# Inefficiency in Agricultural Production: Do Information Frictions Matter? *

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**Abstract**

In settings with variable local geographic conditions, the impact of interventions can be confounded by heterogeneity in farmers' ability to convert input into output. This paper introduces a novel plot-level measure of agricultural inefficiency that accounts for both input use and geographic endowments, enabling a more accurate assessment of intervention impacts compared to the conventional choice of actual yield as the outcome variable. We use this measure to evaluate a mobile phone-based agricultural extension program in rural Bangladesh. We observe that, in treated villages, after intervention, there is a 50 percent reduction in plot-level inefficiency, driven by plots that used rainfed water for cultivation. We found these effects to be driven by increased input usage by farmers doing rainfed farming. In addition, we document that the intervention benefits geographically remote farmers more, and find significant cross-community spillovers through geographic ties.

**JEL Codes:** D83, O13, Q16.
**Keywords:** Agriculture, Heterogeneity, Inefficiency, Extension, ICT, Networks.

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# 1 Introduction

A body of research attributes income differences between rich and poor countries to gaps in agricultural productivity largely driven by non-geographical factors (Gollin et al., 2002, 2004, 2007; Restuccia et al., 2008; Adamopoulos and Restuccia, 2022).[1] An important factor that explains this productivity gap is the lack of adoption of new technology and the use of traditional agricultural practices in poor countries (Foster and Rosenzweig, 2010; Suri, 2011). Evidence shows that information friction can partially explain why farmers may not adopt new technology or may not use it effectively (Magruder, 2018).[2]

Although information frictions are known to contribute to agricultural productivity gaps, the critical role of geographical heterogeneity in conjunction with these frictions remains underexplored. As Suri (2011) notes, farmers face heterogeneous adoption costs often rooted in microgeographic differences. In environments with variable local conditions, we argue that the actual yield is an inadequate metric to assess the effectiveness of information interventions, as this heterogeneity can obscure substantial variation in the farmers' ability to convert input into output.

This paper leverages a novel mobile phone-based agricultural extension program, along with unique geocoded, nationally representative, plot-level panel data, to introduce a new measure of agricultural inefficiency. The approach allows for a more precise evaluation of the impacts of the intervention by taking into account both geographic endowments and input applications. In particular, we examine the impact of a government-led extension program, the Agricultural Call Center Intervention (ACCI), launched in Bangladesh in 2014. The intervention allowed farmers to consult experts at any stage of crop production and was aimed at providing timely, need-based, and farmer-specific services. Our key outcome variable is a novel plot-specific measure of agricultural *inefficiency* constructed as the gap between the observed yield and the potential agroclimatically feasible yield, conditional on the reported use of inputs. We estimate potential yields using high-resolution data from the FAO's Global Agro-Ecological Zones project. We combine this with spatiotemporal variation in access to mobile phone services across villages and temporal variation in the timing of the intervention to identify the impacts of the intervention.

We find that access to the intervention reduces inefficiency by approximately 50

[1] Evidence suggests that policies and institutions in poorer countries play a critical role in restricting economic choices made in the agriculture sector that misallocate resources across farms (Adamopoulos and Restuccia, 2014). Land redistribution reforms, tenancy reforms, progressive land taxes, and input subsidies to small landholders are examples of policies that distort the farm size distribution in poor and developing countries (Adamopoulos and Restuccia, 2014). Some recent papers that have studied misallocation due to distortions in land market institutions are (Restuccia and Santaeulalia-Llopis, 2017; Chen, 2017; Gottlieb and Grobovšek, 2019; Adamopoulos and Restuccia, 2020).

[2] Informational inefficiency is even more detrimental to agricultural outcomes if climate change makes future states of the world more unpredictable (Zilberman et al., 2012).

percent, with effects concentrated among rainfed plots. In contrast, there is no significant impact on farmers using tractors or intensive input bundles. We also document the role of distance-based networks and geographic spillovers in modulating the impact of the intervention. In villages with phone service, compared to better-connected households, the inefficiency of geographically remote households differentially decreased after the intervention. At the same time, their actual yields increased. These improvements are not driven by changes in the use of rainfed farming or tractors, suggesting that the gains come from the more efficient use of the existing mix of these inputs after the intervention. We also find that the inefficiency of a household decreases more if it is geographically closer to a community that received the intervention, indicating that the spillover effects of the intervention strengthen with proximity to treated communities.

In terms of the mechanism of these results, we find that in villages with mobile phone service, farmers with rainfed irrigation intensified input use per hectare after the intervention. This included a higher use of both fertilizer and pesticide, along with an increase in the amount of family labor used on farms. However, we find that farmers who use tractors in their plots reduced their use of both fertilizer and pesticide after the intervention, although they increased their expenses in seed purchases.

Our paper makes three contributions to the existing literature. First, our results highlight the importance of geographical heterogeneity in evaluating the impact of agricultural interventions. We build on the influential literature on agricultural inefficiency and misallocation, which has made novel efforts to study the role of geography and natural endowments as important determinants of agricultural productivity and economic growth (Henderson et al., 2001; Adamopoulos and Restuccia, 2022).[3] Our approach extends this work by incorporating microgeographic variation into the evaluation of agricultural intervention impacts at the plot level. It is interesting to note that although we find a significant reduction of inefficiency post-intervention, we do not get any statistically significant results when using actual yield as the dependent variable. Furthermore, our estimates of inefficiency reduction are higher than those of the impact of ICT-enabled extension services on the actual yield documented in the literature.

Second, we contribute to the literature by studying the role of remoteness and social networks in agricultural productivity. The role of social ties in amplifying the effectiveness of extension efforts is well recognized in the literature (Banerjee et al., 2013; BenYishay and Mobarak, 2018; Breza et al., 2019; Cheng, 2021; Beaman et al., 2021). The

[3]Using the high-resolution gridded micro-geography data made available by the Food and Agricultural Organization (FAO) Global Agro-Ecological Zones (GAEZ) project (that we also use for our analysis), Adamopoulos and Restuccia (2022) perform a cross-country analysis and find that there are virtually no aggregate differences in land quality between rich and poor countries. They find that the agricultural yield gap between top- and bottom-income decile countries almost disappears from 214 percent to 5 percent if the crops were grown at the potential yield. This suggests that the higher agricultural inefficiency of poor countries is mainly due to non-geographical factors, which hinder farmers from achieving the full potential of their farmlands' natural endowments.

literature also argues for the ease of communication between agents who live close to each other, making social ties more likely between geographically proximate agents (Helsley and Zenou, 2014; Kim et al., 2023). This highlights the role of geographic centrality in economic development, also documented in the literature elsewhere (Donaldson and Hornbeck, 2016; Aggarwal, 2018; Shamdasani, 2021). We argue that the advantage of ICT-based interventions is the reduced need to be geographically central in terms of access to information. In this regard, we provide evidence that the intervention differentially benefits geographically remote agents more, whose information needs are otherwise unfulfilled by traditional extension services. However, the diffusion of information via networks remains relevant as we document significant cross-community spillover effects through geographic ties.

Finally, the paper also contributes to the literature that studies the effectiveness of Information and Communication Technology (ICT) based interventions in agriculture. A large body of literature has already studied the role of ICT-based interventions in agriculture (see Aker (2011) and Aker et al. (2016) for an in-depth review). However, the associated evidence is quite mixed. While some find positive productivity impacts of mobile phone-based interventions (Casaburi et al., 2014; Gupta et al., 2024), others find none (Fafchamps and Minten, 2012; Cole and Fernando, 2020). In this paper, we investigate the effectiveness of a government-sponsored large-scale mobile phone-based intervention in Bangladesh. Although similar studies exist in India (e.g. Gupta et al., 2024), we are the first to provide evidence for this type of intervention in Bangladesh. As we argue later, ex-ante, we expect the effectiveness of such intervention to be significantly different in Bangladesh, as compared to India, due to Bangladesh being more linguistically homogeneous than India.

The remainder of this paper is organized as follows. Section 2 provides the contextual background of our study. Section 3 discusses the empirical design of our study, which includes a description of the data sources, some descriptive statistics, and a description of our empirical strategy. We present our results in sections 4 and 5. We provide an array of robustness checks in Section 6. Finally, Section 7 summarizes our main findings and concludes.

# 2 Background

## 2.1 The Agricultural Call Center Intervention

Despite rapid economic growth in recent decades, Bangladesh remains a largely rural country. More than two-thirds of the population resides in rural areas and is primarily engaged in agricultural activities (Asian Development Bank, 2023). Agriculture accounts for 40 percent of the overall employment in Bangladesh (Asian Development Bank, 2023). Rice occupies the dominant place in Bangladesh's agriculture and is cultivated almost the entire year across all three agricultural seasons: *Aman*, or the monsoon season; *Boro*, or the winter season; and *Aus*, the intermediate summer season. It is also the staple crop, accounting for around 80 percent of the cultivated area (Asian Development Bank, 2023).

