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Seeking the treated: The impact of mobile extension on farmer information exchange in India☆

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ABSTRACT

Do digital agricultural services 'disrupt' in-person peer interactions that generate and spread local knowledge? To investigate, I randomize access to a mobile phone-based agricultural extension service and find that while it reduces reliance on peer agricultural advice, it does not crowd-out peer interactions. Instead, treated farmers are more likely to recommend inputs to their peers, who, in turn, prioritize interacting with them. Consequently, exposure to the treatment, directly or via peers, increases willingness-to-pay for the service. Overall, evidence on complementarities between treated respondents suggest ICT-based services may encourage peer interactions and information exchange at scale.

1. Introduction

Information and Communication Technologies (ICTs) have revolutionized the centralized delivery of high quality information to remote areas of the developing world. Yet, in providing an alternative to in-person sources of information, have they also crowded-out social interactions critical to the generation and diffusion of valuable local knowledge? This question is of particular relevance to the study of agricultural technology adoption in the developing world, where an influential body of research[1] has documented the importance of 'social learning' among peer farmers in supporting technology diffusion *and* where mobile phone-based extension initiatives are projected to scale to millions in the near future.[2] In theory, high quality information delivered through ICTs may be a substitute for peer information, *decreasing* the returns to peer interactions and crowding them out (Caria et al., 2020; Barsbai et al., 2020). In contrast, this paper finds that the provision of external information through a mobile-phone based service spurs information sharing suggesting that it may instead *increase* the returns to peer interactions (Duflo et al., 2008).

To examine how ICTs influence the structure of peer interactions centered about information exchange, I use a field experiment that randomizes access to a mobile phone-based agricultural extension service in Gujarat, India. The service, Avaaj Otalo (hereafter, AO), is entirely voice-based and consists of a 'pull' component, whereby farmers can call a helpline, and a 'push' component, in which they receive weekly automated messages that include information on weather and crop conditions. Working with a field partner, 800 out of 1200 cotton farmers were randomly assigned to receive toll-free access to AO. The remaining 400 households served as a control group. The study respondents were surveyed at baseline, midline (1 year later), and at

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[1] See, for example Bandiera and Rasul, 2006; Foster and Rosenzweig (1995); Conley and Udry (2010); BenYishay and Mobarak (2014); Beaman et al. (2018).

[2] For example, Precision Agriculture for Development—a global non-profit—currently reaches four million farmers across six countries through their mobile phone-based extension programs and has a stated goal of reaching 100 million farmers.

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endline (2 years later). Information on peer groups of study respondents was collected at each of these intervals by asking respondents to list a maximum of three peers with whom they frequently discuss their agriculture (hereafter referred to as a 'peer group').[3]

Over the two years during which the experiment was run, over 90% of the treatment group called into the service and used it for approximately 2.5 h; the treated subsequently experience a 2.5% increase cotton-related agricultural knowledge (their primary crop).[4] Consequently, the treated substitute away from using the advice of their peer farmers (−0.14 standard deviations) and towards the AO service (1.14 s.d.) as measured by indices aggregating the sources of information used in making agricultural decisions.[5]

This paper has three main findings.[6] *First, the service does not crowd-out peer interactions and instead increases information exchange and willingness-to-pay (WTP) for an AO subscription.* Treated respondents do not, on average, alter the frequency with which they discuss agriculture with their peers. However, treated farmers are both more likely to share information with their peers (6.6 percentage points) and recommend inputs to their peers (7.9 p.p.) across the two years of surveying. Using a Becker-DeGroot-Marschak (BDM) mechanism to elicit WTP for a 9-month AO subscription reveals that control respondents with treated peers at baseline have a WTP that is 46% higher than pure controls.[7] This effect-size is statistically indistinguishable from the direct effect of the treatment on WTP (45%).

Second, respondents exposed to the service (directly or indirectly via *peers) prioritize discussing their agriculture with the treated, raising their importance as a source of information in the village.* Control respondents with treated peers at baseline are almost 15 p.p. more likely to report speaking frequently to a 'new treated peer' — i.e. one they did not list at baseline — across subsequent rounds relative to pure controls. Similarly, treated respondents, regardless of whether they have a treated peer at baseline, are 4.2 p.p. more likely to report speaking to a new treated peer in subsequent rounds. Overall, treated respondents are more likely to be a 'peak' (4.2 p.p.): the number of peers who consider the respondent a top contact for agricultural information (i.e. their in-degree) is greater than two standard deviations from the sample mean.

Third, there are complementarities between treated respondents in both social interactions and service usage. Treated respondents who listed a treated peer at baseline, relative to those who did not, are even more likely to report using mobile phone-based information for agricultural decisions (1.57 s.d.), call into the AO service (11 p.p.), and use it longer (an additional 2 h). In addition, they also report being more likely to visit the homes of their peers to discuss agriculture (10.8 p.p.).

Collectively, these findings suggest that the introduction of external information results in persistent effects on the structure of peer interactions. Given the censoring of peer groups in my data, I interpret the peer composition results as reflecting systematic ordinal changes in the importance of treated respondents as a source of agricultural information. In order to address concerns about bias in parameter estimates resulting from censored peer groups, I conduct two robustness tests motivated by recent work by Hardy et al. (2019) and Griffith (2019). Weighting estimates by baseline in-degree and restricting analyses to one randomly picked peer do not change the qualitative interpretation of the main results. The absence of a crowd-out effect in peer interactions rules out the case where peers no longer speak to each other, restricting social learning and technology adoption. Rather, evidence on complementarities between treated respondents suggests that at scale, such services may, instead, increase the returns to peer information exchange and—where service usage is itself viewed as an input into production— support technology adoption.

This paper contributes to the literature on peer effects and information exchange in agriculture. Recent empirical work focuses on encouraging peer interactions and technology diffusion among farmers through experimenting with extension models (Duflo et al., 2005, 2020; Kondylis et al., 2017) and targeting networks Beaman et al. (2018); in addition experimental evidence has underscored the importance of knowledge spillovers in driving the adoption of agricultural technologies (Carter et al., 2021). Given the importance of peer interactions to the adoption of agricultural technologies, understanding how ICTs influence peer interactions and whether they have downstream effects on technology adoption is an important policy consideration. This paper shows that even as ICTs influence the content of social interactions and peer group structure, they do not crowd-out peer interactions. Rather, as ICT-based services scale, they may instead encourage peer interaction and technology adoption.

Second, this paper contributes to a literature documenting the effects of information interventions on sources of information accessed by individuals (Reinikka and Svensson, 2005; Banerjee et al., 2011). In particular, I show that respondents substitute between sources of information and this, in turn, influences pre-existing social interactions. In the US, the advent of televisions led to similar substitution away from newspapers and radios, leading to political disengagement (Gentzkow, 2006). Similarly, in Indonesia, the advent of television and radio led to substitution away from social interactions (Olken, 2009). The results of this paper suggest, in contrast, that the use of ICTs to provide agricultural information can stimulate social interactions that support the sharing of new sources of information.

Finally, this paper contributes to a literature using experimental variation to identify peer effects in networks (for a survey, see Bramoull'e et al. (2020)) and, in particular, whether interventions may themselves influence networks (Griffith, 2016; Comola and Prina, 2019). While a partial sampling of networks in this paper prohibits the estimation of network-level parameters, the results suggest that external information alters social interactions centered about information exchange, the composition of peer groups, and may well influence network-level parameters in line with other studies (Vasilaky and Leonard, 2014; Banerjee et al., 2018; Heβ et al., 2020). Collectively, this literature questions a common assumption made in applied work that network structure can be treated as 'fixed' and heterogeneity in its structure can be used to understand economic phenomena.

The paper proceeds as following: Section 2 describes the context of the study and discusses the potential effects of the intervention. Section 3 describes the data sources used and the empirical strategy. Section 4 discusses the results while Section 5 provides a discussion of the mechanisms underlying these results. Section 6 considers threats to validity and Section 7 concludes.

2. Context: Mobile phone-based agricultural extension in rural India

Mobile phone-based agricultural extension systems are becoming increasingly popular in the developing world (Aker, 2011; Fabregas et al., 2019). Pre-existing 'Training & Visit' in-person extension systems typically involve extension agents either visiting farmers in person or inviting them to a central location. Mobile phone-based extension addresses many of the challenges presented by traditional systems of extension. It provides farmers with a dynamic source of information that

[3] The exact wording of the question was: 'Provide the names and phone numbers of three fellow farmers you talk to most frequently about agriculture'. Note that this measure is directed, in that a person may refer to another as a top agricultural contact without this relationship being reciprocal.

[4] These findings are consistent with those documented by Cole and Nilesh Fernando (2021) which uses the same dataset.

[5] The index aggregates responses for sources of information using in making decisions about crop planning, pest management, fertilizer use, among other agricultural decisions. See notes for Table 1 for details on index construction.

[6] All estimates reported are average effects across two years of household surveys and use an ANCOVA specification with covariates picked through double machine learning unless otherwise noted.

[7] Pure controls here are defined as control respondents who do not list a treated respondent as one of their top agricultural contacts at baseline.

can help farmers effectively respond to unanticipated shocks such as changing weather patterns and pest attacks. Mobile phone-based agricultural extension can also address agency problems in working with extension agents in remote areas.

2.1. The Avaaj Otalo program

The intervention studied in this paper is a mobile phone-based platform called *Avaaj Otalo* (AO). AO is an open-source platform that utilizes mobile phone networks to allow information to be delivered to farmers at minimal cost. The AO system allows farmers to call into a hotline and leave questions for agronomists about their agriculture, who can respond either in real-time or by leaving a voice message.[8] In addition, farmers receive weekly 'push-content' that includes information on weather and recommended varieties of crops and inputs which are delivered through an automated voice message.

