield (KG per Bigah)	17.756	17.499	18.063	17.989	17.477	17.570	17.837	0.927
	(3.814)	(4.180)	(3.263)	(3.089)	(3.280)	(3.851)	(3.483)	
Grows only rice	0.480	0.424	0.416	0.474	0.342***	0.475	0.371*	0.107
	(0.500)	(0.494)	(0.493)	(0.499)	(0.474)	(0.499)	(0.483)	
Grows Short-Duration Rice	0.011	0.035	0.007	0.004	0.007	0.018	0.008	0.831
	(0.102)	(0.185)	(0.085)	(0.066)	(0.081)	(0.135)	(0.088)	
Grows Wheat	0.236	0.260	0.243	0.190	0.372**	0.231	0.286	0.353
	(0.425)	(0.439)	(0.429)	(0.393)	(0.483)	(0.422)	(0.452)	
Grows Mango	0.086	0.063	0.071	0.093	0.076	0.076	0.063	0.958
	(0.280)	(0.242)	(0.256)	(0.290)	(0.265)	(0.266)	(0.244)	
Grows Potato	0.083	0.052	0.086	0.082	0.074	0.061	0.077	0.872
	(0.275)	(0.222)	(0.281)	(0.274)	(0.261)	(0.239)	(0.266)	
Grows Pulses	0.047	0.103	0.095	0.076	0.077	0.075	0.048	0.518
	(0.212)	(0.305)	(0.293)	(0.265)	(0.266)	(0.264)	(0.215)	
Grows Onion	0.049	0.037	0.050	0.021*	0.047	0.039	0.057	0.275
	(0.215)	(0.188)	(0.219)	(0.144)	(0.211)	(0.194)	(0.232)	
Grows Garlic	0.017	0.009	0.014	0.013	0.009	0.017	0.006	0.429
	(0.128)	(0.096)	(0.118)	(0.113)	(0.095)	(0.130)	(0.078)	

The summary statistics are calculated using the door-to-door census in Phase I with 21,926 households. Each column shows mean values of each variable for either the control (BD51) group or one of the six treatment groups. Standard deviations are reported in parentheses below each mean value. Asterisks indicate a statistically significant difference (1% ***, 5% **, and 10% *) between that arm and the control arm, where p-values are calculated by regressing each variable on a constant and indicators for each of the six treatment groups (standard errors adjusted for clustering at the village level). The final column shows the joint p-value of each of these regressions. Aman refers to the wet season prior to the door-to-door baseline (2015) and Boro refers similarly to the most recent dry season (2015-2016). 1 Bigah = 0.33 Acres.

Table A.3: Balance of household characteristics for entry points

	Control (BD51)	BD56 Treatment	p-value
Education	5.361	5.392	0.832
	(4.620)	(4.643)	
Age	43.326	43.690	0.577
	(12.585)	(12.225)	
Owns Shallow Tubewell	0.178	0.191	0.528
	(0.383)	(0.393)	
Aman Rice Area (Bigah)	8.553	8.977	0.523
	(11.097)	(10.494)	
Aman Other Crop Area (Bigah)	0.514	0.616	0.415
	(1.648)	(2.037)	
Boro Rice Area (Bigah)	6.483	6.247	0.795
	(7.781)	(8.606)	
Boro Other Crop Area (Bigah)	2.063	2.299	0.454
	(3.709)	(3.951)	
Aman Urea Fertilizer (KG per Bigah)	21.879	21.316	0.541
	(24.672)	(15.565)	
Aman DAP Fertilizer (KG per Bigah)	16.363	15.978	0.735
	(17.281)	(18.909)	
Aman Rice Yield (KG per Bigah)	17.888	17.566	0.207
	(3.797)	(3.881)	
Grows only rice	0.389	0.337	0.132
	(0.488)	(0.473)	
Grows Short-Duration Rice	0.017	0.024	0.488
	(0.129)	(0.153)	
Grows Wheat	0.304	0.312	0.946
	(0.460)	(0.464)	
Grows Mango	0.126	0.117	0.792
	(0.332)	(0.322)	
Grows Potato	0.121	0.098	0.359
	(0.327)	(0.297)	
Grows Pulses	0.078	0.111	0.127
	(0.268)	(0.314)	
Grows Onion	0.048	0.068	0.323
	(0.215)	(0.252)	
Grows Garlic	0.013	0.028	0.065
	(0.115)	(0.166)	

The summary statistics are calculated using the door-to-door census in Phase I. Data are limited to the 1,747 entry points that consented to participate. Column 1 presents mean values (standard deviations are reported in parentheses below) for entry-points cultivating BD51. Column 3 presents mean values (standard deviations are reported in parentheses below) for entry-points cultivating BD56. The final column shows the p-value for the comparison of means, based on a regression of each characteristic on the treatment indicator and upazila (strata) fixed effects. Standard errors are clustered at the village level.