Although Bangladesh is the third largest rice producer globally, compared to other major rice-producing countries, rice productivity in the country is relatively low, around 4.9 tonnes per hectare (see Figure 1 for a comparison with other major rice-producing countries). Given the centrality of rice in Bangladesh's rural economy and the dominance of small-scale agriculture, this low rice productivity threatens the food security and livelihoods of the large agriculture-dependent rural population in the country. Small-holder rice producers face structural limitations in access to information about the availability of new modern seed varieties and agrochemicals (Sarker et al., 2021). Bangladeshi farmers still rely on traditional farming practices, and the use of modern agricultural practices such as soil testing and the use of new varieties, fertilizers, and pesticides remains low (Sarker et al., 2021).

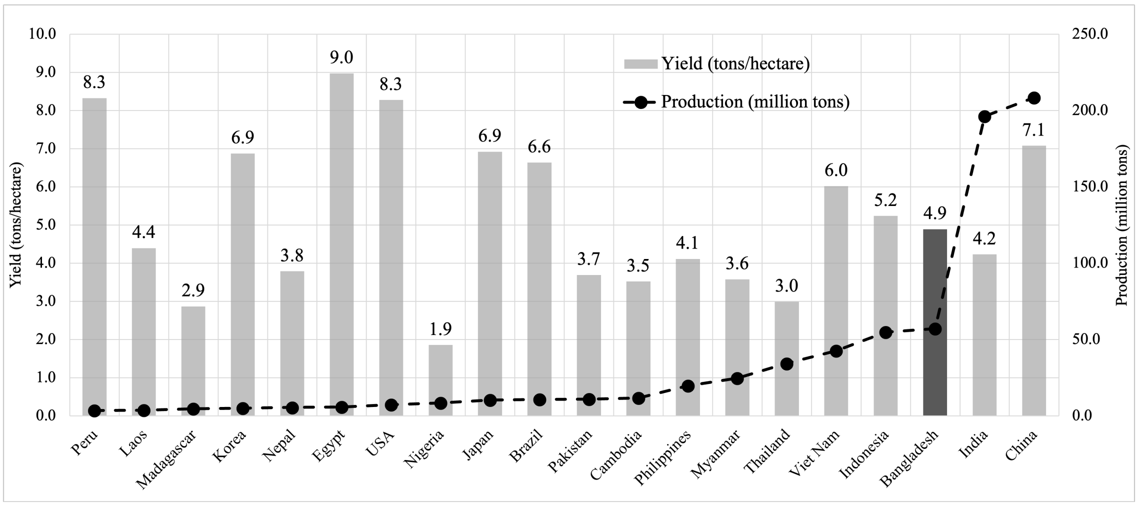



Figure 1: Rice yield of top 20 rice producers

*Notes:* Figure plots the rice yield (bars) and total rice production (dashed line) for the top 20 rice producers globally for the year 2022. Based on data from FAOSTAT obtained from `https://www.fao.org/faostat/en/home`.

Like other developing countries around the world, Bangladesh has also seen a dramatic increase in mobile phone coverage in recent decades (Figure 2). From the negligible coverage of cell phones in the early 2000s, almost all households in Bangladesh reported having access to a mobile phone in 2022 (Bangladesh Bureau of Statistics, 2022). Taking advantage of the widespread dissemination of mobile phone technology in rural Bangladesh, the government-run Agriculture Information Service (AIS) launched a mobile phone-based agricultural helpline in June 2014 (Huber and Davis, 2017; Department of Agricultural Extension, 2018). The AIS established *Krishi Call Centers* (Agricultural Call Centers), where farmers, at a nominal cost of 25 paisa/minute, call and consult experts on various aspects of agriculture (Huber and Davis, 2017).

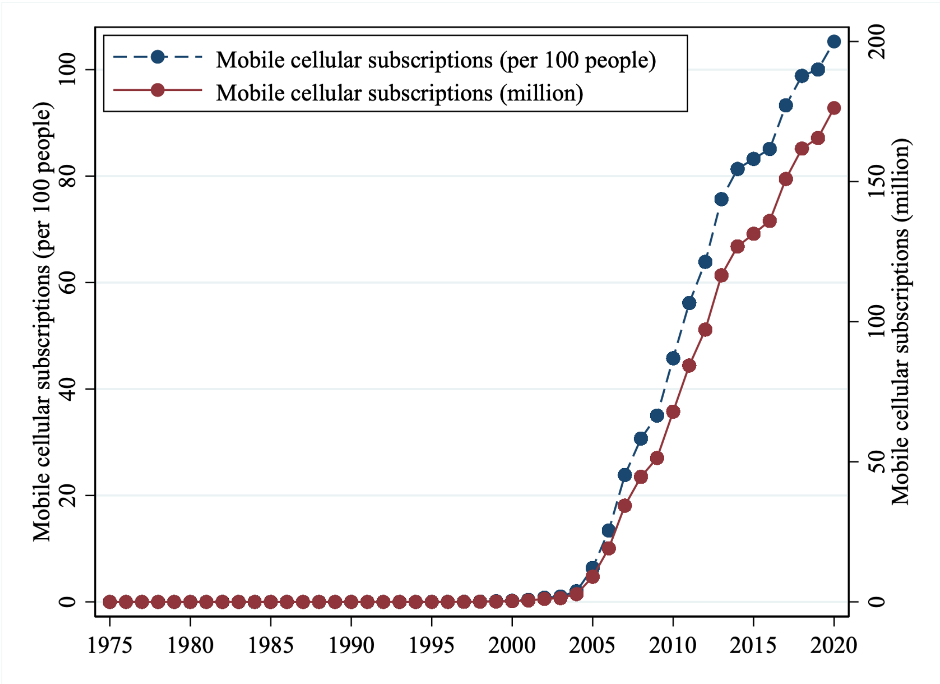



Figure 2: Trends in mobile phone coverage in Bangladesh

*Notes:* Figure plots the trends in overall and per 100 persons mobile phone subscriptions in Bangladesh, as per the data obtained from the World Bank World Development Indicators database.

The program was successful and reached more than 30,000 households within a year of its launch in 2014 (Huber and Davis, 2017). The need of farmers for expert advice and the impact of deep penetration of mobile services is reflected in the fact that around 1 lakh solutions/advice were disbursed to farmers via the Krishi Call Centers as of August 2018.[4] Although we were unable to gather actual data on the usage of the intervention, based on our communications with Bangladeshi officials, farmers would generally seek information on modern agricultural inputs, including advice on diseases and pest management on the farm. These usage patterns are consistent with what is observed in a similar intervention in India (Kumar et al., 2021).

## 2.2 Potential for Telecommunication Extension Services

Farmers have different information needs based on the realization of the state of the world at different stages of crop production. Although farmers may rely on experience and social connections to serve such needs, the quality and relevance of such information

[4]As reported on the official website of the Agriculture Information Service (AIS) Bangladesh. See http://www.ais.gov.bd/site/page/e24c72ff-aed9-4497-a4d3-87ef07bc33c6/-, for details.

would depend on the set of information of other farmers in the village (Bandiera and Rasul, 2006; Deichmann et al., 2016). Agricultural extension can play a critical role in updating the information set of farmers in the village (Anderson and Feder, 2004; Norton and Alwang, 2020). Extension services can be critical to serve information needs and raise awareness of modern practices among farmers (Anderson and Feder, 2004). Even if farmers are using modern inputs such as fertilizers and pesticides, evidence shows that farmers can make errors in the timing and use of such inputs (Islam and Beg, 2021). Extension agents can help farmers guide the correct usage of modern inputs (Anderson and Feder, 2007; Sheahan and Barrett, 2017; Islam and Beg, 2021).

However, in-person agricultural extension services have limited outreach and are expensive to run and operate (Fabregas et al., 2019b). In addition, in-person extension services are primarily operated by the public sector and are fraught with inefficiencies (Aker, 2011; Cole and Fernando, 2020; Alam and Kijima, 2024). The widespread access to mobile phones and telecommunication services provides a cheap and effective way to reach distant farmers (Magruder, 2018; Fabregas et al., 2019b). Although traditional in-person extension may not be available to all farmers at all times, mobile phone-based agricultural extension programs can provide farmers with timely and need-specific information services at different stages of crop production (Aker, 2011; Duncombe, 2016). Experimental evidence on the effects of mobile extension services on modern technology adoption and agricultural outcomes has been encouraging (Casaburi et al., 2014; Aker and Ksoll, 2016; Fu and Akter, 2016; Cole and Fernando, 2020; Campenhout, 2021).