2.2. Potential effects on information exchange and peer interactions

A number of studies suggest that social learning induces technology adoption in an agricultural context.[9] However, experimental work suggests the propensity of farmers to discuss their agriculture with peers may in part be determined by the availability of valuable information.[10] In the study context, over 80% of the sample report interacting with a peer at least once a week to discuss agriculture at baseline. As such, prior to the introduction of AO, I assume there are positive returns to peers exchanging *local information*. For example, farmers with similar production conditions may share their experiences of the dosage response of an input, allowing them to better understand the shape of their production function.

The introduction of AO produces exogenous variation in the availability of *external information*, and, as such, farmers and/or their peers may now be able to have a back and forth about the dosage response of an input with an expert instead of (or in addition to) a peer. Whether such external information is a complement or substitute to local information then determines how a farmer may adjust their interactions with peers in response to direct (own treatment status) or indirect access (via peers) to the treatment.[11] If a farmer's time endowment for peer interactions is binding prior to the introduction of AO—over 80% of respondents in this study report speaking to their peers weekly about agricultural issues—it may be more reasonable to expect a reallocation of interactions across peers rather than a level change. However, distinguishing between these scenarios is complicated by the fact that the data relies on censored peer groups, as study respondents were asked to list up to three peers they speak to frequently about agriculture in each survey round.

Consequently, estimates that compare the average time spent on peer interactions before and after the treatment may combine changes on an intensive margin (time spent interacting with a peer) and an extensive margin (identity of peers). As such, the reduced form estimates will combine the effect of access to the treatment assuming a fixed peer group, and the effects of *peer sorting*, which may itself influence the information endowment and behavior of a respondent.

3. Data and empirical strategy

The households in this experiment are located in Surendranagar district in Gujarat, India. Lists of farmers were enumerated in cooperation with a field partner, the Development Support Center (DSC) in 40 villages, with the criteria for selection being that they were 1.) interested in participating in the study, 2.) grew cotton, 3.) owned a mobile phone, and 4.) are the chief agricultural decision maker of their household.

A sample of 1200 respondents was selected from this pool, with 30 households in each village participating in the study. Treatments were then randomly assigned at the household-level using a scratch-card lottery. The control group consists of 400 households, the AO service was randomly assigned to a further 400 households and another 400 households received both the AO service and traditional extension.[12] The traditional extension component consisted of a single in-person session each year lasting roughly two-and-a-half hours on DSC premises in Surendranagar. Treated respondents in this arm were invited to this session and provided transport to attend. In the results that follow, the reported estimates combine the two treatment arms (hereafter the 'AO Group' or 'Treatment') as Cole and Nilesh Fernando (2021) do not find important differences between these two treatment arms.[13]

The combined AO group (800 households) received toll-free access to AO. In addition to a baseline survey, approximately half of the treatment group and the entire control group were surveyed by phone after 5 months (hereafter, the 'phone survey'). All households were then surveyed after one year (hereafter, 'midline survey') and again after two years (hereafter, 'endline survey'). Furthermore, the top 3 agricultural contacts of individuals in the phone survey group—who were elicited during the baseline survey— were surveyed by phone 8 months after the baseline (1523 respondents, hereafter, the 'peer survey'). In order to elicit demand for the AO service, the Becker-DeGroot-Marshcak (BDM) mechanism was administered at endline (Becker et al., 1964). Please see Appendix A3 for a complete timeline.

Because of random assignment, the causal effect of the intervention can be gauged by comparing the treatment to the control mean. I use the ANCOVA specification as suggested by McKenzie (2012) in order to increase the statistical power to detect effects, given the low autocorrelation of most outcomes in this data. In particular, the main specification only uses the midline and endline data and it controls for the baseline value of the outcome of interest:

$$y_{ivt} = \alpha_v + \alpha_t + \beta_1 \ Treat_{iv} + \beta_2 \ y_{iv0} + \varepsilon_t \tag{1}$$

where α_v is a village fixed effect, $Treat_{iv}$ is a dummy variable for whether a respondent was randomized to receive the AO service, α_t is a fixed effect for the survey round and y_{iv0} is the baseline value of the outcome of interest. Finally, I use data on the treatment status of peers listed at baseline to estimate peer effects with the following specification:

$$\begin{aligned} y_{ivt} = {} & \alpha_v + \alpha_t + \beta_1 \ Treat_{iv} + \beta_2 \ Treat \ Frac_{iv} + \beta_3 \ Treat * Treat \ Frac_{iv} \\ & + \beta_4 \ y_{iv0} + \sum_{t=0}^{3} I(\# \ Peers = i)_{iv} + \varepsilon_{ivt} \end{aligned} \tag{2}$$

where α_v and α_t are as above, $\sum_{t=0}^{3} I(\# Peers = i)_{iv}$ is a fixed effect for the number of peers listed as top agricultural contacts at baseline and $Treat \ Frac_{iv}$ is the fraction of peers assigned to treatment at baseline. In the results that follow, I refer to control group respondents with no baseline treated peers as 'pure controls'.

Note, I do not here attempt to distinguish between 'endogenous peer effects' and 'contextual peer effects' using the framework from Manski (1993) and its adaptation to a network context as in Bramoull'e et al. (2009). In addition, while this paper is similar to Comola and Prina (2019) in that they are interested in understanding how networks respond to treatments, they take a structural approach (i.e. a linear-in-means model) to estimate effects that operate through peer outcomes. I take a reduced form approach to estimating spillover effects

[8] See Appendix A12 for examples of QA on the AO system.

[9] For a review, see Foster and Rosenzweig (2010).

[10] See, for example, Duflo et al. (2005) and Duflo et al. (2020).

[11] Appendix A15 provides a formal treatment of this problem.

[12] See Appendix A2 for details on the experimental design.

[13] The reported estimates are robust to the factorial design concerns about using the 'short' and 'long' form regressions (Muralidharan et al., 2019).

acknowledging that the effect may or may not operate through peer outcomes. This is both because I do not observe all outcomes for peers and because the 'contextual' attribute of interest is randomly assigned. As such, even if (own or peer) treatment assignment influences subsequent treatment exposure, I interpret this as part of the reduced form effect (i.e. a peer sorting effect) and not a question of bias as in Comola and Prina (2019). Peer networks were constructed using a name-matching algorithm.[14] Each respondent was asked to provide the names of up to three 'fellow farmers you talk to most frequently about agriculture' (hereafter, 'top agricultural contact') during each survey round. The treatment status of a peer is assigned based on a match between their name and that of a respondent. I find that roughly one in three peers listed at baseline were subsequently assigned to the treatment group.[15]

3.1. Summary statistics and balance

Respondents in the control group are 46 years old, have approximately 4 years of education, own roughly 6 acres of land, and earn a profit of roughly $186 a month on average.[16] Over 80% of study respondents report speaking to their peers weekly about agricultural issues, with the vast majority of these interactions being in person (84%) rather than on the phone (3%).

Overall, Appendix A1 shows that the treatment group and the control group are balanced along a number of standard covariates both with respect to a respondent's own treatment status and the treatment status of their peers. Two important exceptions are the area of cotton planted and respondent in-degree, which counts the number of study respondents who consider the respondent a top agricultural contact. In particular, the fraction of peers treated for control respondents is systematically correlated to their own in-degree at baseline.[17]

Given the importance of accounting for these differences, the estimates that follow use a double LASSO machine learning approach (hereafter, DML) to pick an optimal set of baseline control variables as proposed by Belloni et al. (2014).[18] The subsequent tables either report the ANCOVA specification (eqn. (1)) and the same specification with DML or just the latter to improve the organization of the tables.

4. Results

4.1. AO use, agricultural knowledge, and sources of information

Table 1 reports the baseline mean and standard deviation in column 1, the treatment coefficient from the ANCOVA specification in column 2, and the coefficients with the inclusion of DML controls in column 3.[19] Panel A shows that farmers made extensive use of the AO Service. Across the two rounds of data, nearly 80% of the treatment group called into the line and used the service for nearly 6 h on average per year.[20]

Appendix A7 shows questions asked on the AO system disaggregated by crop and theme.

By the endline, cotton accounts for nearly half of all questions asked

Table 1
Sources of agricultural information and knowledge.

Dependent Variable	Control Mean (Baseline/ Midline*)	Treat-Control ANCOVA	Treat-Control DML
	(1)	(2)	(3)
Panel A: AO Usage			
Called in to the AO line	0.000	0.771***	0.775***
	0.000	(0.011)	(0.011)
Incoming AO Usage + Push Calls listened (minutes)	0.000	316.033***	318.762***
	0.000	(11.398)	(11.573)
Panel B: Agricultural Knowledge			
Total Correct Answers to Questions (44 questions)	14.156	0.350	0.358
	5.279	(0.232)	(0.219)
Cotton-related (20 questions)	10.568	0.221*	0.249**
	3.062	(0.128)	(0.121)
Panel C: Sources of Information			
Index of Mobile Phone-Based Information (Standard deviation units)	0.000	1.143***	1.145***
	1.000	(0.170)	(0.170)
Index of Information from Farmer Friends (Standard deviation units)	0.000	−0.136***	−0.130***
	1.000	(0.036)	(0.035)
Index of Information from Input Seller (Standard deviation units)	0.000	−0.068*	−0.065*
	1.000	(0.037)	(0.038)
Panel D: Information Exchange			
Shared Information with a Peer	0.617	0.061***	0.066***
	0.487	(0.022)	(0.021)
Recommended Input to Peer	0.485	0.081***	0.079***
	0.500	(0.022)	(0.022)
Received Information from Peer	0.766	0.007	0.009
	0.424	(0.020)	(0.020)
Learned Information by Observing Peer's Fields	0.328	0.007	0.009
	0.470	(0.021)	(0.021)
N	398	2203	2203

Notes: This table reports treatment effects on AO usage, sources of information used in making agricultural decisions, and agricultural knowledge. Usage statistics were collected on the AO server. Robust standard errors are reported in parentheses. The results use data from both the Midline survey and the Endline survey. The indices aggregate information over multiple outcomes for which we expect unidirectional treatment effects. Each index consists of the average of the z-scores for each component of the index, with the control group mean and standard deviation as reference. The component scores are then weighted by the inverse of the covariance matrix of the components as in Anderson (2008). Mobile phone-based information usage index: Aggregates mobile phone use across a series of decisions including: crop decisions, soil preparation, pest management, pest identification, fertilizer decisions, weather, and irrigation. As a measure of agricultural knowledge, respondents were asked agricultural questions across crop and topic, and a knowledge score was computed based on the proportion of correct answers. The question categories are not mutually exclusive (see Appendix A14 for a full list of questions). 'Treat' group refers to the 802 farmers that received access to AO. Column 1 provides the mean and standard deviation for the control group at baseline, except for 'shared information' and 'recommend input to peer' for which there is no baseline data, so the midline mean is reported instead. Column 2 reports the treatment effect estimate from an ANCOVA specification where baseline data for the variable is available. Column 3 reports the ANCOVA specification and uses double ML to pick an optimal set of control variables. All specifications include village fixed effects, survey round fixed effects and a set of fixed effects for the number of peers listed at baseline. Asterisks denote statistical significance: *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

[14] The 'Masala merge' algorithm calculates a modified Levenshtein distance adapted to English transliterations of Hindi words (Novosad, 2017).