Table A.4: Differences in baseline characteristics for different entry points

		Coefficients and SE:		
	(1) Constant	(2) SAO	(3) Large farmers	(4) p-value (2)-(3)
Network Variables:				
Degree	4.562***	3.582***	4.481***	0.473
	(0.355)	(1.042)	(0.853)	
Eigenvector centrality	0.089***	0.042***	0.071***	0.030
	(0.006)	(0.012)	(0.011)	
Betweenness centrality	164.186***	394.084***	315.640***	0.509
	(27.926)	(103.540)	(69.762)	
Household Characteristics:				
Area cultivated all seasons (bigah)	9.013***	5.865***	21.396***	0.000
	(0.658)	(1.368)	(2.689)	
Times named best farmer	0.790***	4.477***	5.589***	0.275
	(0.206)	(0.785)	(0.707)	
Log revenue per bigah	10.061***	-0.016	-0.014	0.970
	(0.057)	(0.077)	(0.075)	
Number livestock owned	3.950***	-0.008	1.968***	0.000
	(0.217)	(0.284)	(0.512)	
Number of overseas migrants	0.138***	-0.021	-0.026	0.881
	(0.031)	(0.039)	(0.037)	
Education	4.647***	1.247***	0.925*	0.536
	(0.304)	(0.464)	(0.488)	
Age	42.222***	0.712	3.594***	0.007
	(0.739)	(1.026)	(1.078)	
Tubewell owner	0.097***	0.094***	0.181***	0.108
	(0.022)	(0.036)	(0.051)	

The data are limited to the 960 selected entry points in the 192 BD56 villages. Each row is the result from a separate regression where the characteristic is regressed on a constant and indicators for SAO and large farmer villages. The omitted group is the villages where demonstrators were selected randomly (meaning the first column is the mean value for random entry points). The standard errors in each regression are clustered at the village level. Asterisks indicate statistical significance at the 1% ***, 5% **, and 10% * levels.

Table A.5: Balance of household characteristics across treatment arms

	Random Non-Demo	Random Demo	(D) vs. (ND)
Do you still cultivate rice?	0.98	0.97	0.14
Did you talk to anyone about rice farming during the last Aman season?	0.95	0.97	0.20
Total number of people talked to	6.60	6.39	0.02
Have you heard about BRRI dhan 91?	0.02	0.05	0.06
Have you heard about BRRI dhan 87?	0.11	0.07	0.38
Boro Rice Area (Bigah)	2.79	3.21	0.93
Boro Other Crop Area (Bigah)	1.47	1.10	0.30
Aman Rice Area (Bigah)	3.94	4.27	0.70
Aman Other Crop Area (Bigah)	0.47	0.48	0.98
Number of rice varieties grown in Aman	1.15	1.11	0.20
Aman Urea Fertilizer (KG per Bigah)	20.80	21.66	0.41
Aman DAP Fertilizer (KG per Bigah)	15.35	16.30	0.18
Aman Rice Yield (KG per Bigah)	17.49	18.33	0.02
Owns Shallow Tubewell	0.11	0.10	0.14
Number of farmers you talk to about rice farming (phase I)	2.49	2.45	0.62

The summary statistics are calculated using the door-to-door census with 5,688 households in phase II. Column 1 shows mean values of each variable for the Random non-demo villages. Column 2 shows mean values of each variable for the random demo villages. The final column shows the difference between the two groups (the p-value of each of these regressions). Standard deviations are reported in parentheses below each mean value. Asterisks indicate a statistically significant difference (1% ***, 5% **, and 10% *)

Table A.6: Correlation between Adoption and Learning

	Phase II		
	(1) WTP	(2) WTP	(3) WTP
BD87 yield is higher	1.972**		
	(0.914)		
Same lifespan duration		1.324	
		(1.997)	
BD87 height is taller			0.784
			(1.075)
Mean in Random No-Demo	22.63	22.63	22.63
Number of Observations	750	750	750

The table shows whether farmers' willingness to pay correlates with their knowledge of the varieties' traits. The data are for the set of farmers we were able to reach in our post-harvest survey in phase II who said they heard about BD87. Each column is a separate regression where farmers' willingness to pay is regressed on a measure of farmer learning (yield, lifespan and height). Standard errors that are clustered at the village level are included in parentheses. Asterisks indicate statistical significance at the 1% ***, 5% **, and 10% * levels.

Table A.7: Cultivation practices by treatment

	Panel A: Plots with either BD56 or BD51			
	(1) Harvest Date	(2) 2nd Crop	(3) Boro Crop	(4) N Crops
Treated Village	-25.350***	0.278***	-0.035	0.243***
	(1.384)	(0.035)	(0.039)	(0.046)
Strata fixed effects	Yes	Yes	Yes	Yes
Mean in Control	8.64	0.24	0.82	2.06
Number of Observations	1242	1242	1242	1242

	Panel B: TOT using 3 random plots per farmer			
	(1) Harvest Date	(2) 2nd Crop	(3) Boro Crop	(4) N Crops
BD56 plot	-30.494***	0.344***	-0.129	0.215*
	(3.940)	(0.081)	(0.113)	(0.130)
Strata fixed effects	Yes	Yes	Yes	Yes
Mean in Control	9.47	0.21	0.82	2.03
Number of Observations	4174	4174	4174	4174

This table presents cultivation practices for BD56 relative to BD51. The data are from the agronomic surveys collected in phase I. Panel A limits the data to plots where either BD56 or BD51 was planted. Panel B uses the data on 3 randomly selected plots for which we asked production information during all surveys. Panel B shows treatment on the treated (TOT) estimates where the BD56 plot indicator is instrumented with random assignment to the BD56 treatment group. The dependent variable in column 1 is the date of the harvest, measured in days after November 10, 2016. The dependent variables in columns 2 and 3 are indicators for whether the plot was sown with the Rabi (in-between) crop and the Boro (dry-season) crop. The dependent variable in column 4 is the total number of crops grown across all seasons. Standard errors are clustered at the village level. Asterisks indicate statistical significance at the 1% ***, 5% **, and 10% * levels.