In addition, mobile phones also allow for greater information exchange via social networks (Norton and Alwang, 2020). The importance of existing social ties in the success of agricultural extension interventions is well documented (Breza et al., 2019; Cheng, 2021). Learning from social ties was even more effective than learning from extension agents (Krishnan and Patnam, 2013). The literature documents a complementarity between the delivery of information through extension services and the dissemination of the same through existing social networks (BenYishay and Mobarak, 2018). Studies have shown that extension agents can use this complementarity to design cost-effective interventions to deliver information to a larger set of agents in a limited time and budget (Akbarpour et al., 2020; Beaman et al., 2021; Banerjee et al., 2023).

However, the literature also documents that the effectiveness of such interventions in reaching a population with heterogeneous information needs may be limited (Chakraborty, 2024). This is particularly true if the cost and benefits of adopting some practices differ from one agent to another (as discussed in Suri (2011)) or the speed of learning relies on population heterogeneity (as documented in Munshi (2004)). The results of this literature highlight the importance of investigating the possible heterogeneity in social learning in the amplification of any extension efforts.

In light of the evidence from the literature discussed above, it is thus necessary to assess the ground-level impacts of large-scale ICT-based extension programs such as Bangladesh's Agricultural Call Center Intervention (ACCI). Although there are studies documenting the impact of a similar government-sponsored large-scale mobile phone extension program in India, there are no studies for Bangladesh.[5] An important feature of the Indian program is that the language in which agricultural advice was offered varied according to the official language of each Indian state. Gupta et al. (2024) document that this can lead to a barrier if there is a mismatch between the official language and the languages spoken and understood by subpopulations within a state. Unlike India, this additional friction does not exist in Bangladesh as the advice was given in *Bengali*, the official language of Bangladesh, which is spoken and understood by almost the entire population of the country.

# 3 Empirical Design

## 3.1 The Bangladesh Integrated Household Survey (BIHS)

Our primary data comes from Bangladesh Integrated Household Surveys (BIHS).[6] The BIHS, funded and implemented by the United States Agency for International Development (USAID) and the International Food Policy Research Institute (IFPRI), collects detailed information on all aspects of the social and economic lives of households in rural Bangladesh. The BIHS is based on a multistage stratified sampling procedure and is nationally representative and representative of the seven administrative divisions of rural Bangladesh.[7] The surveys were conducted in three rounds: 2011-2012, 2015, and 2018-2019. The first two rounds covered 6,500 households across 325 Primary Sampling Units. The third round covered the same number of PSUs and could resample 5,604 of the original households.

A unique feature of the BIHS is the access to the geocoded location of the surveyed households. Harmonized survey data provide the latitude and longitude of the sampled households with a 2-kilometer offset to maintain anonymity. This information is critical for us both from the point of view of constructing the inefficiency measure and the empirical strategy.[8] Our primary focus is the roster of all land and water bodies owned by households and the agricultural module of the survey. The roaster provides us with

[5] See, for example, Gupta et al. (2024) for evidence on the Indian mobile phone-based extension program.

[6] These surveys are publicly available and can be found at `https://dataverse.harvard.edu/dataverse/IFPRI/?q=Bangladesh+Integrated+Household+Survey`

[7] The seven administrative divisions are Barisal, Chittagong, Dhaka, Khulna, Rajshahi, Rangpur, and Sylhet.

[8] The 2-kilometer random offset to actual household locations should not bias our estimates, as it is time-invariant and uncorrelated with the intervention.

information on all the agricultural plots operated by the household, including their size, operational status, and distance from the place of residence. The agricultural module collects plot-level information on cultivated crops, planted areas, variety, and types. It also collects detailed information on the inputs used and the quantity harvested. Of the total plots grown during the three rounds, households reported cultivating paddy in 71 percent of the plots. Given that rice or paddy is a major staple crop in Bangladesh and the dominant crop in BIHS, we focus only on it.[9]

The BIHS also provides detailed information on the access of households to agricultural extension services and various input subsidies provided by the government of Bangladesh. The extension module collects responses about extension agent visits, the type of advice given for different inputs, and whether it was useful. The module also records whether the household received an input subsidy from the government. In addition to information on cultivation and access to extension services, we use data from modules on household composition, access to various facilities, housing conditions, assets, food and non-food consumption, non-farm enterprises, loans and borrowings, and self-reported economic shocks.

Another attractive feature of the BIHS is the community module of the survey, which collects information on access to facilities for the villages sampled. The community module collects data on the availability of facilities such as roads, banks, police stations, and mobile and telephone networks, along with the year in which it was established.[10] Our empirical framework will particularly focus on the timing of the arrival of telephone and mobile services in the village.

## 3.2 Main Outcome Variable: Agricultural Inefficiency

Although rice productivity per unit of land is a natural choice for an outcome variable, it may not be the most appropriate metric for our analysis. Productivity differences between households reflect not only variations in natural endowments but also differences in input use. For example, a farmer cultivating poor-quality soil may achieve relatively high yields by adopting an intensive input mix, whereas another farmer operating on more favorable land may underperform due to suboptimal input use. This highlights that potential yields will vary between farmers, both due to natural conditions and input use. Moreover, the production possibility frontier may also shift in response to the intervention itself. Consequently, the potential yield a farmer can achieve, which is the relevant benchmark for assessing inefficiency, can change after intervention. Although farmer fixed effects can control for time-invariant unobserved

[9]We restrict our analysis to households that report cultivating rice and exclude those that do not produce paddy. This leaves us with approximately 40 percent of the surveyed households.

[10]Complete data for community facilities is available only for the second and third rounds of the BIHS. We use the community survey module for only the third round.

heterogeneity, meaningful comparisons would ideally require counterfactual estimates of potential yields that account for local agroclimatic conditions under varying input scenarios.

To make productivity comparisons meaningful, we utilize a counterfactual measure of potential yield that accounts for both geographic endowments and input bundles. We obtain these potential yield estimates from the Global Agro-Ecological Zones (GAEZ) dataset. The GAEZ database provides high-resolution, agroclimatically feasible yield estimates for four input combinations – rainfed-low, rainfed-high, irrigated-low, and irrigated-high – in each grid cell. These four potential yield estimates establish a production possibility frontier based on natural endowments and the actual input mix, against which actual productivity can be compared.[11] Furthermore, based on actual input choices, the frontier can also be allowed to change over time.

Our main outcome variable is a measure of inefficiency, defined as the gap between actual and potential yields at the plot level. To construct this measure, we combine household geolocation data (latitude and longitude) and plot-level input usage from the BIHS dataset with agro-climatically feasible potential yields from the Global Agro-Ecological Zones (GAEZ) dataset. Specifically, we match the geographic coordinates of each plot to the corresponding GAEZ grid cell and retrieve potential yields conditional on the observed input combinations. The resulting plot-specific potential yield reflects what could conceivably be produced given the natural endowment of the plot and the actual use of inputs. We then define inefficiency as the percentage difference between actual and potential yield:

$$\text{Inefficiency}_{ijcdst} = \left( \frac{\text{Potential Yield}_{ijcdst}}{\text{Actual Yield}_{ijcdst}} - 1 \right) \times 100 \tag{1}$$

where both potential and actual yields vary spatially and over seasons and years.

The potential yield for growing the same crop could vary for two reasons. First, with the same type of cultivation inputs, it could vary between different grid cells due to the differences in their geographical attributes. Second, potential yields can also be different for agricultural plots that lie within the same GAEZ grid cell but use different combinations of cultivation inputs. Different inputs to cultivation lead to different rates of various biophysical growth processes for a given crop, resulting in different maximum attainable yields. As a result, our measure of *Inefficiency* varies depending on both the geographical location of the agricultural plots and the actual input choices made by the farmers.

We consider two critical inputs in the construction of plot-level potential yield. The first input is the type of water supply, which is classified as rainfed or irrigated. The

[11] Appendix A for details on the GAEZ database. Also, see Adamopoulos and Restuccia (2022).

second input is the use of tractors, which we treat as a proxy for high-input farming. This choice is motivated by two reasons. First, tractors are a costly and versatile form of machinery that can be used at various stages of rice production, including soil preparation, seedling transplantation, spraying (which improves irrigation efficiency by reducing water and fertilizer use), harvesting, and postharvest transport. Their use is typically associated with commercial farming, rather than subsistence. For context, the price of a tractor ranged from 1 to 2.2 million Bangladeshi Takas in 2018, while the average per capita income was only 0.13 million Takas.[12] Second, while nearly all plots in our sample report the use of fertilizers (98.6%) and pesticides (86.7%), only a small share (8.35%) used tractors. Most (88.8%) used powertillers, which is a handheld machine that performs similar functions but with lower efficiency. This further supports the use of tractor usage as a meaningful indicator of high-input farming.