[15] Appendix A4 provides a distribution of the treatment status of peers.

[16] Appendix A1 reports summary statistics and assesses balance with respect to both own treatment status and peer treatment status. Profit here refers to agriculture and is calculated as the difference between total income from of all crops grown less total input expenditure in the past year, where the latter includes seeds, fertilizers, irrigation, pesticides, hired labor, and household labor priced at the mean wage of hired labor.

[17] Section 6 probes the robustness of the main estimates with respect to this baseline imbalance in in-degree. More generally, Appendix A5 estimates a difference-in-difference specification for main outcomes where baseline data is available. The results are largely consistent with the estimates from the ANCOVA.

[18] Online Appendix A6 details the set of control variables (including their interactions) to which the algorithm is applied.

[19] Note, in the case of Panel A, baseline service usage is zero minutes for all respondents so an ANCOVA specification is not possible. Similarly, there is no baseline data for sharing information and recommending an input to a peer.

[20] This estimate includes both time spent calling into the line —roughly 2 h on average—and the time spent listening to automated calls.

on the AO system, while pest management accounts for 54% of all questions asked, with significant overlap between the two.[21] The content of push calls, in comparison, focused more heavily on fertilizer use (34%) and on advice related to cumin cultivation (38%).

Panel B suggests that the information received by respondents had a positive, but imprecise (t-stat = 1.63) effect on overall agricultural knowledge as gauged by an index of 44 questions.[22] However, restricting attention to questions about cotton cultivation—these account for 40% of the questions on the index and cotton is the main crop for these farmers and the subject of a majority of questions on the AO platform—reveals a significant, albeit modest, effect (2% relative to the baseline mean). In Panel C, indices aggregating the source of information used to make agricultural decisions reveal that farmers offered the service turn less often to their peers (−0.13 s.d.) and input dealers (−0.07 s.d.) and switch to using mobile phone-based advice (1.14 s.d.).[23] However, across both rounds treated farmers also report they are both more likely to share agricultural information (6.6 p.p.) with their peers and recommend an input to them (7.9 p.p.). Appendix A8 shows that the intervention substantially changes the source of information that is shared with peers, skewing it towards mobile phone-based information (46.8 p.p.). In contrast, the treated do not appear more likely to receive information from their peers and there is no change in whether they learn by observing their peer's fields.

4.2. Social interactions and peer group interactions

Table 2 analyzes whether exposure to the treatment directly or through one's peers influenced social interactions and peer group composition (i.e. it estimates eqn. (2)). To recall, all study respondents were asked to list up to three peers they speak to frequently about agriculture at baseline. The treatment status of these baseline peers is used to determine the fraction of one's peer group treated. In subsequent rounds, respondents could change which peers they reported speaking to frequently about agriculture.

Column 1 suggests that exposure to the treatment has no effect on the likelihood of frequently (weekly or better) speaking to a peer in-person about agriculture.[24] In addition, there is also limited evidence that exposure to the treatment influences the size of peer groups (column 3).[25] As discussed in Section 2.2, estimates on the frequency of peer interactions combine both changes on an extensive margin (i.e. churn in peer groups) and on an intensive margin. However, given that respondents report the peers with whom they interact with *most* frequently, there appears to be little evidence that exposure to the service crowds out peer interactions. If anything, I find some evidence to suggest the opposite. In column 2, I find that treated respondents with treated peers are *more* likely to visit their peer's home to discuss agriculture and list larger peer groups, indicative of complementarities.[26]

Turning to the composition of peer groups, on the midline and endline surveys roughly one in three peers listed was a 'new peer' – a peer not listed at baseline – suggesting churn in the set of peers with whom respondents share information. However, there are patterns to this churn: control respondents who had a treated peer at baseline are almost four times as likely (18.8 p.p.) to list a new *treated* respondent to their peer group as treated respondents with (4.2 p.p.) and without treated peers (4.7 p.p.) at baseline.[27] Appendix A9 shows that these newly listed treated peers are 16 p.p. more likely to call into the AO service and have used the service for 50 min more than the average treatment respondent. A corollary of this increased demand for information from treated respondents is the increase in average peer in-degree for both those directly and indirectly exposed to the treatment (col. 5).

Table 2
PEER interactions and peer group composition.

	Spoke to Peer Weekly	Went To Peer's Home to Discuss Ag.	Total Peers	Added Treated Peer	Avg. Peer In-Degree
	(1)	(2)	(3)	(4)	(5)
Treatment	0.005	−0.023	0.071*	0.042**	0.104**
	(0.023)	(0.027)	(0.042)	(0.016)	(0.047)
Fraction of Peers Treated	0.019	−0.092	0.071	0.146**	0.293*
	(0.068)	(0.079)	(0.128)	(0.060)	(0.149)
Treat*Frac. Peers Treated	−0.004	0.223**	0.010	−0.141**	−0.366*
	(0.083)	(0.096)	(0.154)	(0.070)	(0.191)
N	2190	2190	2190	2190	2190
Baseline Control Mean*	0.807	0.605	2.809	0.165	1.918

Notes: This table reports treatment effects on peer interactions and the composition of peer groups. The estimates show how the own treatment status ('Treatment'), the fraction of a respondent's baseline peer group who received treatment ('Fraction of Peers Treated') and the interaction between own treatment status and the fraction of one's peers who were treated (Treat*Frac.Peers Treated) influence outcomes. The estimates average over data from both the midline and the endline. The baseline control mean is reported except in the case of 'Add Treated Peer' where the midline control mean is report as the variable is not defined at baseline. The dependent variable in Column 1 is a dummy for whether the respondent spoke to any of their peers on a weekly (or more frequent) basis. Column 2 describes whether the respondent went to their peer's house (or if their peer came to their own house) to discuss their agriculture. Column 3 reports the total number of peers listed. Column 4 is a dummy variable for whether a respondent reported a peer at midline or endline who was not listed at baseline and was assigned to the treatment group. Column 5 reports the average in-degree (i.e. the number of times a peer is listed by respondents as a top agricultural contact) of peers listed by the respondent. The estimates reported here use an ANCOVA specification with double machine learning (i.e. double LASSO) to pick control variables as in Belloni et al. (2014). The set of covariates is picked from those listed in Appendix A6. All specifications include village fixed effects, survey round fixed effects and a fixed effect for the number of peers listed at baseline. Asterisks denote statistical significance: *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

4.3. Input use and the demand for agricultural information

Table 3 explores the consequences of own and peer exposure to the treatment on the use of and demand for agricultural information. Column 1 shows that treated respondents with treated peers are 11 p.p. more likely to call into the AO line, while column 2 shows that they use the AO service for nearly 2 h more compared to those without treated peers. This marginal usage is substantial, amounting to 36% of the

[21] Overall, among all questions asked about pest management, 60% relate to cotton cultivation, while among all questions asked about cotton, 64% relate to pest management.

[22] See Appendix A14 for detailed questions.

[23] Each index aggregates responses for the respondent's primary source for crop planning, soil preparation, seed, pest management, fertilizer, harvest, and weather information. The index reports the average of the normalized responses for each index component and is then weighted by the inverse of the covariance matrix as in Anderson (2008).

[24] Conversations with peers over the phone are negligible and unaffected by the treatment.

[25] While the maximum number of peers they could list (3) imposes censoring, in results not reported here, I find that there is also no effect of the treatment on the probability of listing the maximum number of peers.

[26] For both of these estimates and the estimate for new treated peer addition, I can reject the joint null that coefficients on 'Treatment', 'Fraction of Peers Treated' and 'Treat x Frac. Peer Treated' are equal to zero.

[27] I note here that there is no effect of the treatment on adding new peers in general.

Table 3
Demand for and use of agricultural information.