Table A.8: Awareness and peer effects (reduced form - path length)

	(1)	(2)
Demonstration Village (β_1)		0.015
		(0.108)
Mean Length to Entry Points (β_2)	-0.020	-0.097**
	(0.036)	(0.039)
Mean Length to Entry Points * Demonstration Village (β_3)		0.147**
		(0.071)
Mean Length to all Nodes (β_4)	-0.005	0.056
	(0.042)	(0.044)
Mean Length to all Nodes * Demonstration Village (β_5)		-0.127
		(0.082)
Mean in Random No Demo	0.598	0.598
p-value: $\beta_2 + \beta_3$		0.389
Number of Observations	548	548

The table presents rates of awareness for farmers as a function of their mean path length to the entry-point. The data are for the 10 random farmers per village that were selected for the information survey in phase I – excluding entry points. The dependent variables in columns (1-2) are whether the farmer heard about the new variety in phase I. We regress awareness on the mean path length between the farmer and the 5 entry-points, the mean path-length between the farmer and all nodes in the villages, and these two variables interacted with an indicator for being in a demonstration village. Asterisks indicate statistical significance at the 1% ***, 5% **, and 10% * levels.

Table A.9: Heterogeneous treatment effects of all interventions

	(1) Female	(2) Rice Area	(3) Age	(4) Years Education	(5) Rice Yield	(6) Has Tubewell	(7) Eigenvector Centrality	(8) Degree Centrality
SAO no demo	0.047	0.084	-0.138	0.133**	-0.196	0.075*	0.131*	0.092*
	(0.043)	(0.054)	(0.122)	(0.060)	(0.139)	(0.045)	(0.072)	(0.051)
SAO w/ demo	0.043	0.063	-0.075	0.127**	0.044	0.064	0.186***	0.058
	(0.042)	(0.051)	(0.122)	(0.057)	(0.045)	(0.045)	(0.063)	(0.047)
Large no demo	0.071*	0.081*	-0.145	0.163***	0.101**	0.070*	0.213***	0.102**
	(0.039)	(0.048)	(0.126)	(0.056)	(0.042)	(0.040)	(0.063)	(0.047)
Large w/ demo	0.034	0.065	-0.036	0.095	-0.063	0.051	0.155**	0.037
	(0.047)	(0.055)	(0.126)	(0.058)	(0.105)	(0.049)	(0.071)	(0.054)
Random w/ demo	0.058	0.092*	-0.098	0.145**	-0.194	0.058	0.170***	0.118**
	(0.046)	(0.049)	(0.133)	(0.058)	(0.142)	(0.048)	(0.059)	(0.046)
Covariate	-0.212***	0.002	-0.004**	0.018***	-0.002***	-0.023	0.912***	0.005
	(0.064)	(0.004)	(0.002)	(0.006)	(0.000)	(0.083)	(0.308)	(0.005)
SAO no demo *	0.202**	-0.002	0.005*	-0.013	0.014**	-0.008	-0.784	-0.006
Covariate	(0.089)	(0.005)	(0.003)	(0.009)	(0.007)	(0.107)	(0.528)	(0.007)
SAO w/ demo *	0.189*	0.000	0.003	-0.012	0.002***	0.043	-0.964**	0.003
Covariate	(0.101)	(0.004)	(0.003)	(0.008)	(0.000)	(0.105)	(0.470)	(0.007)
Large no demo *	0.091	-0.001	0.005*	-0.018**	-0.001*	0.066	-1.192**	-0.006
Covariate	(0.092)	(0.004)	(0.003)	(0.008)	(0.000)	(0.097)	(0.474)	(0.007)
Large w/ demo *	0.183**	-0.001	0.002	-0.007	0.007	0.052	-0.967*	0.003
Covariate	(0.087)	(0.004)	(0.003)	(0.008)	(0.006)	(0.112)	(0.573)	(0.008)
Random w/ demo *	0.160*	-0.002	0.004	-0.015*	0.015**	0.158	-1.062***	-0.009*
Covariate	(0.090)	(0.005)	(0.003)	(0.008)	(0.007)	(0.103)	(0.375)	(0.005)
Strata fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean in Random No Demo	0.60	0.60	0.60	0.60	0.60	0.60	0.61	0.60
Number of Observations	1910	1910	1910	1910	1676	1910	1463	1919

The table shows heterogeneous treatment effects by variables from the census of households in Phase I. Each column is a separate regression where a covariate (column title label) is interacted with each of the treatments. The heterogeneity variables are an indicator variable for females (column 1), total rice area from the wet and dry seasons in bigah (column 2), age in years (column 3), years of education (column 4), rice yield (column 5), an indicator for households with their own tubewell (column 6), eigenvector centrality in the village network (column 7), and degree centrality in the village network (column 8). Standard errors that are clustered at the village level are included in parentheses. Asterisks indicate statistical significance at the 1% ***, 5% **, and 10% * levels.