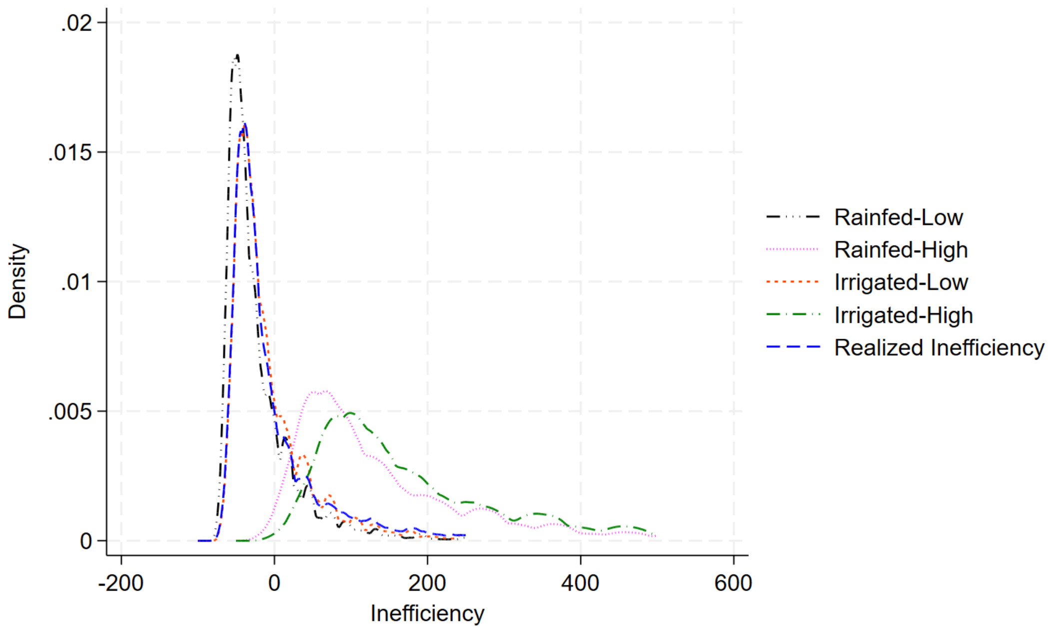



Figure 3: Variation in Inefficiency Densities

*Notes:* (1) The four possibilities for plot-level inefficiency correspond to the potential yield of four possible input combinations compared with the actual yield, assuming the same inputs for all plots. Whereas, the realized inefficiency corresponds to the comparison of actual yield with the potential yield as per the actual inputs usage on the plot. (2) The realized inefficiency distribution is a conservative estimate given our choice of "tractor-usage" as the proxy for a high level of complementary input usage. As evident in the figure, both its mean and spread would have been higher if more plots were classified as using "high" inputs. The mean and standard deviation for realized inefficiency are 15 and 167 percentage points, respectively. The mean for "low" inputs scenarios is $-13$ and 4 percentage points, whereas for "high" inputs cases, it is 182 and 238 percentage points for rainfed and irrigated water supply, respectively. While, the standard deviation for "low" inputs scenarios is 111 and 132 percentage points, whereas that for "high" inputs cases, it is 359 and 430 percentage points for rainfed and irrigated water supply, respectively.

[12]Sources: https://www.thedailystar.net/business/news/tractor-sales-drop-1835503 and the Bangladesh Bureau of Statistics (http://nsds.bbs.gov.bd/en).

Figure 3 shows the distribution of our inefficiency measure under different *hypothetical* input choices. The figure demonstrates how the same set of agricultural plots can face different levels of inefficiency due to differences in their corresponding input choices. In the figure, the distribution of realized inefficiency corresponds to the actual input choices made by farmers. As is evident in the figure, both the mean and the spread of inefficiency are higher in the case of high input usage. Our choice of having tractor usage as a proxy for high-yielding input seems to be a more conservative assumption, as the realized inefficiency distribution is closer to that of low-input scenarios with a mean of 15 and a standard deviation of 167 percentage points, respectively.

There are many plots where the actual yield is greater than the potential yield, resulting in a negative inefficiency measure. First, this could be because the farmer might be compensating for poorer natural endowments or lack of irrigation infrastructure or mechanization by overusing other inputs, such as fertilizer and pesticides. This might lead to higher productivity now at the cost of lower productivity in the future. Evidence from the literature suggests that Bangladeshi farmers use chemical fertilizers excessively (Islam and Beg, 2021). We will explore this in our discussion of mechanisms. Alternatively, we also check the robustness of our estimates after controlling for other input usage.

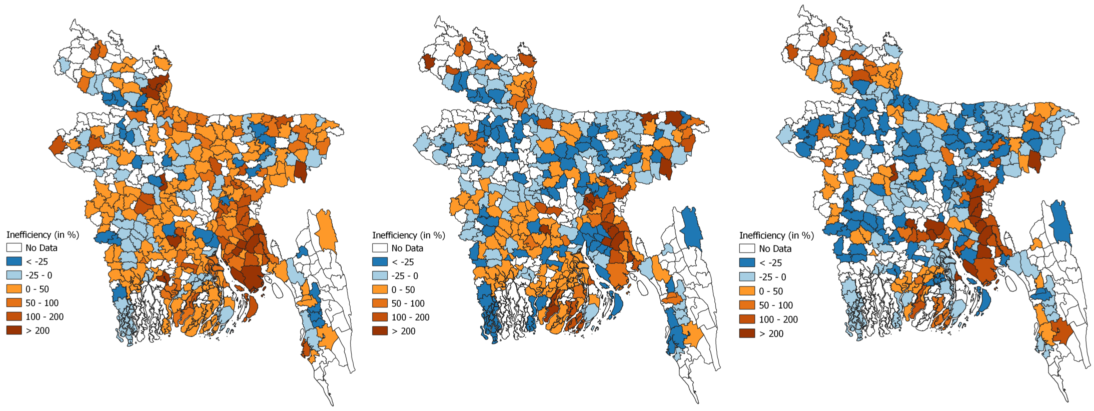
The second reason for having negative inefficiency values could be more mechanical, due to the way we assign potential yield to plots. For example, a plot might get assigned a rainfed-low input combination because they did not report using a tractor in the survey, but it is possible that they used other inputs, qualifying as high input usage. So, in this case, the negative inefficiency is due to the actual yield being compared to a lower, more conservative estimate of potential yield. To address this issue, we tested for the sensitivity of our estimates to the use of alternative input mixes for potential yield construction, which we report in the appendices.

Finally, even with the right assignment of input combination at the plot level, the geographical location of the farming plot could have a higher potential yield than the average potential yield reported at the GAEZ cell level. Given the large size of a GAEZ cell, around 8000 hectares for Bangladesh on average, there exists heterogeneity in land productivity (see footnote 26) for growing any crop within it (Sotelo, 2020). Thus, a plot with better land quality than the average land quality of the GAEZ cell in which it lies will be able to achieve a higher actual yield compared to the average GAEZ potential yield. We check the robustness of our estimates to this by assuming that the plot-level potential yields follow the independent and identically distributed Frećhet distribution and then compare the 90th percentile plot-level potential yield with the actual yield to measure plot-level inefficiency.[13] Details of the simulation procedure and the implied

[13]Historically, farmers positively select the land for cultivation and given the large size of a simulation plot (5 hectares compared to average plot size less than 1 hectares in data), it is a fair assumption to

parcel yield density can be found in Appendix B.

In figure 4, we look at the inefficiency measure aggregated at the village level as the simple average of the plot inefficiencies. Clearly, there has been a declining trend of inefficiency over the years, with a greater number of villages falling in the lower inefficiency brackets over time. For example, the share of villages with negative inefficiency (blue-colored) increased from 30 percent in 2011 to 54 percent in 2015 and 64 percent in 2018. The figure also shows the spatial variation of inefficiency in rice production in Bangladesh. One stark observation is that the villages along the eastern boundary and the coastal villages in the south-east have positive inefficiencies, which do not go down in the post-ACCI period as well.




(a) For survey year 2011 (b) For survey year 2015 (c) For survey year 2018

Figure 4: Village-level inefficiency over survey years using surveyed households

*Notes:* For each survey year, we calculate the village-level inefficiency by taking a simple average of plot-level inefficiency in a village. The "No Data" villages are the ones that were not a part of BIHS.