	Called in to AO line	Dependent Variable					
		AO Usage (mins)	Index of Mobile Phone-Based Information	Index of Input Recommendations	BDM Valuation	Respondent In-Degree	Peak
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Treatment	0.578***	300.508***	0.910***	0.151	32.256***	0.012	0.042***
	(0.016)	(12.821)	(0.205)	(0.102)	(9.407)	(0.034)	(0.015)
Fraction of Peers Treated	0.006	17.882	−0.682	0.276	31.674**	0.276**	0.093*
	(0.021)	(21.108)	(0.495)	(0.285)	(14.811)	(0.138)	(0.048)
Treat*Frac. Peers Treated	0.116**	114.941**	1.573**	−0.087	−39.883**	0.038	−0.077
	(0.057)	(48.342)	(0.799)	(0.366)	(18.623)	(0.162)	(0.061)
N	2190	2190	2190	2190	836	2190	2190
Baseline Control Mean	0.000	0.000	0.000	0.000	71.667	0.601	0.085

Note: This table reports treatment effects on the demand for and use of agricultural information. The estimates show how the own treatment status ('Treatment'), the fraction of a respondent's baseline peer group who received treatment ('Fraction of Peers Treated') and the interaction between own treatment status and the fraction of one's peers who were treated (Treat*Frac.Peeers Treated) influence outcomes. The baseline control mean is reported except in the case of 'BDM valuation' where data is only available for the endline. In this case, the endline control mean is, instead, reported. The estimates average over data from both the midline and the endline. The dependent variable in column 1 is a dummy variable for whether a respondent called into the AO line. Column 2 reports the minutes of AO usage (both incoming and outgoing). Columns 3 and 4 use indices that aggregate information over multiple outcomes for which we expect unidirectional treatment effects. Each index consists of the average of the z-scores for each component of the index, with the control group mean and standard deviation as reference. The component scores are then weighted by the inverse of the covariance matrix of the components as in Anderson (2008). Mobile phone-based information usage index: Aggregates mobile phone use across crop decision, soil preparation, pest management, pest identification, fertilizer decisions, weather, and irrigaition. Input Recommendations Index: all seed, pest, and fertilizer input recommendations made by the AO system (See Appendix A13 for details). Column 5 reports the respondent's willingness to pay for a 9-month AO service using a Becker-DeGroot-Marschak game. Column 6 reports respondent in-degree (i.e. the number of times a peer is listed by respondents as a top agricultural contact). Column 7 is a dummy variable for whether a respondent's in-degree was greater than or equal to two standard deviations from the sample (i.e. all respondents) mean. The estimates reported here use an ANCOVA specification with double machine learning (i.e. double LASSO) to pick control variables as in Belloni et al. (2014). The set of covariates is picked from those listed in Appendix A6. All specifications include village fixed effects, survey round fixed effects and a fixed effect for the number of peers listed at baseline. Asterisks denote statistical significance: $^*p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

average usage in the treatment group. Similarly, an index capturing the source of information used across a series of agricultural decisions (col. 3) shows that treated respondents with treated peers are over 1.5 standard deviations more likely to use mobile phone-based information relative to treated respondents without treated peers. Together with the finding that treated peers visit each other's homes more frequently, these results suggest important complementarities between the treated.

However, for treated respondents with treated peers, this increased usage does not translate into the adoption of recommended inputs (col. 4) nor a higher willingness to pay (WTP) for a 9-month subscription to AO (col. 5).[28] While there are no detectable complementarities in input adoption between treated respondents, recent evidence from a meta-study of the returns to 'digital extension' suggest that the adoption and use of extension services is itself an important input into production (Fabregas et al., 2019). Seen in this light, complementarities in AO service usage—on both an intensive and extensive margin— is itself evidence of technology diffusion. Importantly, control respondents with treated peers have a WTP for a 9-month AO subscription that is 43% higher than pure controls and statistically indistinguishable from the treatment effect on WTP for treated respondents. While control respondents with treated peers are not more likely to report using mobile phone-based information, this is not surprising as the information they get from treated peers is second hand and not directly from the AO service.

Columns 6 and 7 capture how exposure to the treatment influences one's importance within a village for agricultural information. Treated respondents are 4.2 p.p. more likely to be a peak: an extremely important source of agricultural information, but there is no differential effect for treated respondents with treated peers. While control respondents with treated peers are also 9.3 p.p. more likely to be a peak (and have a higher in-degree) this is likely a remnant of the baseline imbalance.[29]

5. Discussion of results

Collectively, these results suggest that exposure to the treatment alters the structure of peer interactions and, in particular, increases the importance of the treated as a source of agricultural information in the village. This change in the ordinal ranking of treated respondents in farmer peer groups suggests a reallocation of social interactions towards the treated. However, rather than a result of complementarities between local and external information, it appears more likely that control respondents with treated peers simply value access to external information: their WTP for an AO subscription is similar to that of treated respondents.

In order to understand how digital extension programs at scale may influence peer interactions, a perhaps more relevant group to consider are treated respondents with baseline treated peers. Here, the service appears to produce complementarities between the treated, increasing peer interactions and service adoption. Treated respondents with treated peers are more likely to use mobile phone-based information to make agricultural decisions, more likely to call into the AO service and use it for longer (suggesting more robust diffusion), and are more likely to visit the homes of their peers to discuss agriculture.

These changes in peer interactions suggest that information treatments may influence outcomes through a 'peer sorting' channel. While

[28] Willingness to Pay was measured at endline using the Becker-DeGroot-Marshcak (BDM) mechanism.

[29] In Appendix A5 I report estimates from a difference-in-difference specification which more carefully controls for baseline imbalances (albeit at the cost of reduced power). Here, we see that the sign for respondent in-degree flips. While the coefficient for peak is still positive, it is now more imprecise.

ideally I would compute the marginal return to an added treated peer, I do not have an instrument to separately identify this effect.[30]

6. Threats to validity

6.1. Attrition

Appendix Table A10 shows that 77 respondents were no longer a part of the respondent group at the time of the midline survey and 120 were attritees by the time of the endline. However, they appear to be statistically indistinguishable across their treatment status for a standard set of covariates, including age, area of land owned, years of education, and amount of cotton planted.

6.2. Censored peer groups

A concern common to studies using a partial sampling of networks is bias in the estimation of network-level parameters that results from mismeasurement of connections and interactions (Chandrasekhar and Lewis, 2011). While I do not estimate network-level parameters, censored peer groups may also result in mismeasurement of *indirect* treatment exposure (Hardy et al., 2019). In particular, the probability of being exposed to the treatment indirectly (i.e. through a peer) may not be constant. Appendix A11 suggests this possibility as there is an imbalance with respect to respondent in-degree and whether they have a treated peer. Reassuringly, the estimates I present allow the DML algorithm to pick controls for baseline in-degree and this leaves the results unchanged. In addition, when I estimate the baseline ANCOVA specification with controls for baseline in-degree and its interaction with survey round fixed effects, this also leaves the main estimates unchanged.

In addition, I conduct two robustness tests: first, I estimate the results using a Horvitz- Thompson estimator as discussed in Hardy et al. (2019). In Panel A of Appendix A11, I restrict the sample to respondents who have a non-zero baseline in-degree and then weight the estimates by baseline in-degree so as to take into account varying peer exposure probabilities. In Panel B, I conduct a test proposed by Griffith (2019), where the main analyses are run after censoring the list of peers to a single randomly picked peer.

In general, the qualitative interpretation of the estimates is unchanged in both of these robustness tests. In Panel A, the precision of estimates is understandably lower as the sample restriction reduces the size of the sample by over 60%. In this case WTP, however, the censoring test (Panel B) flips the sign of the coefficient. While this estimate is very imprecise, it suggests we should treat the indirect effect of the treatment on WTP with some caution.

7. Conclusion

In this paper, I investigate the effects of a mobile phone-based agricultural extension service in Gujarat, India. While the service substantially lowers the importance of peers as a source of agricultural information, it does not crowd-out peer interactions, instead altering the composition of peer groups. Indeed, if anything, I find that complementarities between the treated result in an increased likelihood of using the service and more frequent interactions among peers.

When comparing study villages to villages in the same sub-district and district in Gujarat, I find that the study villages have a smaller population and lower literacy on average.[31] As with any experiment, further study is needed to understand whether these results generalize to other populations; understanding how village structure—for example, population density and segregation—influences peer effects and the potential for information interventions to crowd out (or in) in-person interactions is a fruitful area for future research.

In addition, examining this question with a full elicitation of networks and experimental variation in peer group structure would allow researchers to isolate the marginal effect of changes in peer composition. A more complete understanding of the relative importance of the channels—direct effect vs. peer sorting— through which information interventions influence outcomes can guide policy makers in assessing the optimal approach to scaling interventions. These results also suggest that applied economists should be mindful of social structures (peer groups, networks, etc …) being endogenous to policies in contrast to standard assumptions in the literature which treat them as fixed.

Appendix A1. Summary Statistics and Balance

Dependent Variable	Control Mean	Eqn (1): Own Treatment Status	Eqn (2): Peer Treatment Status		
		Treat-Control	Treat	Treat Frac	Treat*Treat Frac
	(1)	(2)	(3)	(4)	(5)
Age	46.539	−0.369	−0.432	−3.417	0.220
	15.161	(0.915)	(1.088)	(2.765)	(3.496)
Education (Years)	4.235	−0.187	−0.148	−0.810	−0.154
	3.836	(0.230)	(0.272)	(0.720)	(0.929)
Land Owned (Acres)	6.077	0.095	0.198	−0.377	−0.617
	5.596	(0.332)	(0.390)	(0.918)	(1.117)
Profit from Agriculture (Rupees, winsorized fraction = 0.01)	1.36e+05	5082.579	8959.709	−8848.859	−2.38e+04
	1.26e+05	(7665.933)	(9345.799)	(21175.266)	(28372.549)
Index of Mobile Phone-Based Information Usage	−0.000	0.090	0.107	0.044	−0.105
	1.000	(0.078)	(0.081)	(0.188)	(0.337)
Planted Cotton in 2010	0.985	−0.003	−0.002	0.005	0.002
	0.122	(0.008)	(0.009)	(0.020)	(0.031)
Area of Cotton Planted in 2010 (Acres)	4.448	0.422*	0.449	0.030	−0.062
	3.622	(0.232)	(0.275)	(0.634)	(0.872)
Spoke to Peer Weekly	0.807	−0.003	0.021	0.100	−0.118
	0.396	(0.024)	(0.029)	(0.079)	(0.094)
Avg. Agricultural Knowledge of Peers					

(*continued on next page*)

[30] I am unable to use instruments proposed by Comola and Prina (2019) as I don’t have a full mapping of the network and, therefore, cannot identify higher order peers.