Table A.10: Correlates of Network Centrality

	(1) Eigenvector Centrality	(2) Degree Centrality
Female	-0.002	-0.382***
	(0.003)	(0.139)
Education	0.002***	0.144***
	(0.000)	(0.019)
Age/10	0.005***	0.282***
	(0.001)	(0.057)
Aman Rice Area (Bigah)	0.001*	0.106**
	(0.001)	(0.050)
Number Rice Varieties	0.012***	0.804***
	(0.003)	(0.231)
Aman Urea Fertilizer (qtl per Bigah)	0.046*	-2.504**
	(0.024)	(1.262)
Aman Rice Yield (qtl per Bigah)	-0.001	0.144***
	(0.001)	(0.054)
Owns Shallow Tubewell	0.013***	0.839***
	(0.004)	(0.225)
Mean Outcome	0.09	5.07
Number of Observations	15380	18490

The table shows correlates of eigenvector centrality (column 1) and degree centrality (column 2). All data come from the network census conducted at the beginning of phase I. Standard errors that are clustered at the village level are included in parentheses. Asterisks indicate statistical significance at the 1% ***, 5% **, and 10% * levels.

Table A.11: Conversations and peer effects (reduced form - path length)

	Phase I		Phase 2	
	(1) Convos w/ Entry	(2) Convos w/ Entry	(3) Convos w/ Entry	(4) Convos w/ Entry
Demonstration Village (β_1)		0.078		-0.023
		(0.244)		(0.131)
Mean Length to Entry Points (β_2)	-0.081	-0.122	-0.032	-0.066**
	(0.081)	(0.100)	(0.028)	(0.028)
Mean Length to Entry Points * Demonstration Village (β_3)		0.054		0.068
		(0.180)		(0.049)
Mean Length to all Nodes (β_4)	0.048	0.075	0.037	0.044
	(0.104)	(0.133)	(0.038)	(0.037)
Mean Length to all Nodes * Demonstration Village (β_5)		-0.035		-0.002
		(0.200)		(0.060)
Mean in Random No-Demo	0.743	0.743	0.306	0.306
p-value: $\beta_2 + \beta_3$		0.614		0.975
Number of Observations	549	549	4143	4143

The table presents conversations with entry-points as a function of farmers' mean path length to the entry-point. The dependent variables are the number of conversations farmers had with entry-points in phase I (column 1,2), and the number of conversations farmers had with entry-points during the growing season in phase II (column 3,4). We regress conversation with entry points on the mean path length between the farmer and the 5 entry-points, the mean path-length between the farmer and all nodes in the villages, and these two variables interacted with an indicator for being in a demonstration village. Asterisks indicate statistical significance at the 1% ***, 5% **, and 10% * levels.

Table A.12: Effects of BD56 on cultivation practices

	(1) Harvest Date	(2) 2nd Crop	(3) Boro Crop	(4) N Crops
Random no demo	-23.933***	0.143**	0.009	0.153*
	(2.297)	(0.066)	(0.056)	(0.084)
Random w/ demo	-26.520***	0.203***	-0.145**	0.058
	(1.759)	(0.055)	(0.066)	(0.096)
Large no demo	-25.416***	0.314***	-0.085	0.229**
	(1.869)	(0.067)	(0.067)	(0.089)
Large w/ demo	-24.235***	0.378***	-0.060	0.317***
	(3.256)	(0.068)	(0.059)	(0.078)
SAO no demo	-23.577***	0.308***	0.043	0.351***
	(4.168)	(0.063)	(0.054)	(0.067)
SAO w/ demo	-27.492***	0.262***	0.011	0.273***
	(1.590)	(0.058)	(0.054)	(0.073)
SAO	1.533*	-0.040	-0.048	-0.087**
	(0.797)	(0.033)	(0.029)	(0.035)
Large	0.784	-0.051	-0.014	-0.065*
	(0.802)	(0.031)	(0.029)	(0.034)
Mean in BD51	7.88	0.25	0.84	2.09
p: Rand Demo = Rand No Demo	0.301	0.414	0.037	0.390
p: Rand No demo = Large No Demo	0.590	0.050	0.228	0.489
p: Rand No demo = SAO No Demo	0.935	0.053	0.601	0.038
p: Rand Demo = Large Demo	0.514	0.037	0.300	0.028
p: Rand Demo = SAO Demo	0.628	0.423	0.035	0.051
Number of Observations	1242	1242	1242	1242

The data consist of plot-level cultivation practices during the Phase I study. The omitted group in each regression is that randomly selected farmers in BD51 (long-duration rice) villages. The dependent variable in column 1 is the date of the harvest, measured in days after November 10, 2016. The dependent variables in columns 2 and 3 are indicators for whether the plot was sown with the Rabi (in-between) crop and the Boro (dry-season) crop. The dependent variable in column 4 is the total number of crops grown across all season. The data are limited to the plots where either BD56 or BD51 was planted by the entry points. Asterisks indicate statistical significance at the 1% ***, 5% **, and 10% * levels.