## 3.3 Enhanced Vegetation Index and Climate Data

We also use data on satellite-based gridded measures of green cover and vegetation coverage from NASA's MODIS instrument.[14] These indices are available at a very high spatial resolution of 250 meters for 16-day intervals. Although the Enhanced Vegetation Index (EVI) is not a direct measure of crop productivity, studies show that it correlates well with actual yields and can be a useful measure when actual data are not available (Jaafar and Ahmad, 2015). We use household geocodes to extract and aggregate EVI within a radius of 2 kilometers of each of the households.[15] We use this proxy measure to generate long-term event plots to test for parallel trends.

compare a higher percentile potential yield for measuring inefficiency.

[14] Publicly available from https://modis.gsfc.nasa.gov/data/dataprod/mod13.php.

[15] Given that household geo-location is randomly displaced by 2 kilometers, this procedure helps in averaging out measurement errors.

As time-varying weather conditions serve as an important input in the agricultural production process, we control for these in our regression specifications. We extract weather variables from the TerraClimate dataset.[16] TerraClimate provides global gridded monthly rainfall and temperature data from 1958 to 2020 with an approximately 4-kilometer spatial resolution. We use these global surfaces and the geo-location of BIHS sample clusters to calculate total seasonal rainfall and temperature for the three BIHS survey years.

### 3.4 Descriptive Statistics

Table 1: Summary Statistics for Key Variables over the Survey Years

| Variable | 2011 | 2015 | 2018 | Total |
|---|---|---|---|---|
| Inefficiency (in Percentages) | 28.070 | 9.061 | 1.028 | 14.683 |
| | (182.174) | (153.484) | (94.813) | (154.116) |
| Actual Yield (in Kilograms per Hectare) | 3586.791 | 4101.699 | 4194.39 | 3916.273 |
| | (1686.916) | (1632.24) | (1475.167) | (1638.473) |
| Phone Service in the Village (=1 if Yes) | 0.413 | 0.465 | 0.457 | 0.442 |
| | (0.492) | (0.499) | (0.498) | (0.497) |
| Used Rainfed Farming (=1 if Yes) | 0.327 | 0.311 | 0.281 | 0.309 |
| | (0.469) | (0.463) | (0.450) | (0.462) |
| Used Tractor (=1 if Yes) | 0.072 | 0.078 | 0.102 | 0.082 |
| | (0.258) | (0.268) | (0.303) | (0.274) |
| Plot Ownership (=1 if owned) | 0.562 | 0.594 | 0.572 | 0.575 |
| | (0.496) | (0.491) | (0.495) | (0.494) |
| Has Agricultural Subsidy Card (=1 if Yes) | 0.191 | 0.358 | 0.272 | 0.267 |
| | (0.393) | (0.479) | (0.445) | (0.442) |
| Minimum Temperature of the Village (in °C) | 18.054 | 17.364 | 17.709 | 17.737 |
| | (5.347) | (5.040) | (4.206) | (4.974) |
| Maximum Temperature of the Village (in °C) | 29.926 | 29.092 | 29.080 | 29.429 |
| | (3.160) | (4.836) | (3.459) | (3.881) |
| Average Yearly Rainfall of the Village (in mm) | 299.255 | 165.936 | 240.471 | 240.087 |
| | (506.818) | (243.298) | (247.398) | (378.904) |
| Observations | 11254 | 9018 | 7320 | 27592 |

*Notes:* The table reports the means for the main dependent, explanatory, and control variables employed in our analysis. Standard deviations are in parentheses. The values are for observations restricted to non-missing values of all the variables reported here. The variables *Inefficiency*, *Actual Yield*, *Used Rainfed Farming*, *Used Tractor*, and *Plot Ownership* are captured at the plot level. *Agricultural Subsidy Card* dummy is captured at the household level. Weather measures are captured at the village level.

Let us now look at the trend of some of our key variables over time. Table 1 presents the descriptive statistics of key variables for the three years of the survey. In general, we observe a declining trend in the inefficiency measure and an increase in average rice

[16] Publicly available from `https://www.climatologylab.org/terraclimate.html`.

yields in Bangladesh. These trends are consistent with Figure 4. Around 44 percent of the villages in our sample report the availability of phone service. In terms of household and plot characteristics, about one-third of households report practicing rainfed farming. The reported machine use is low, with only 8 percent of households reporting tractor use. Finally, 27 percent of households report having an agricultural subsidy card, which allows them to purchase input at government-subsidized prices. These statistics highlight that the average inefficiency in rice production has been reduced even with relatively low levels of mechanization, rainfed irrigation, and limited coverage of input subsidies. In the next section, we discuss how the ACCI contributed to the observed trends in rice productivity and inefficiency.

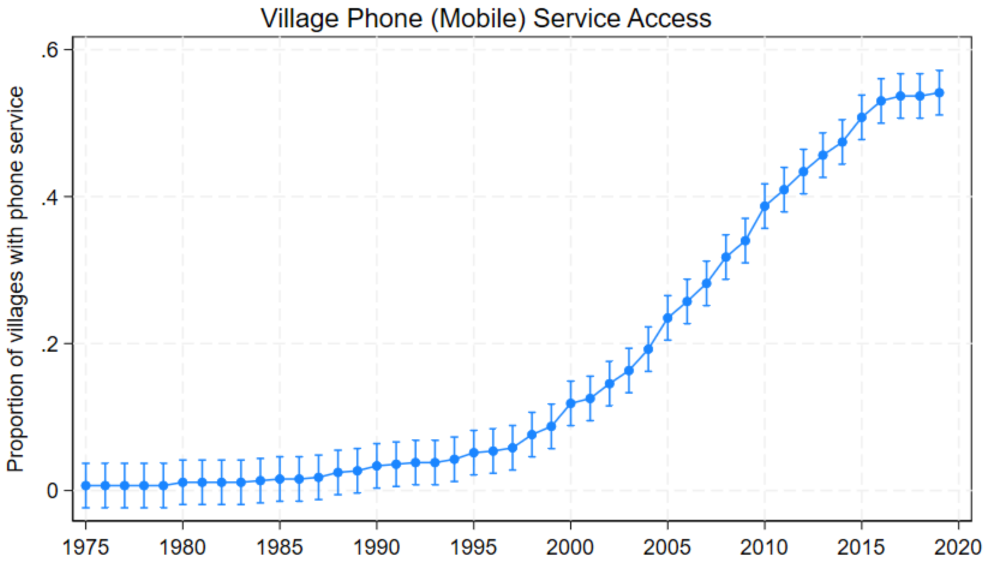



Figure 5: Telephone (or mobile phone) coverage in the surveyed villages

*Source:* Based on the community survey module for the third round of BIHS.

Figure 5 shows the trend in phone coverage in BIHS villages over time. As we can see, similar to Figure 2, the BIHS sample communities have also reported a rapid increase in access to phone services over time, starting in the early 2000s. However, during the survey years, the overall access has remained mostly stable between 41-47 percent. This indicates that the access to the ACCI did not vary much for these villages during the survey round. Therefore, the spatial dimension of this access is more important for our analysis than the temporal dimension. As it remains possible that communities improved their access to phone services as a response to the intervention, in the Appendix D we also demonstrate the robustness of our results, keeping access to phone services fixed at the baseline.

## 3.5 Empirical Strategy

### 3.5.1 Identifying the Impact of the Intervention on Agricultural Outcomes

We start with the canonical difference-in-differences (DID) specification to identify the impact of the Agricultural Call Center Intervention (ACCI) on plot-level outcomes:

$$\begin{aligned}\text{Outcome}_{ijcdpst} =& a_0 + a_2\text{Phone Service}_c \times \text{Post ACCI}_t + a_3 X_{ijcdt} + \\ & \sigma_i + \delta_p + \phi_s + \lambda_t + \psi_d \times \lambda_t + \varepsilon_{ijcdpst}\end{aligned} \tag{2}$$

where $Outcome_{ijcdpst}$ is the outcome for agricultural plot $j$, cultivated by household $i$ from community $c$ of division $d$ at year $t$ for season $s$ and crop-type $p$. We define *Phone Service*$_c$ as a dummy that indicates whether the community $c$ reported having phone service at the baseline (i.e. in 2011). *Post ACCI*$_t$ is the time dummy that captures whether the survey year $t$ is post-introduction of the Agricultural Call Center Intervention. Note that for this specification, we consider the phone access to be fixed at the baseline and remove all communities that received phone service in 2015 and 2018.

The levels of both *Phone Service*$_c$ and *Post ACCI*$_t$ are omitted from the specification since the regression includes fixed effects for households ($\sigma_i$) and years ($\lambda_t$). The specification also includes $\delta_p$ and $\phi_s$ as fixed effects of crop type and season, respectively. It also includes the interaction of fixed effects of divisions ($\psi_d$) with fixed effects of year ($\lambda_t$) to control for characteristics that vary over time at the division level. In the specification, $X_{ijcdt}$ controls for some time-varying observable characteristics (such as weather), with $\epsilon_{ijpst}$ being the random error in the regression. The coefficient $a_2$ captures the difference in the average outcome between communities with and without access to phone service in the baseline, before and after the intervention. If the intervention improved farmers' productivity, we would expect a decrease in the inefficiency measure, leading to $a_2 < 0$ with our inefficiency measure as the outcome variable.