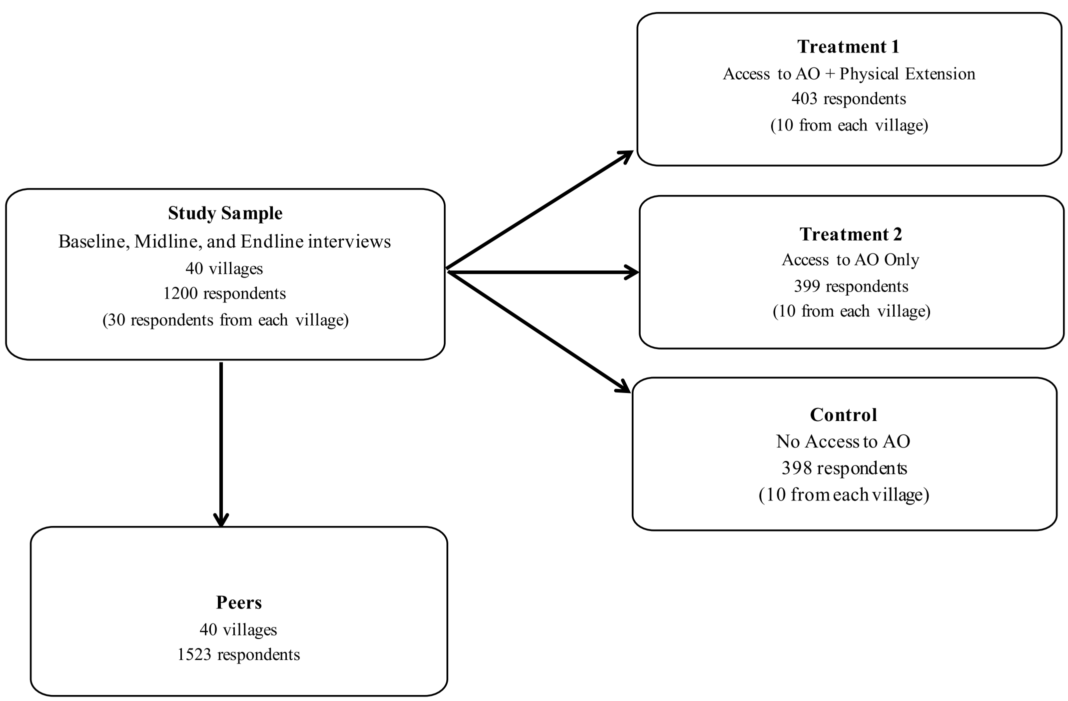
[31] These comparisons were made using the 2011 Population Census.

(*continued*)

Dependent Variable	Control Mean	Eqn (1): Own Treatment Status	Eqn (2): Peer Treatment Status		
		Treat-Control	Treat	Treat Frac	Treat*Treat Frac
	(1)	(2)	(3)	(4)	(5)
	3.881	0.004	0.041	0.212	−0.255
	0.699	(0.042)	(0.052)	(0.156)	(0.189)
Respondent In-Degree	0.601	−0.019	−0.013	0.584**	0.032
	1.113	(0.063)	(0.068)	(0.260)	(0.292)
Peak (2 sd > mean of normalized in-degree)	0.083	0.011	0.020	0.071	−0.044
	0.276	(0.016)	(0.018)	(0.069)	(0.077)
Avg. Peer In-Degree	1.918	−0.083	−0.061	0.352	−0.080
	1.166	(0.063)	(0.077)	(0.264)	(0.322)
N	398	1200	1200	–	–

Note: This table compares baseline characteristics for respondents assigned to the control and treatment groups. Column 1 reports the control mean at baseline while column 2 reports the simple difference between the treatment and the control group. A separate regression shows how baseline respondent characteristics vary by own treatment status (column 3), the fraction of a respondent's baseline peer group who received treatment (column 4) and the interaction between own treatment status and the fraction of one's peers who were treated (column 5). 'Avg. Agricultural Knowledge of Peers' reports a respondent's average rating of their peer's agricultural knowledge on a scale of 1–5. Respondent In-Degree counts the number of farmers within a village who consider the respondent a top agricultural contact. 'Peak' is defined as an in-degree that is > 2 standard deviations from the mean. The in-degree of peers is first normalized by subtracting the (cross) village mean in-degree of all respondents and dividing by its standard deviation. 'Spoke to Peer Weekly' codes whether the respondent spoke to at least 1 peer about agricultural topics on at least a weekly basis in a typical agricultural season. All peer characteristics are averages across all peers reported by a respondent, and the unit of observation in each regression is a respondent. Peer effects specifications include dummies for total number of peers listed at baseline, and village effects. Asterisks denote statistical significance, where *** significant at 1% level ** significant at 5% level * significant at 10% level.

Appendix A2. Experimental design



Appendix A3. Project timeline

Date	Event
May/2011	Cotton planting decisions begin
May/2011	Listing for baseline survey
Jul/2011	Baseline (paper) survey
Aug/2011	AO training for treatment respondents
Aug/2011	AO service activated for all treatment respondents
Sep/2011	Reminder calls started
Nov/2011	Physical extension Round 1
Nov/2011	Phone Survey Round 1
Jun/2012	Midline (Paper) Survey

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(*continued*)

Date	Event
Aug/2012	AO training for treatment respondents Round 2
Oct/2012	Field visits to gather information on Rabi planting decisions
Nov/2012	Physical Extension Round 2
Jul/2013	Endline (Paper) Survey
Jul/2013	Willingness to Pay Study
Jul/2013	Ending push calls/intervention

Appendix A4. Distribution of peer treatment status at baseline

Fraction of Peers Treated	Control Group		Treatment Group	
	Count	%	Count	%
0	256	64.3%	534	66.6%
1/3	95	23.9%	183	22.8%
1/2	17	4.3%	33	4.1%
2/3	24	6.0%	41	5.1%
1	6	1.5%	11	1.4%
Total	398		802	

Notes: The table above describes the treatment status of respondent peer groups at baseline.

Appendix A5. Difference-In-difference estimates

	Dependent Variable						
	Called AO	AO Usage (mins)	Respondent In-Degree	Peak	Index of Mobile Phone-Based Information	Spoke to Peer Weekly	Total Peers
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Treatment*Post	0.575***	299.640***	0.011	0.032	0.817***	−0.009	0.101*
	(0.016)	(13.384)	(0.079)	(0.025)	(0.220)	(0.038)	(0.057)
Fraction of Peers Treated*Post	−0.003	4.704	−0.240	0.032	−0.321	−0.066	0.155
	(0.015)	(18.331)	(0.299)	(0.093)	(0.480)	(0.105)	(0.176)
Treat*Frac. Peers Treated*Post	0.131**	114.891**	0.008	−0.096	1.636*	0.086	−0.036
	(0.056)	(52.369)	(0.343)	(0.109)	(0.853)	(0.128)	(0.217)
N	3390	3390	3390	3390	3390	3390	3390

Notes: This table reports estimates from a difference-in-difference specification where baseline data is available. The specification includes a dummy variable for the treatment group, the fraction of one's peers who are assigned to the treatment, the interaction between the two preceding terms, and the interaction of all three preceding terms with a dummy variable for whether the survey round is after the baseline. Column 1 reports whether a respondent called into the AO line. Column 2 reports total AO usage in minutes. Column 3 reports respondent in-degree (i.e. the number of times a peer is listed by respondents as a top agricultural contact). Column 4 is a dummy variable for whether a respondent's in-degree was greater than or equal to two standard deviations from the sample (i.e. all respondents) mean. The dependent variable in column 5 is an index that aggregates mobile phone usage across crop decision, soil preparation, pest management, pest identification, fertilizer decisions, weather, and irrigation. The component scores are then weighted by the inverse of the covariance matrix of the components as in Anderson (2008). The dependent variable in column 6 is a dummy for whether the respondent spoke to any of their peers on a weekly (or more frequent) basis. The dependent variable in column 7 is the total number of peers listed by a respondent in each round. All specifications include village fixed effects, survey round fixed effects, and a fixed effect for the number of peers listed at baseline (except for column 6). Asterisks denote statistical significance: *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

Appendix A6. Double lasso control variables

Variable Name	Variable Description
ls_a0_2_age_BM	Age of household head
ls_edu_years_BM	Years of Education
ls_ag_income_BM	Agricultural income for past 12 months (Rupees)
ls_b1_1_BM	Total Land Owned - Area in Acres
ls_k1_3_1_BM	Used Info from Past Experiences to make agricultural decisions?
ls_k1_3_2_BM	Used Info from TV Program to make agricultural decisions?
ls_k1_3_3_BM	Used Info from Mobile Phone-Based Sources to make agricultural decisions?
ls_k1_3_4_BM	Used Info from Newspaper/magazine - to make agricultural decisions?
ls_k1_3_5_BM	Used Info from Extension Workers to make agricultural decisions?
ls_k1_3_6_BM	Used Info from NGO's to make agricultural decisions?
ls_k1_3_7_BM	Used Info from Other Farmer Friends - to make agricultural decisions?
ls_k1_3_8_BM	Do you use - Ag_dealer - to make agricultural decisions?
ls_k1_3_9_BM	Do you use - commission_agent - to make agricultural decisions?
ls_overall_corre ~ M	Total correct answerson agricultural knowledge
ls_c1_3_BM	Cotton Planted in Kharif 2010
ls_c1_5a_BM	Cotton Area Planted in Kharif 2010 (Acres)
ls_c2_3_BM	Wheat Planted in Rabi 2010
ls_c2_5a_BM	Wheat Area Planted in Rabi 2010 (Acres)
ls_c3_3_BM	Cumin Planted in Rabi 2010
ls_c3_5a_BM	Cumin Area Planted in Rabi 2010 (Acres)

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Variable Name	Variable Description
ls_cotton_yield_BM	Cotton Yield in 2010 (Kg/Acre)
ls_wheat_yield_BM	Wheat Yield in 2010 (Kg/Acre)
ls_cumin_yield_BM	Cumin Yield in 2010 (Kg/Acre)
ls_totcost_pest_rs	Total Cost of Pesticides (Rupees)
ls_totcost_fert_rs	Total Fertilizer Cost (Rupees)
ls_totcost_irrig ~ s	Total Irrigation Cost (Rupees)
ls_totcost_labor ~ s	Total Hired Labor Cost (Rupees)
ls_peak	Peak (>2 sd from in-degree mean)
ls_in_degree	Respondent In-Degree

Notes: This table reports the set of baseline variables used in implementing the double LASSO/machine learning approach to selecting control variables (Belloni et al., 2014).