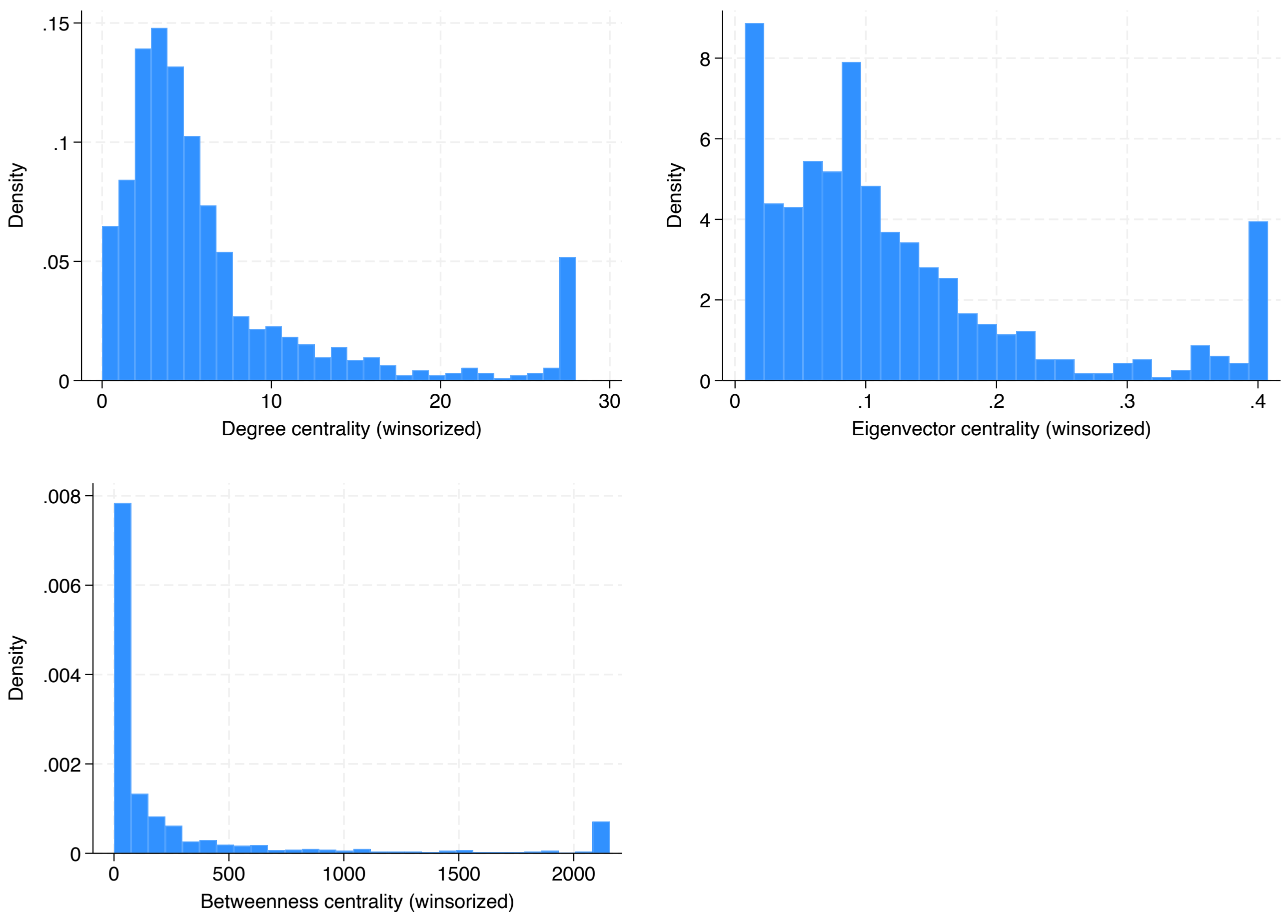
Table A.13: Network degree and actions taken by large/SAO farmers explain information effects

	(1)	(2)
SAO no demo	0.093***	0.078**
	(0.034)	(0.033)
SAO w/ demo	0.090**	0.081**
	(0.036)	(0.036)
Large no demo	0.098***	0.084***
	(0.034)	(0.033)
Large w/ demo	0.093**	0.069*
	(0.041)	(0.038)
Random w/ demo	0.083**	0.073*
	(0.038)	(0.038)
Number entry points		0.021***
growing rabi crop		(0.008)
Mean in Random no demo	0.59	0.59
Number of Observations	1767	1767

The table presents rates of awareness of BD56 and whether growing a second crop mediates the effect. The data is from the information survey in phase I where farmers were asked their knowledge of BD56 – excluding minikit recipients. The dependent variable in each regression is an indicator for knowing that BD56 exists as a new variety. The average network degree of entry points is computed from the baseline network census. The number of entry points growing the rabi crop captures the number of people who demonstrated the main benefit of BD56. All regressions include upazila fixed effects and standard errors are clustered by village. Asterisks indicate a statistically significant difference (1% ***, 5% **, and 10% *).