Building on the specification (2), we define a second model in which we use data from all communities in estimation. Consider the following DID equation:

$$\begin{aligned}\text{Outcome}_{ijcdpst} =& b_0 + b_1\text{Phone Service}_{cdt} + b_2\text{Phone Service}_{cdt} \times \text{Post ACCI}_t \\ & + b_3 X_{ijcdt} + \sigma_i + \delta_p + \phi_s + \lambda_t + \psi_d \times \lambda_t + \epsilon_{ijcdpst}\end{aligned} \tag{3}$$

where the key difference is that *Phone Service*$_{cdt}$ dummy now also varies with the year of the survey to capture improving access over time. All other variables are defined as before. In this specification, only the level term of Post ACCI$_t$ is omitted due to collinearity with year-fixed effects. As before, we expect $b_2 < 0$ with our measure of inefficiency as the outcome variable, implying that the intervention led to lower inefficiency in rice production.

#### 3.5.2 Exploring the Heterogeneity in the Impact by Input Usage

In order to examine whether the effect of ACCI varies differentially by input use, we exploit the spatiotemporal variation in the plot-level input usage of the households, in addition to the spatiotemporal variation in community-level exposure to phone services and the temporal variation in the introduction of the ACCI. In particular, we use the following triple-differences specification:

$$\begin{aligned}\text{Outcome}_{ijcdpst} = {} & \alpha_0 + \alpha_1 \text{Phone Service}_{cdt} + \alpha_2 \text{Input}_{ijcdt} + \alpha_3 \text{Phone Service}_{cdt} \times \text{Input}_{ijcdt} \\ & + \alpha_4 \text{Phone Service}_{cdt} \times \text{Post ACCI}_t + \alpha_5 \text{Input}_{ijcdt} \times \text{Post ACCI}_t \\ & + \alpha_6 \text{Phone Service}_{cdt} \times \text{Input}_{ijcdt} \times \text{Post ACCI}_t + \alpha_7 X_{ijcdt} \\ & + \sigma_i + \delta_p + \phi_s + \lambda_t + \psi_d \times \lambda_t + \epsilon'_{ijcdpst} \end{aligned} \tag{4}$$

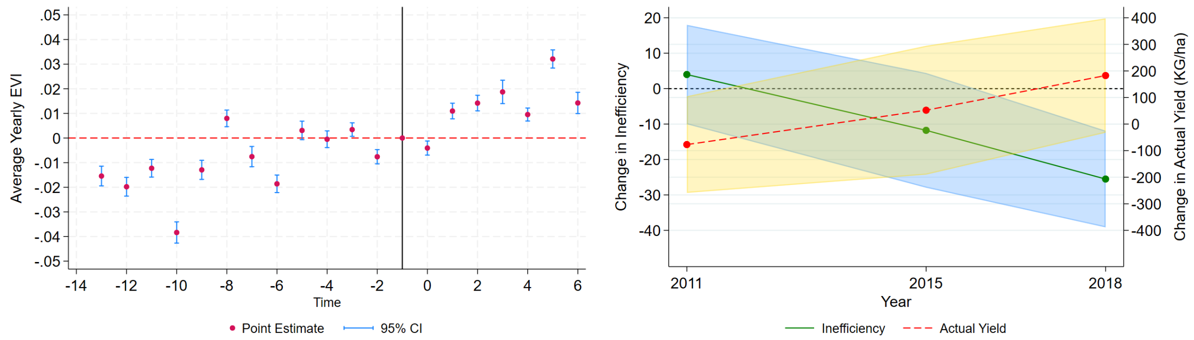
where $Input_{ijcdt}$ are dummies capturing whether the household $i$ from community $c$ of division $d$ use different inputs on their plot $j$ at time $t$. Our coefficients of interest are $\alpha_6$, which capture the differential effect of ACCI post-intervention by different input use. The sign of the coefficients depends on whether the intervention was successful in communicating the effective use of the input.

# 4 Results

## 4.1 Impact of ACCI on Agricultural Performances

We begin by presenting event plots based on the EVI-based household-level crop productivity measure. Although having long-term data on actual paddy yields would have been ideal, we nevertheless check for differential crop productivity trends using EVI data. Figure 6a displays the average difference in EVI between communities with and without phone access from 2001 to 2019. Before the intervention, there was no consistent pattern in EVI differences, with estimates largely fluctuating around zero. However, after 2014, we observe a consistent increase in average EVI for treated communities compared to control communities.

Figure 6b presents the event plots using data from the three BIHS survey rounds. Although the differences in average rice yields and inefficiency between treated and control communities are close to zero in the pre-intervention period (2011), we find that the average inefficiency is much lower in treated communities compared to control communities after the intervention in 2014. These patterns are largely consistent for both the EVI-based measure and actual rice yields, indicating that rice farming became more productive in communities with phone service only after the intervention.




(a) Enhanced Vegetation Index

(b) Actual Yield and Inefficiency from BIHS

Figure 6: Event Study Plots

*Notes:* Panel (a) shows the event plots with 2014 as the base year. Based on household-level monthly Enhanced Vegetation Index (EVI) estimated from the NASA MODIS gridded data. Panel (b) plots the DID coefficient estimates from the BIHS rice yield and inefficiency measure, focusing on the plots that are within 2 kilometers of their respective household locations. The regressions for this panel include season and year-fixed effects, crop-type fixed effects, and time-varying controls. Time-varying controls include the dummy capturing whether the household owns the plot, a dummy capturing whether the household has an agricultural input subsidy card, and the weather of the household's village as reflected by the minimum and maximum temperature of the year (in °C) and average yearly rainfall (in mm). Both panels depict regression results that are clustered at the community level. The monthly weather variables of the household's village are also controlled for in producing the event plots of the panel (a).

Table 2 presents the baseline estimates from the canonical difference-in-differences specification (regression (2)) in panel (A) and from specifications that allow for time-varying community phone access (regression (3)) in panel (B). Both panels also include results from the corresponding triple difference specifications (regression (4)), which estimate the post-intervention effect of the ACCI on agricultural outcomes at the plot level and document heterogeneity in these effects based on input use. Although we report results from the canonical DID model for robustness, our preferred specifications are with time-varying measures of community phone service access. For comparison, we report estimates using both plot-level inefficiency and actual yield as outcome variables.

Table 2 panel (A) reports estimates from the double and triple difference specifications, where we keep the access to the community-level phone service fixed at the baseline. Consistent with the event plots in figure 6b, column (1) shows a negative and statistically significant coefficient on the interaction term, indicating a decrease in inefficiency in treated communities following the intervention. Although estimates with actual yield are in the expected direction, they are statistically insignificant (column (2)). We causally interpret the coefficient on only the triple interaction terms. Estimates from the triple difference specification in column (3) show that this decrease in inefficiency was mainly driven by rainfed plots.

Panel (B) of Table 2 presents the estimates of our preferred specifications with time-varying community phone access. Looking at columns (1) and (2), we observe that the

Table 2: Post-Intervention Effect of the Agricultural Call Center Intervention on Plot-level Agricultural Performances