Appendix A7. Topics of question asked and push calls

Cell Contents	No. of Questions		% of Total Questions		No. of Push Calls		% of Total Push Calls	
	Midline	Endline	Midline	Endline	Midline	Endline	Midline	Endline
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: By Crop								
Cotton	679	960	0.50	0.46	30	59	0.68	0.62
Cumin	80	151	0.06	0.07	15	36	0.34	0.38
Wheat	26	43	0.02	0.02	11	27	0.25	0.28
Panel B: By Theme								
Pest Management	739	1126	0.54	0.54	23	73	0.52	0.77
Crop Planning	197	363	0.14	0.17	30	64	0.68	0.67
Fertilizer	106	154	0.08	0.07	13	32	0.30	0.34
Weather	66	88	0.05	0.04	10	26	0.23	0.27
Irrigation	12	21	0.01	0.01	2	5	0.05	0.05
N	1370	2079			44	95		

Notes: This table reports information on push calls and questions asked on the AO server, categorized by crop and theme. All push calls contain information on multiple themes. A total of 95 push calls were sent out during September 2011–August 2013, with an average length of approximately 5 min. The midline survey took place between 4th June and July 8, 2012. The Endline survey took place between 23rd July and August 30, 2013.

Appendix A8. Source of information shared with peers

Cell contents:	Control Mean	Treat-Control
	(1)	(2)
Source of shared info: Past experience	0.329	−0.175***
	0.470	(0.031)
Source of shared info: TV program	0.060	−0.033**
	0.237	(0.015)
Source of shared info: Cell phone based info	0.008	0.468***
	0.090	(0.026)
Source of shared info: Other farmers	0.185	−0.064**
	0.389	(0.026)
Source of shared info: Input Dealers	0.196	−0.085***
	0.397	(0.025)
N	398	797

Notes: This table reports the effect of AO on the sources of information shared with peers. This table uses the phone survey which included 797 respondents in total (the control group and a randomly selected 50% of the treatment group). Column 1 provides the mean and standard deviation of the control group at the time of the phone survey. Column 2 provides an Intention to Treat (ITT) estimate of the difference in means (and the robust standard error) between the treated group and the control group at the time of the phone survey. Robust standard errors are reported in parentheses. Asterisks denote statistical significance, where *** significant at 1% level; ** significant at 5% level; * significant at 10% level.

Appendix A9. Peer characteristics

	(1)	(2)	(3)	(4)
	Respondent mean	Treatment mean	New Peer Mean	New AO Peer Mean
Age	46.381	46.215	45.890	45.479
	(14.533)	(14.505)	(12.868)	(13.550)
Education	4.121	4.015	5.384	5.766
	(4.017)	(3.970)	(4.134)	(4.439)
Landholding (acres)	6.055	6.105	5.663	5.243
	(6.111)	(6.240)	(4.725)	(4.874)

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	(1) Respondent mean	(2) Treatment mean	(3) New Peer Mean	(4) New AO Peer Mean
Ag Income	143468.684	145399.847	158292.547	156631.255
	(129189.022)	(136721.799)	(133427.283)	(113059.027)
Planted cotton in K′10	0.985	0.985	1.000	1.000
	(0.122)	(0.120)	0.000	0.000
Area of cotton planted	5.205	5.312	4.859	4.713
	(4.263)	(4.455)	(3.539)	(3.538)
Planted wheat in R′10	0.360	0.358	0.279	0.255
	(0.480)	(0.480)	(0.451)	(0.441)
Area of wheat planted	0.383	0.390	0.294	0.253
	(0.734)	(0.754)	(0.628)	(0.588)
Peak	0.099	0.103	0.022	0.041
	(0.299)	(0.304)	(0.149)	(0.200)
Called AO	0.352	0.527	0.382	0.694
	(0.478)	(0.500)	(0.489)	(0.466)
Total Usage (mins.)	38.195	57.149	58.657	106.539
	(105.583)	(124.909)	(125.113)	(153.264)
Has AO	0.668	1.000	0.551	1.000
	(0.471)	0.000	(0.500)	0.000
N	1200	802	89	49

Notes: This table computes sample means and standard deviations for all study respondents (column 1), treatment respondents (column 2), peers who were added by study respondents at midline (column 3) and peers in the treatment group who were added by study respondents (column 4) to their list of top agricultural contacts.

Appendix A10. Characteristics of attritors by treatment status

Dependent Variable	Control Mean (Midline)	Treat-Control (Midline)	Control Mean (Endline)	Treat-Control (Endline)
	(1)	(2)	(3)	(4)
Age of Household Head	44.174	1.151	47.090	−1.467
	(11.116)	(3.791)	(13.173)	(2.819)
Years of Education	2.696	0.865	4.077	−0.086
	(3.470)	(1.243)	(4.138)	(0.989)
Agricultural Income (log rupees)	10.745	1.269	11.628	0.198
	(2.677)	(0.880)	(1.033)	(0.235)
Planted Cotton	1.000	−0.045	0.974	0.014
	(0.000)	(0.056)	(0.160)	(0.034)
Total Area, Cotton (Acres)	4.304	0.663	4.859	1.216
	(4.085)	(0.824)	(4.454)	(0.914)
Planted Wheat	0.826	−0.285	0.744	−0.054
	(0.388)	(0.184)	(0.442)	(0.109)
Total Area, Wheat (Acres)	1.617	−0.350	1.121	−0.278
	(1.892)	(0.655)	(1.555)	(0.291)
Planted Cumin	0.391	−0.024	0.308	0.114
	(0.499)	(0.172)	(0.468)	(0.115)
Total Area, Cumin (Acres)	1.449	−0.886	0.559	0.082
	(3.307)	(1.123)	(1.388)	(0.310)
N	23	77	39	120

Notes: This table compares baseline characteristics of respondents of attritors from the midline and endline. Agricultural income refers to income earned from all crops from the past 12 months. Columns 1–2 compare baseline characteristics (from 2010) for the 23 control group respondents, and 54 treatment group respondents were not reached during the midline survey. Columns 3–4 compare baseline characteristics for the 39 control group respondents, and 81 respondents were not reached during the endline survey. The midline survey took place between 4th June and July 8, 2012. The Endline survey took place between 23rd July and August 30, 2013. Asterisks denote statistical significance: *p $<$ 0.10, **p $<$ 0.05, ***p $<$ 0.01.

Appendix A11. Robustness to partial sampling

	Dependent Variable				
	AO Usage (mins)	Peak	Index of Mobile Phone-Based Information	Added AO Peer	BDM Valuation
	(1)	(2)	(3)	(4)	(5)
Panel A: Horvitz-Thompson Estimator					
Treatment	299.839***	0.081**	0.382	0.037	38.599*
	(16.535)	(0.037)	(0.364)	(0.034)	(20.299)
Fraction of Peers Treated	30.151	0.142	−1.012	0.258**	7.299
	(43.446)	(0.093)	(0.807)	(0.109)	(58.324)
Treat*Frac. Peers Treated	52.362	−0.152	2.936**	−0.193	−46.168
	(53.706)	(0.112)	(1.144)	(0.123)	(66.396)
N	836	836	836	836	323
Panel B: Censoring Test					
Treatment					

(*continued on next page*)

(*continued*)

	Dependent Variable				
	AO Usage (mins)	Peak	Index of Mobile Phone-Based Information	Added AO Peer	BDM Valuation
	(1)	(2)	(3)	(4)	(5)
	298.504***	0.032**	1.093***	0.048***	19.125**
	(9.962)	(0.014)	(0.189)	(0.015)	(9.077)
Fraction of Peers Treated	29.073**	0.043	−0.326	0.143***	−1.492
	(12.521)	(0.030)	(0.236)	(0.039)	(22.718)
Treat*Frac. Peers Treated	129.213**	−0.016	0.331	−0.174***	−6.285
	(52.626)	(0.038)	(0.470)	(0.045)	(27.227)
N	2190	2190	2190	2190	829

Notes: This table reports probes the main results for robustness to potential bias resulting from the censoring of peer groups. Panel A uses a Horvitz-Thompson estimator that uses inverse probability weights that are a function of baseline in-degree. As such, the goal is to produce an estimator such that the probability of a peer being assigned to the treatment is constant (and non-zero). As such, those with a baseline in-degree of 0 are dropped from the sample. Panel B randomly picks a single peer of those listed at baseline in order to assign the treatment status of peers. Column 1 reports total AO usage in minutes. The dependent variable in column 1 is a dummy for whether the respondent spoke to any of their peers on a weekly (or more frequent) basis. Column 2 is a dummy variable for whether a respondent's in-degree was greater than or equal to two standard deviations from the sample (i.e. all respondents) mean. The dependent variable in column 3 is an index that aggregates mobile phone usage across a series of decisions including: crop decisions, soil preparation, pest management, pest identification, fertilizer decisions, weather, and irrigation. The component scores are then weighted by the inverse of the covariance matrix of the components as in Anderson (2008). Column 4 is a dummy variable for whether a respondent reported a peer at midline or endline who was not listed at baseline and was assigned to the treatment group. Column 5 reports the respondent's willingness to pay for a 9-month AO service using a Becker-DeGroot-Marschak game. The estimates reported here use an ANCOVA specification with double machine learning (i.e. double LASSO) to pick control variables as in Belloni et al. (2014). The set of covariates is picked from those listed in Appendix A6. All specifications include village fixed effects, survey round fixed effects, and a fixed effect for the number of peers listed at baseline. Asterisks denote statistical significance: *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