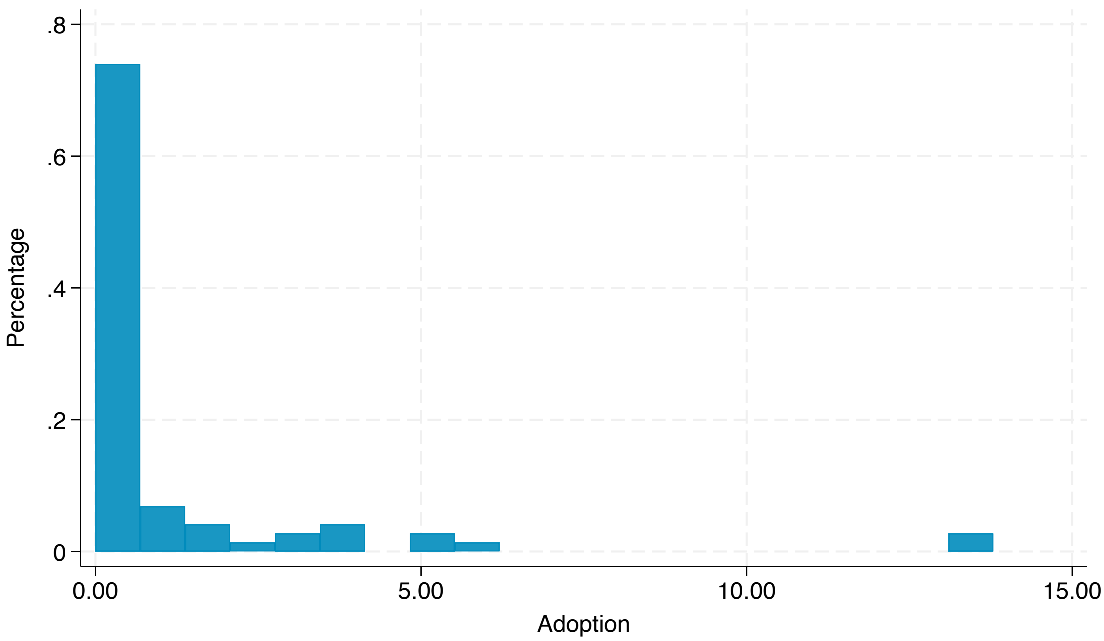
A.2 Figures

Figure A.1: Distribution of centrality measures from social network survey



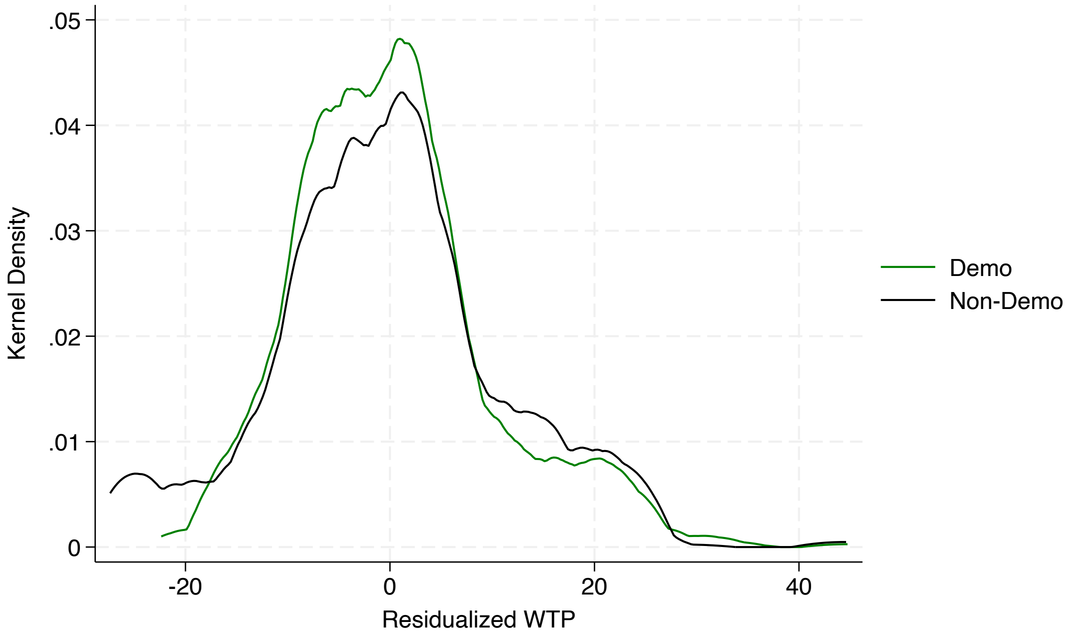
Notes: This figure shows the histograms for the 3 centrality measures from the baseline social network survey with all households from phase I census (N=21,926).

Figure A.2: Distribution of adoption rates of wet-season rice varieties in Bangladesh, 2022-2023



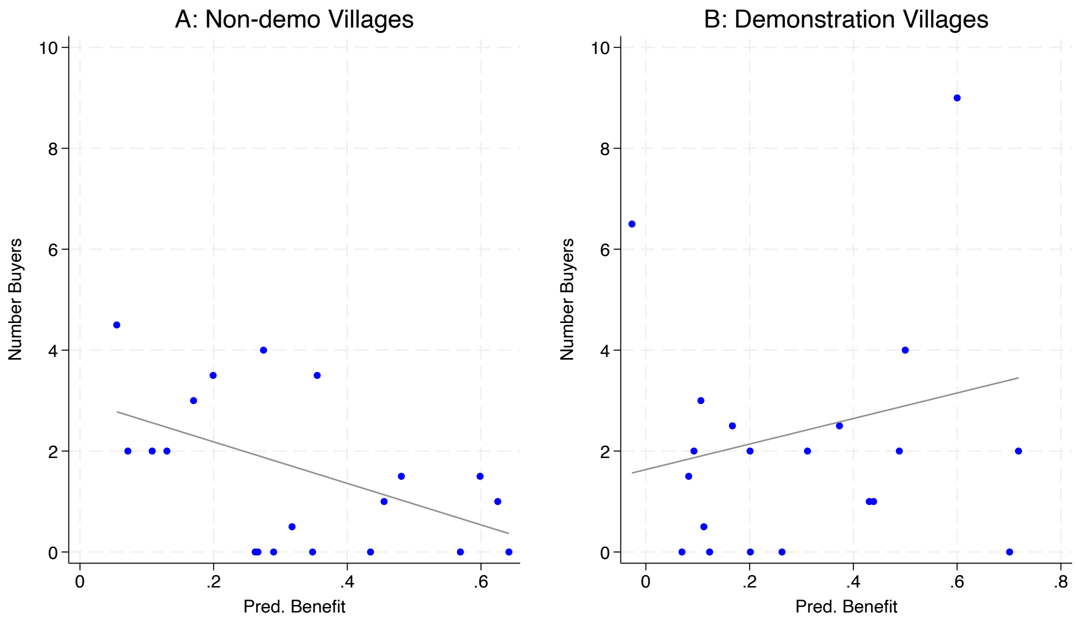
Notes: The figure shows the distribution of estimated adoption rates for 73 wet-season rice varieties during the 2022-2023 agricultural season, as reported in BRRI (2023). A total of 55 of the 73 varieties (75%) have adoption rates less than 1%. BD87 (phase II) has an estimated adoption rate of 5.14%, while BD56 (phase I) has an estimated adoption rate of 0.11%.