| | (1)<br>Inefficiency | (2)<br>Actual Yield | (3)<br>Inefficiency | (4)<br>Actual Yield |
|---|---|---|---|---|
| *Panel A: Specifications with Phone Access fixed at the Baseline* | | | | |
| Phone Service in the Village × Post ACCI | -17.272** | 137.230 | -1.089 | 135.936* |
| | (7.012) | (97.112) | (4.046) | (81.920) |
| Used Rainfed Farming | | | -8.736 | -136.971* |
| | | | (7.251) | (78.366) |
| Used Tractor | | | 221.094*** | 8.536 |
| | | | (12.733) | (78.731) |
| Used Rainfed Farming × Phone Service in the Village | | | 31.804*** | -257.311*** |
| | | | (11.718) | (94.069) |
| Used Tractor × Phone Service in the Village | | | 25.567 | -13.962 |
| | | | (32.850) | (140.240) |
| Used Rainfed Farming × Post ACCI | | | 4.991 | 62.457 |
| | | | (9.466) | (94.501) |
| Used Tractor × Post ACCI | | | -60.923*** | 276.328* |
| | | | (23.109) | (151.066) |
| Used Rainfed Farming × Phone Service in the Village × Post ACCI | | | -46.242*** | 178.714 |
| | | | (12.977) | (126.687) |
| Used Tractor × Phone Service in the Village × Post ACCI | | | 0.095 | -664.543** |
| | | | (44.399) | (271.156) |
| Observations | 24901 | 25519 | 24901 | 25297 |
| $R^2$ | 0.401 | 0.617 | 0.464 | 0.620 |
| *Panel B: Specifications with Temporal Variation in Phone Access* | | | | |
| Phone Service in the Village | -5.640 | -164.784 | -8.381 | -111.050 |
| | (11.410) | (101.555) | (7.746) | (96.423) |
| Phone Service in the Village × Post ACCI | -15.634** | 110.545 | -1.963 | 87.096 |
| | (6.794) | (99.436) | (4.048) | (80.204) |
| Used Rainfed Farming | | | -0.423 | -161.954** |
| | | | (7.245) | (73.481) |
| Used Tractor | | | 230.904*** | -5.803 |
| | | | (11.984) | (70.683) |
| Used Rainfed Farming × Phone Service in the Village | | | 24.223** | -222.761*** |
| | | | (10.750) | (85.864) |
| Used Tractor × Phone Service in the Village | | | 16.643 | 43.134 |
| | | | (30.384) | (131.907) |
| Used Rainfed Farming × Post ACCI | | | -1.518 | 87.067 |
| | | | (9.273) | (92.611) |
| Used Tractor × Post ACCI | | | -63.520*** | 257.615* |
| | | | (22.440) | (147.503) |
| Used Rainfed Farming × Phone Service in the Village × Post ACCI | | | -43.539*** | 163.653 |
| | | | (12.223) | (120.209) |
| Used Tractor × Phone Service in the Village × Post ACCI | | | -15.905 | -82.591 |
| | | | (39.255) | (252.435) |
| Observations | 27298 | 27991 | 27298 | 27723 |
| $R^2$ | 0.399 | 0.631 | 0.468 | 0.633 |
| Mean Baseline Outcome | 29.625 | 3582.026 | 29.625 | 3582.026 |
| (SD) | (208.816) | (1734.7) | (208.816) | (1734.7) |

*Notes:* * p<0.10, ** p<0.05, *** p<0.01. All results report cluster robust standard errors in the parentheses. The clustering is at the community level for the results in columns (1)-(2) and at the household level for the results in columns (3)-(4). *Phone Service in the Village* dummy measures whether the household's community reported having phone service in that year, and Post ACCI is the time dummy capturing whether the survey year is post introduction of the Agricultural Call Center Intervention. *Used Rainfed Farming* and *Used Tractor* dummies capture whether the household used rainfed farming and tractor in their plot, respectively. All regressions use data from plots that are within 2 kilometers of their respective household locations. All regressions include year and season-fixed effects, time-varying controls, household, crop type, and the interaction of the division with year-fixed effects. Time-varying controls include the dummy capturing whether the household owns the plot, a dummy capturing whether the household has an agricultural input subsidy card, and the weather of the household's village as reflected by the minimum and maximum temperature of the year (in °C) and average yearly rainfall (in mm).

arrival of phone service in the village itself does not influence the inefficiency or actual yields of the paddy. Consistent with the estimates in panel (A), the availability of village phone service reduces inefficiency only after intervention. In terms of magnitude, the intervention led to a 50 percent reduction in the average baseline inefficiency.

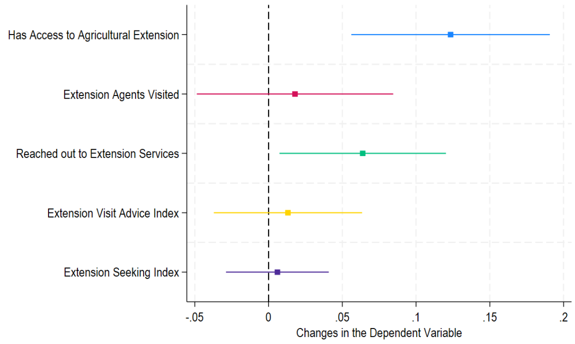
Columns (3) and (4) in panel (B) show that the reduction in inefficiency after the intervention was primarily driven by rainfed farming plots. Although the triple interaction between tractor use, village telephone service, and the post-ACCI period produces a negative coefficient, it is not statistically significant. Given that approximately 31 percent of farmers in our sample rely on rainfed agriculture, the estimated differential impact of the intervention on inefficiency reduction for the average farmer is around 45 percentage points. This translates to a decrease of approximately 0.1 standard deviations in our constructed inefficiency measure.

How do these estimates compare to the existing experimental evidence? Casaburi et al. (2014), for example, find an 11.5 percent increase in sugarcane yields from SMS-based randomized extension advice in Kenya. Comparing several experimental studies, Fabregas et al. (2019b) report that digital extension programs to farmers increased crop yields by about 4 to 6 percent. Our estimates are somewhat larger but not directly comparable with these estimates for two reasons. First, the dependent variable we consider is not just crop yield, but rather the deviation from the potentially achievable yield. In fact, we get a null result by using actual yields. Second, our estimates also incorporate the possible spillover and network effects of such extension programs. We discuss such effects in Section 5.

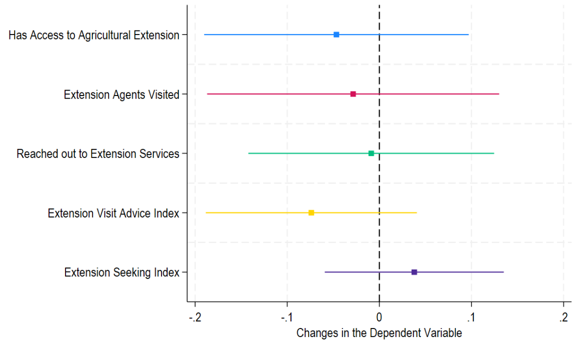
## 4.2 Mechanisms

We further investigate the possible mechanisms behind the effects observed in the previous section. First, we test whether the effects are driven by improved extension services in villages with phone service after the ACCI. For this purpose, we estimate the triple difference specification (4) with information on in-person extension services as dependent variables. As documented in panel A of Figure 7, we do find some post-intervention evidence of differentially greater access to extension agents for farmers that use rainfed farming, but we do not find statistically significant effects on the likelihood of an extension visit or whether the farmer actively seeks advice from an agent.

We also estimate the triple difference specification (4) with input use (other than water source or tractor usage) per hectare as dependent variables. Panel B of Figure 7 documents the associated results. Farmers may not achieve potential paddy yields because they are under or overusing critical inputs such as fertilizer and other agrochemicals. We observe that in treated villages, after the intervention, farmers using rainfed farming differentially increased the use of fertilizers and pesticides, and farmers using tractors differentially reduced the use of fertilizers and pesticides after the intervention.

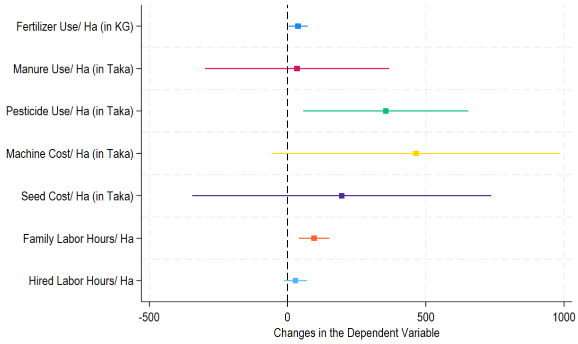



(a) By Rainfed Farming Usage

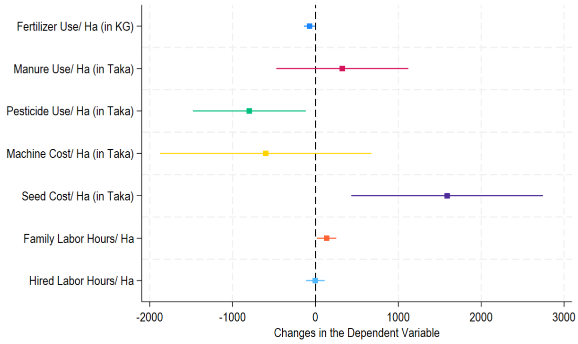



(b) By Tractor Usage

Panel A: Impact on Interaction with Extension Services




(c) By Rainfed Farming Usage




(d) By Tractor Usage

Panel B: Impact on Other Input Uses

Figure 7: Mechanism for the effect of Agricultural Call Center Intervention

*Notes:* The reported triple-difference coefficients are from the specification (4), reported here with respect to the corresponding outcome variables. The coefficients are reported with their corresponding 90 percent confidence intervals. For each panel, the coefficients correspond to the interaction of the respective input usage with the variables *Phone Service in the Village* and Post ACCI in the same regression. *Phone Service in the Village* dummy measures whether the household's community reported having phone service in that year, and Post ACCI is the time dummy capturing whether the survey year is post introduction of the Agricultural Call Center Intervention.