Appendix A12. Examples of questions and answers from AOservice

Crop	Topic	Question	Answer
Cotton	Pests	Leaves of cotton crop have become curly. Which pesticide should I use for this?	Cotton leaves can become curly due to pests. To get rid of the pests Acephate powder (1 pump- 30 gm) or Imidacloprid (1 pump - 10 ml) can be used.
Cotton	Pests	Which pesticide can I use to control mealy bug in cotton?	To rid the crop of mealy bug, Imidacloprid can be used. It is available under the brand names Confidor or Tatamida in the market. To control the pest 1 pump or 10 ml should be used.
Cotton	Pests	My cotton crop is infected with Thrips and other pests. Which pesticide should I use to treat my crop and how much?	To get rid of Thrips and other pests Imidacloprid (1 pump - 10 ml), Acetamiprid (1 pump - 4 to 5 gm) or Dimethoate (1 pump - 30 ml) can be used. These are available in the market under the brand names Pride, Supreme and Roger, respectively. Moreover, Profenofos (1 pump - 20 ml) can also be used.
Cotton	Pests	Aphids (Molo mashi) are attacking my cotton crop. Which pesticide should I use to control these?	For Aphids (Molo mashi), you can use Imidacloprid (1 pump- 10 ml) which is available in the market under the brand names Confidor or Tatamida. Alternatively, Acetamiprid (1 pump - 5 gm) or Thiamethoxam (1 pump - 4 gm) can also be used to control the pests.
Cotton	Pests	White fly and other pests are attacking my cotton crop. Which pesticide can I use to address this problem?	To protect your crop from white fly and other pests you can use Imidacloprid (1 pump- 10 ml) which is available in the market under the brand names Confidor or Tatamida. This is can be used with Acephate powder (1 pump- 20 ml).
Cotton	Fertilizer	I cannot find Urea and DAP at the market. How can I ensure that my cotton crop gets nutrients like Nitrogen without Urea and DAP?	Ammonium Sulphate can be used, in case Urea and DAP is not available. 1 vigha-1 bag should be used which will provide nutrients to the crop such as nitrogen and sulphur.
Cotton	Fertilizer	My cotton crop is turning yellow. How can I save my crop?	There can be a number of reasons for this. It can primarily be due to deficiency of micronutrients. You can treat the crop with Urea fertilizer or Ammonium Sulphate (1 vigha- 20 to 25 kg).
Cotton	Seeds	I want to sow cotton crop and there is a limited quantity of water available. Should I sow the crop now or not?	Cotton crop can be sown within 15 days of a good rainfall. For this use seed varieties which grow quickly such as Ganga, Ganga Kaveri, Ankur, Vikram and so forth.
Cotton	Seeds	Which seeds should I use to grow a cotton crop?	There are no recommended BT cotton seeds but the government has certified the seeds from some companies. You can use the seeds from these companies such as Ankur, Ganga Kaveri, Ajit and Vikram.
Cotton	Irrigation	I want to practice irrigation for my cotton crop. Can I get information about rain and weather for this?	According to the Weather Department and Krishi University no rain is expected between 7th to 11th September. You can use irrigation during this time.

Notes: The table above displays a set of actual questions posed by treatment farmers in our study and the answers they received by an agronomist on the Avaaj Otalo (AO) platform. The questions and answers have been transcribed from the Gujarati voice recordings and translated into English.

Appendix A13. Components of aggregate indices

Variable Name	Variable Description
Panel A: Cotton Management Index	
s1_seed_1	Purchased Vikram
s1_seed_2	Purchased Rasi
s1_seed_3	Purchased Ajit
s1_seed_4	Purchased Navbharat
s1_seed_5	Purchased Tulsi
s1_seed_6	Purchased Ankur
s1_seed_7	Purchased Nath

(*continued on next page*)

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Variable Name	Variable Description
s1_seed_9	Purchased Ganga Kaveri
s1_seeduse_1	Used Vikram
s1_seeduse_2	Used Rasi
s1_seeduse_3	Used Ajit
s1_seeduse_4	Used Navbharat
s1_seeduse_5	Used Tulsi
s1_seeduse_6	Used Ankur
s1_seeduse_9	Used Ganga Kaveri
p1_7c6	Purchased Chlorpyrifos
p1_7c6_use	Used Chlorpyrifos
p1_8c1	Purchased Phosphamidon
p1_8c1_use	Used Phosphamidon
p1_71_8	Purchased Imidacloprid
p1_71_8_use	Used Imidacloprid
p1_71_9	Purchased Acetamiprid
p1_71_9_use	Used Acetamiprid
p1_71_10	Purchased Acephate
p1_71_10_use	Used Acephate
p1_8c6	Purchased Dicofol
p1_10tf	Used Tricoderma
f1_8b	Purchased Ammonium Sulphate
f1_8b_use	Used Ammonium Sulphate
f1_8d	Purchased Muriate of Potash
f1_8d_use	Used Muriate of Potash
f1_8e	Purchased NPK Grade 1
f1_8e_use	Used NPK Grade 1
f1_12a	Purchased Manure
f1_12a_use	Used Manure
f1_12b	Purchased Biofertilizer
f1_12b_use	Used Biofertilizer
f1_12d	Purchased Castor Cake
f1_12d_use	Used Castor Cake
Panel B: Wheat Management Index	
c2_7a	Added Organic Manure
s2_seed_1	Purchased GW 496
s2_seeduse_1	Used GW 496
s2_seed_5	Puchased LOK 1
s2_seeduse_5	Used LOK 1
s2_10c	Used Biological Method
s2_10b	Used Pesticides
f2_8d	Purchased Muriate of Potash
f2_8d_use	Used Muriate of Potash
f2_8e	Purchased Micronutrients
f2_8e_use	Used Micronutrients
f2_12a	Purchased Manure
f2_12a_use	Used Manure
f2_12b	Purchased Biofertilizer
f2_12b_use	Used Biofertilizer
Panel C: Cumin Management Index	
s3_seed_4	Purchased GC 4
s3_seeduse_4	Used GC 4
s3_10a	Used Fungicides
s3_10b	Used Pesticides
p3_71_6	Purchased Phosphamidon
p3_71_6_use	Used Phosphamidon
p3_71_8	Purchased Imidacloprid
p3_71_8_use	Used Imidacloprid
p3_71_9	Purchased Acetamiprid
p3_71_9_use	Used Acetamiprid
p3_71_16	Purchased Mancozeb
p3_71_16_use	Used Mancozeb
p3_8c1	Purchased Carbendazim
p3_8c1_use	Used Carbendazim
p3_71_20	Purchased Sulphur
p3_71_20_use	Used Sulphur
p3_9tf	Used Tricoderma
f3_8b	Purchased Ammonium Sulphate
f3_8b_use	Used Ammonium Sulphate
f3_8d	Purchased Muriate of Potash
f3_8d_use	Used Muriate of Potash
f3_8e	Purchased Micronutrients
f3_12a	Purchased Manure
f3_12a_use	Used Manure
f3_12b	Purchased Biofertilizer
f3_12b_use	Used Biofertilizer
f3_12d	Purchased Castor Cake

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(*continued*)

Variable Name	Variable Description
f3_12d_use	Used Castor Cake
Panel D: Seed Management Index Recommended Cotton Seed Varieties	
s1_seed_1	Purchased Vikram
s1_seed_2	Purchased Rasi
s1_seed_3	Purchased Ajit
s1_seed_4	Purchased Navbharat
s1_seed_5	Purchased Tulsi
s1_seed_6	Purchased Ankur
s1_seed_7	Purchased Nath
s1_seed_9	Purchased Ganga Kaveri
s1_seeduse_1	Used Vikram
s1_seeduse_2	Used Rasi
s1_seeduse_3	Used Ajit
s1_seeduse_4	Used Navbharat
s1_seeduse_5	Used Tulsi
s1_seeduse_6	Used Ankur
s1_seeduse_9	Used Ganga Kaveri
Recommended Wheat Seed Varieties	
s2_seed_1	Purchased GW 496
s2_seed_2	Purchased GW 322
s2_seed_3	Purchased GW 173
s2_seed_4	Purchased GW 273
s2_seed_5	Purchased LOK 1
s2_seeduse_1	Used GW 496
s2_seeduse_2	Used GW 322
s2_seeduse_3	Used GW 173
s2_seeduse_4	Used GW 273
s2_seeduse_5	Used LOK 1
Recommended Cumin Seed Varieties	
s3_seed_4	Purchased GC 4
s3_seeduse_4	Used GC 4
Panel E: Pesticide Management Index	
Pesticides Recommended for Cotton Cultivation	
p1_7c6	Purchased Chlorpyrifos
p1_7c6_use	Used Chlorpyrifos
p1_8c1	Purchased Phosphamidon
p1_8c1_use	Used Phosphamidon
p1_71_8	Purchased Imidacloprid
p1_71_8_use	Used Imidacloprid
p1_71_9	Purchased Acetamiprid
p1_71_9_use	Used Acetamiprid
p1_71_10	Purchased Acephate
p1_71_10_use	Used Acephate
p1_8c6	Purchased Dicofol
p1_8c6_use	Used Dicofol
p1_10tf	Used Tricoderma
Pesticides Recommended for Cumin Cultivation	
p3_71_6	Purchased Phosphamidon
p3_71_6_use	Used Phosphamidon
p3_71_8	Purchased Imidacloprid
p3_71_8_use	Used Imidacloprid
p3_71_9	Purchased Acetamiprid
p3_71_9_use	Used Acetamiprid
p3_71_16	Purchased Mancozeb
p3_71_16_use	Used Mancozeb
p3_8c1	Purchased Carbendazim
p3_8c1_use	Used Carbendazim
p3_71_20	Purchased Sulphur
p3_71_20_use	Used Sulphur
p3_9tf	Used Tricoderma
Panel F: Fertilizer Management Index Fertilizers Recommended for Cotton Culivation	
f1_8b	Purchased Ammonium Sulphate
f1_8b_use	Used Ammonium Sulphate
f1_8d	Purchased Muriate of Potash
f1_8d_use	Used Muriate of Potash
f1_8e	Purchased NPK Grade 1
f1_8e_use	Used NPK Grade 1
f1_12a	Purchased Manure
f1_12a_use	Used Manure
f1_12b	Purchased Biofertilizer
f1_12b_use	Used Biofertilizer
f1_12d	Purchased Castor Cake
f1_12d_use	Used Castor Cake
Fertilizers Recommended for Wheat Culivation	
f2_8d	Purchased Muriate of Potash
f2_8d_use	Used Muriate of Potash