Figure A.3: Distribution of WTP in treatment and control group



Notes: This figure plots farmers' residualized (by enumerator and upazila fixed effects) willingness to pay in demonstration vs non-demonstration villages in Phase II of the experiment. We can reject equality of demo and non-demo distributions by applying a KS test (p-value = 0.006).

Figure A.4: Correlation between BD56 adoption and predicted benefits



Notes: This figure shows binned scatter plots of the correlation between predicted benefits of BD56 at the village level (horizontal axis) and the number of BD56 buyers in that village (vertical axis).

B Heterogeneity Analysis of Average Treatment Effects

B.1 Methodology

Our sample of farmers is first divided into two samples: a "training" sample where we seek to estimate the Conditional Average Treatment Effect (CATE), denoted as $s_0(z_i)$, and a "validation" sample where we seek to verify whether this estimate $\hat{s_0}(z_i)$ is a significant determinant of heterogeneity in the diffusion treatment effect. First for the training sample, we estimate separate LASSO regressions for the groups who receive the treatment seed (BD56) and the comparison variety (BD51), respectively to pick which of the observed covariates predict the number of crops grown y. Next, we run OLS regressions with the covariates selected by the two LASSO procedures, and recover the coefficients from these regressions.

We then turn to the validation dataset and calculate the conditional expectation functions, $E(y_i|D_i = 1, z_i)$ and $E(y_i|D_i = 0, z_i)$, applying the coefficients estimated with the training dataset. We take the difference between the two, which serves as the predicted benefit index, $\hat{s_0}(z_i)$. The next step is to verify that the predicted benefit index proxies for the actual BD56 treatment effect. We do this in two ways. First, we add an interaction between the treatment indicator and $\hat{s_0}(z_i) - \bar{s_0}$ in a regression where the dependent variable is the number of crops grown, and $\bar{s_0}$ is the average predicted benefit.[22] Second, we estimate separate treatment effects for the four quartiles of the distribution of $\hat{s_0}(z_i)$. Finally, this process is iterated 100 times, delivering 100 separate sample divisions and 100 estimates of the predicted benefit index.

Our results show that the observed covariates predict treatment-effect heterogeneity in the validation sample. Figure B.1 shows the 100 estimates of the ATE and the linear heterogeneity term. The heterogeneous effect is almost always larger than zero[23], suggesting that the predicted benefit index $\hat{s_0}(z_i)$ does proxy for the true heterogenous effect of BD56 on the number of crops grown. In other words, farmers with larger values of $\hat{s_0}(z_i)$ appear more likely to increase cropping intensity if adopting short-duration rice. Figure B.2 shows the separate treatment effects by quartile of the predicted benefit index. Treatment effects increase from 0.1 to 0.3 with the predicted benefit index and are largest in the top two

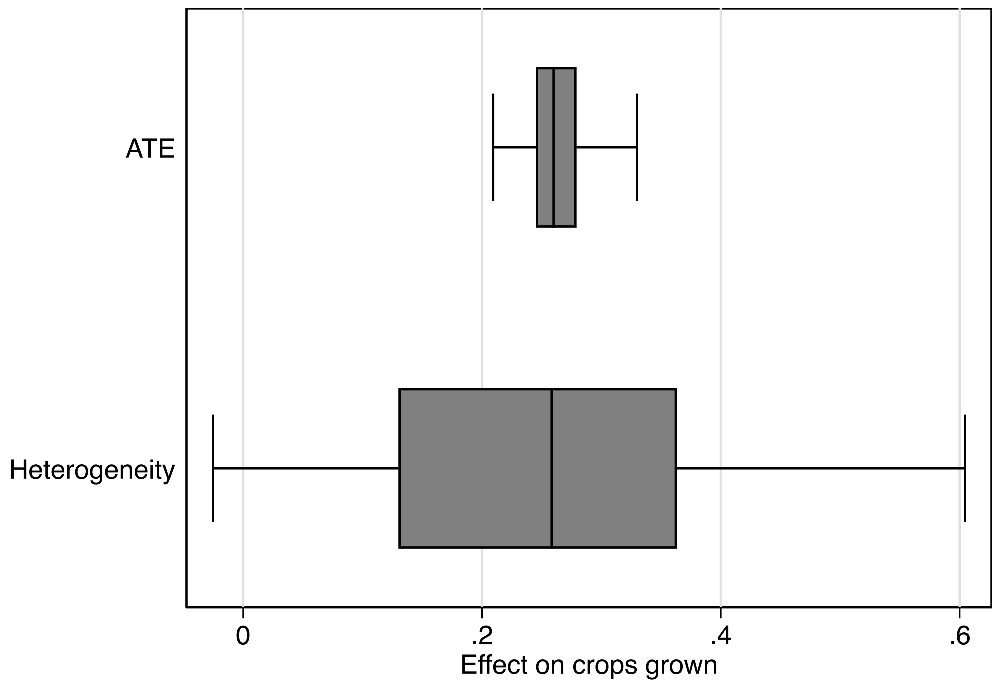
[22]The coefficient on the treatment indicator in this regression measures the average treatment effect, while the coefficient on the interaction between treatment and $\hat{s_0}(z_i) - \bar{s_0}$ measures whether the predicted benefit index predicts actual treatment-effect heterogeneity.