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(*continued*)

Variable Name	Variable Description
f2_8e	Purchased Micronutrients
f2_8e_use	Used Micronutrients
f2_12a	Purchased Manure
f2_12a_use	Used Manure
f2_12b	Purchased Biofertilizer
f2_12b_use	Used Biofertilizer
Fertilizers Recommended for Cumin Culivation	
f3_8b	Purchased Ammonium Sulphate
f3_8b_use	Used Ammonium Sulphate
f3_8d	Purchased Muriate of Potash
f3_8d_use	Used Muriate of Potash
f3_8e	Purchased Micronutrients
f3_8e_use	Used Micronutrients
f3_12a	Purchased Manure
f3_12a_use	Used Manure
f3_12b	Purchased Biofertilizer
f3_12b_use	Used Biofertilizer
f3_12d	Purchased Castor Cake
f3_12d_use	Used Castor Cake

Notes: The panels above detail the variables used to compute aggregate indices. The 'Index of Input Recommendations' combines all panels and their constituent variables. Each index consists of the average of the z-scores for each component of the index, with the control group mean and standard deviation as reference. The component scores are then weighted by the inverse of the covariance matrix of the components as in Anderson (2008). Note, no pesticides were recommended for wheat cultivation.

Appendix A14. Knowledge index questions

The following are the agricultural questions used to gauge agricultural knowledge.

A. General
Q1. Which essential plant nutrients does urea contain?
Q2. Which is the best fertilizer for adding phosphorus in the soil?
Q3. If you had the option of using 50 kg (1 bag) of diammonium phosphate (DAP) or 50 kg (1 bag) of 20–20-20 grade
Q4. Which is the best fertilizer for adding potash in the soil?
Q5. If you had the option of using 50 kg (1 bag) of muriate of potash or 50 kg (1 bag) of 12–32-36 grade NPK fertilizer,
Q6. Which is the best fertilizer for adding sulphur in the soil?
Q7. If you had the option of using 50 kg of ammonium sulphate or 50 kg of sulphur fertilizer, which would you use to add
Q8. When mixing pesticides in the pump, do you add powder concentrate or liquid concentrate first?
B. Cotton-Related Questions
Q1. What types of pests does BT cotton provide resistance against?
Q2. Do you know what a pheromone trap is?
Q3. What is the use of a pheromone trap in agriculture?
Q4. After the flowering stage, which type of fertilizers should you spray for good development of bolls and to stop falling
Q5. During the flowering stage, which fertillizer should you spray to stop yellowing of plants and to increase production?
Q6. Monocrotophos is used to control which pests?
Q7. Have you heard of Imidachlorpid (or Confidor/Tatamida/Imidagold)
Q8. Imidachlorpid (or Confidor/Tatamida/Imidagold) is used to control which pests?
Q9. Have you heard of acetamaprid?
Q10. Acetamaprid is used to control which pests?
Q11. Which pests is acephate pesticide used to control ?
Q12. If you had the option of using 1 L of prophanophos or 1 L of monocrotophos to treat Mealybug in cotton, which
Q13. If you had the option of using 1 L of acetamaprid or 1 L of monocrotophos to treat Whitefly in cotton, which
Q14. If you had the option of using 1 L of imidachlorpid or 1 L of monocrotophos to treat Leaf Curl or Aphid in
Q15. If you had the option of using 1 L of dithan or 1 L of monocrotophos to treat Wilt disease in cotton, which would
Q16. Which fungus or bio-product can be used with compost as a seed treatment or soil application to control Wilt disease?
C. Wheat Related Questions
Q1. What is the ideal time period for sowing of wheat?
Q2. For those practicing late sowing, wheat crop should be planted by when at the latest? Q3. Which disease affects the grain quality, and ultimately the price of wheat grains
Q4. Which variety of wheat is recommended in Gujarat for those practicing late sowing? Q5. What is the recommended dose of nitrogen in irrigated wheat?
Q6. What is the recommended dose of phosphorus in irrigated wheat?
Q7. After the first irrigation at the time of sowing, when should the next irrigation for wheat take place?
D. Cumin -Related Questions
Q1. Which recommended varieties of cumin are resistant to wilt? Q2. What is the best time for planting cumin?
Q3. What should be done to cumin seeds before sowing to prevent fungal diseases? Q4. What is the recommended dose of nitrogen for cumin?
Q5. Which fungicide is used to control the harmful effects of Wilt disease in cumin?
Q6. If you had the option of 1 kg of mancozeb or 1 L of monocrotophos, which would you use to treat Wilt disease in
Q7. If you had the option of 1 kg of sulphur or 1 L of monocrotophos, which would you use to treat powdery mildew in
Q8. Which herbicide is used to control weed growth in cumin?
Q9. Which fungus or bio-product can be used as a seed treatment or soil application to control Wilt disease in cumin?

Appendix A15. Conceptual Framework: Returns to Seeking Information

Information Exchange between Peer Farmers

A number of studies suggest that social learning induces technology adoption in an agricultural context.[32] However, experimental work suggests the propensity of farmers to discuss their agriculture with peers may in part be determined by the availability of valuable information.[33] To aid the interpretation of empirical results that follow, I present a simple conceptual framework describing how a farmer's decision to seek out agricultural information from their peers may change in response to the introduction of external information.

I consider the case where farmer *i* is deciding whether they should spend some time, s_j, with their agriculture peer *j*.[34] Both farmer *i* and peer *j* have an information endowment, v_i and v_j, respectively, that consists of either 'external' (t) information or 'local' (n) information: i.e. $v_i \in \{t, n\}$ and $v_j \in \{t, n\}$. Local information here consists of a farmer's own experiences about the choice of inputs or how the dosage of an input produces varying outputs given one's production conditions, whereas external information consists of expert advice regarding input intensity or the choice of inputs.

The Introduction of AO

Prior to the introduction of AO, I assume farmers only have access to local information – i.e. $(v_i, v_j) = (n, n)$ – and that exchange is driven by complementarities that result in social learning. For example, farmers with similar production conditions may share their experiences of the dosage response of an input, allowing them to better understand the shape of their production function. Put otherwise, where the benefit of sharing information, $H(s_j; v_i, v_j)$ is a function of the exogenously given information endowments, v_i and v_j, and the time spent interacting s_j, there is a return to the exchange of local information: $H_s(s_j; n, n) > 0$.[35] Additionally, farmer *i* incurs a convex cost in order to interact with their peer, $c(s_j).c'(s) > c''(s) > 0$, $c(0)$

The introduction of AO produces exogenous variation in the availability of external information (t). Farmer *i* and/or peer *j* may now be able to have a back and forth about the dosage response of an input with an expert instead of (or in addition to) a peer. Whether such external information is a complement or substitute to local information then determines how farmer *i* will pick s_j. More generally, for a peer group G with k peers, a farmer with a fixed endowment of social time, E^s, solves:

$$\max_{s_j \forall j \in G} \sum_{j=1}^{k} \left[H\left(s_j; v_i, v_j\right) - c\left(s_j\right) \right] s.t. \sum_{j=1}^{k} s_j \leq E^s \tag{3}$$

The first order condition for peer *j* implies that the marginal return to s_j given different information endowments, $H_s(t, n), H_s(n, n), H_s(n, t)$, and $H_s(t, t)$ determines how farmer *i* chooses s_j.[36] For example, consider the case where farmer *i* is randomized into the treatment group, while peer *j* is not, and now has access to external information (t). If external information is a perfect substitute for the benefits of local information exchange, then farmer *i* will set s_j, crowding out peer interactions. If, instead, $H_s(t,n) > H_s(n,n) > 0$, implying that not only are the information types complements, but that the marginal return to interacting is higher, then farmer *i* will increase s_j relative to the pre-treatment level.[37] Similarly, if there are complementarities between peers assigned to the treatment group, this could either crowd-in $(H_s(t, t) > H_s(n, n) > 0)$ or out $H_s(n, n) > H_s(t, t) \geq 0$ peer interactions.

Access to AO may also generate asymmetric returns to information exchange. Even where external information is a substitute for the knowledge generated by peers with local information, access to AO may also provide access to previously unavailable and valuable information (e.g. a new method for addressing pests). In such a case, if farmer *i* is randomized into the treatment but peer *j* is not, then there is no benefit to farmer *i* interacting with peer *j*, but peer *j* may want access to the new information available to farmer *i*. Particularly given the non-rival nature of information, it seems likely that farmer *i* would continue to share information even if it did not influence their own knowledge or production. In addition, such sharing may well produce non-pecuniary benefits such as influencing farmer *i*'s status in the village.

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[32] For a review, see Foster and Rosenzweig (2010).

[33] Duflo et al. (2005) find that peers of farmers invited to a demonstration of the use of fertilizer were more likely to adopt the fertilizer than the peers of farmers in the control group. Yet, information collected by the authors suggest that farmers do not organically share information about agricultural production outside the context of their experiment.

[34] s_j could be an interaction entirely intended to discuss agriculture or additional time spent during an interaction otherwise unrelated to the strategic exchange of information.

[35] Additionally, I assume that H is concave in s: $H_{ss}(s_j; n, n) < 0$ and that $H(0; n, n) = 0$.

[36] As described previously, the notation here follows the convention $H(v_i, v_j)$, so $H(t, n)$ is $H(v_i = t, v_j = n)$. H_s denotes the derivative with respect to s_j.

[37] Assuming E^s is not binding.

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