[23]The minimum value of the predicted benefit index is only just below zero, and on average is equal to 0.24.

quartiles of the distribution of $\hat{s_0}(z_i)$.

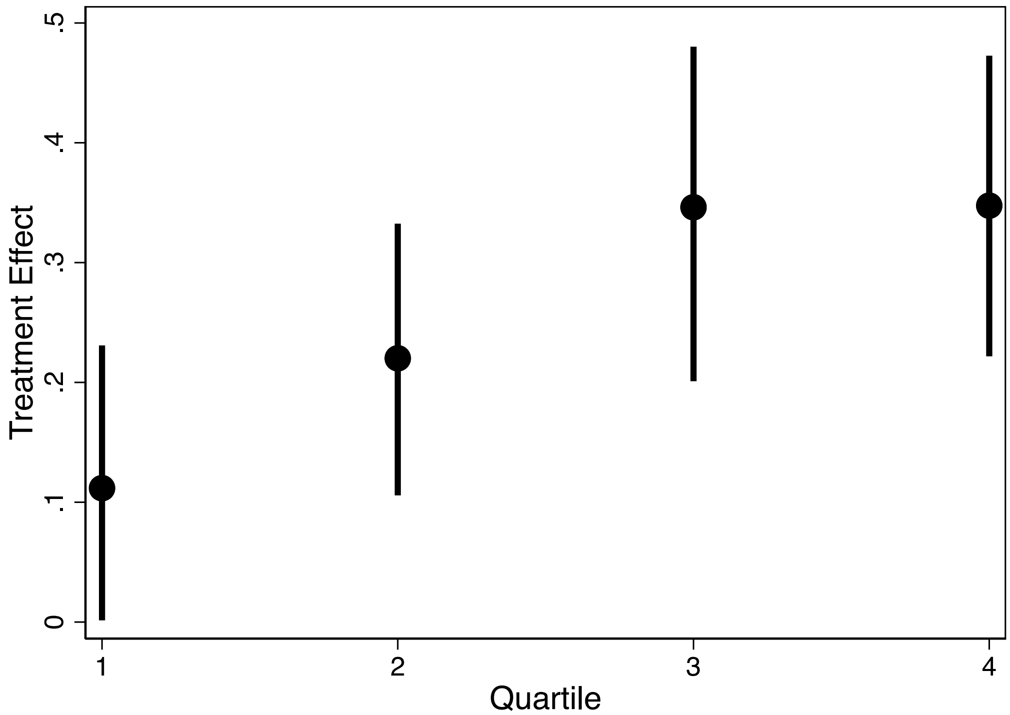
B.2 Figures

Figure B.1: ATE and heterogeneous effect on number of crops grown



Notes: The figure shows the average treatment effects and the heterogeneous effect on the number of crops grown across 100 equal-sized splits into training and validation datasets. For each split, we estimate separate LASSO regressions for BD56 recipients and BD51 farmers in the training dataset. In each case the number of crops grown is regressed on a set of 24 covariates, z_i. Using the selected covariates for each group, we calculate the estimated benefit index for each farmer in the validation dataset as $\hat{s_0}(z_i) = E(y_i|D_i = 1, z_i) - E(y_i|D_i = 0, z_i)$. Using the validation dataset, we then regress the observed number of crops on the treatment, $\hat{s_0}(z_i) - \bar{s_0}$, the interaction between treatment and $\hat{s_0}(z_i) - \bar{s_0}$, and upazila fixed effects. The top bar in the figure shows the distribution of the 100 estimates of the ATE (the coefficients on the treatment indicator). The bottom bar shows the 100 estimates of the heterogeneity effect (the coefficient on the interaction between treatment and $\hat{s_0}(z_i) - \bar{s_0}$). The vertical line represents the average across the 100 splits, the box the interquartile range, and the whiskers give the min and max.

Figure B.2: Effects on number of crops grown by quartiles of the predicted effect



Notes: The figure shows the estimated BD56 treatment effects by quartile of the benefit index for 100 equal-sized splits into training and validation datasets. For each split, we estimate separate LASSO regressions for BD56 recipients and BD51 farmers in the training dataset. In each case the number of crops grown is regressed on a set of 24 covariates, z_i. Using the selected covariates for each group, we calculate the estimated benefit index for each farmer in the validation dataset as $\hat{s_0}(z_i) = E(y_i|D_i = 1, z_i) - E(y_i|D_i = 0, z_i)$. Using the validation dataset, we then regress the observed number of crops on the treatment and upazila fixed effects *separately for the four quartiles of* $\hat{s_0}(z_i)$. The heavy dots show the averages across the 100 sample divisions while the bands display the range from the 5th to 95th percentiles.