These findings are consistent with the fact that incorrect fertilizer use (for example, urea) can be easily diagnosed by the color of leaves, and the remedies can be easily and quickly distributed by experts from agricultural call centers (Islam and Beg, 2021). Similarly, pest infestation can be easily visually diagnosable by farmers. For example, rice blast, a common paddy fungal disease, manifests itself as large white and yellow spots on the leaves. Evidence shows that farmers generally consult call center services for advice on agrochemicals, as they are concerned about plant protection to avoid severe damage due to pest attacks (Kumar et al., 2021). In addition, panel B of Figure 7 shows that farmers using tractors differentially spent more on seeds after the intervention. Interestingly, we also find evidence of longer work hours for family labor after intervention. These results are consistent with an intensification of input use on farms after the intervention.

# 5 Heterogeneity Analysis: The Role of Networks

## 5.1 Construction of Geographic Networks

We now turn to understanding the role of social networks in amplifying the impact of the intervention. To investigate the role of social networks in enhancing the effect of ICTs in the transmission of information related to efficient use of resources, we need to first construct these networks. Ideally, data on social interactions are collected and used for this purpose.[17] In scenarios where the data on social interactions are not available, geographic proximity can be used as a proxy measure of these interactions. The rationale behind this approach lies in the ease of communication between agents who live close to each other (Goldenberg and Levy, 2009; Helsley and Zenou, 2014; Kim et al., 2023). This is the approach that we follow for our analysis.

Using the geographic location of the households surveyed in BIHS, we construct an undirected network of households based on the geographic distance between these households. In our constructed network, each pair of households is considered to be connected as long as they live within 5 kilometers of each other's house, irrespective of whether they are part of the same community. This allows for cross-community connections that help us study the spillover effect of the intervention between communities. Figure 8 presents the geographic network that we constructed. The nodes represent the households in our sample as documented in the baseline, colored by their respective administrative divisions. The edges between each pair of nodes represent the geographic connection between the pair of households, with no edges between the households that are not geographically close to each other. Nodes with more edges are more central in the network and are in the center of the figure. In contrast, nodes with fewer edges are less central and are in the periphery. The less central nodes represent households that are geographically remote from most of the other households and are probably the main expected beneficiaries of the intervention.

The role of geography in economic development is well documented in the literature (Donaldson and Hornbeck, 2016; Aggarwal, 2018; Asher and Novosad, 2020; Banerjee et al., 2020; Shamdasani, 2021) and central households are already well connected to benefit from the transmission of information from their social connections. However, most remote households lack the number of connections required for effective knowl-

[17] For details on how to collect data on social networks, one can consult: `https://blogs.worldbank.org/en/impactevaluations/how-to-collect-data-on-social-networks-`

edge diffusion. [18] Thus, we expect the remote households to benefit more from the intervention. This is the hypothesis that we test below using the specification (5).

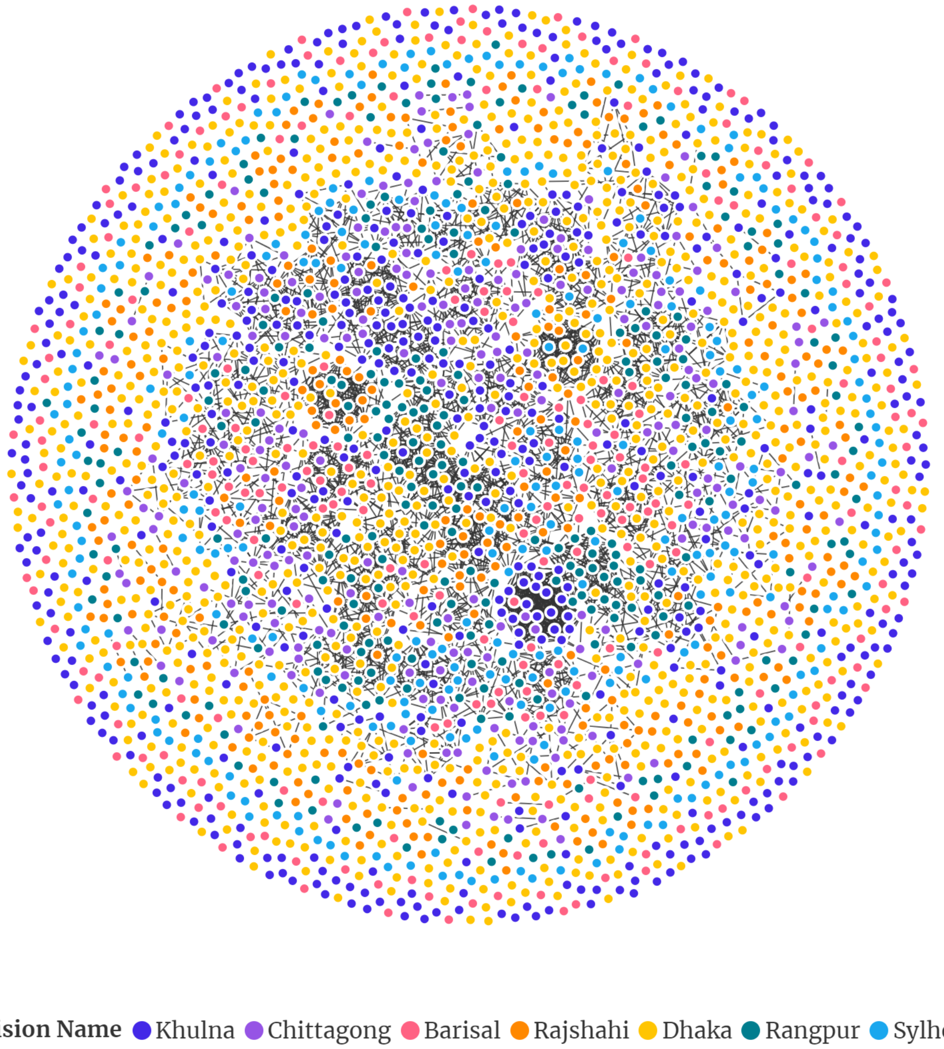



Figure 8: Geographic Distance Network

*Notes:* The figure displays the undirected geographic distance network using the Bangladesh Integrated Household Survey (BIHS) data from the baseline (2011). The nodes represent households, and the edges represent the geographic connection between two households. Any pair of households are assumed to be geographically connected if they live within 5 kilometers of each other.

For our analysis of heterogeneous network effects, we use *Betweenness Centrality* as the measure of network centrality. The measure captures the importance of a node in terms of connecting with other nodes in a network and accessing information from them (Jackson, 2010; Bloch et al., 2023).[19] The measure is widely used in the literature on network-based interventions as a measure of the centrality of nodes (see, for example,

[18] Beaman et al. (2021) documents that multiple connections are required for effective diffusion of knowledge.

[19] Let $N_{ij}^{k}$ denote the number of geodesic paths between nodes $i$ and $j$ that pass through node $k$ in

Banerjee et al., 2013; Beaman and Dillon, 2018; Beaman et al., 2021). For our purpose, it is particularly useful since the nodes with the highest betweenness centrality are often considered the gatekeepers of information.[21] So, by investigating whether households with lower betweenness centrality differentially benefit from ACCI, we effectively study whether the intervention is successful in helping the information needs of the population that finds it particularly difficult to obtain such information.

## 5.2 Empirical Specifications

**Do the effect of ACCI vary differentially depending on the centrality of the geographic network?**

To answer the above question, we use the following triple differences specification that takes advantage of the household-level variation in network centrality:

$$\begin{aligned}
\text{Outcome}_{ijcdpst} &= \beta_0 + \beta_1 \text{Phone Service}_{cdt} + \beta_2 \text{Phone Service}_{cdt} \times \text{Inverse Betweenness}_{icd} \\
&+ \beta_3 \text{Phone Service}_{cdt} \times \text{Post ACCI}_t + \beta_4 \text{Inverse Betweenness}_{icd} \times \text{Post ACCI}_t \\
&+ \beta_5 \text{Phone Service}_{cdt} \times \text{Inverse Betweenness}_{icd} \times \text{Post ACCI}_t + \beta_6 X_{ijcdt} \\
&+ \sigma_i + \delta_p + \phi_s + \lambda_t + \psi_d \times \lambda_t + \mu_{ijcdpst},
\end{aligned} \tag{5}$$

where $\mathit{Inverse\ Betweenness}_{icd} = \frac{1}{1+\mathit{Betweenness\ Centrality}_{icdt}}$ captures the inverse of betweenness centrality for household $i$ from community $c$ of division $d$. The objective of this specification is to understand the differential effect of ACCI post-intervention by geographic proximity away from geographically central households.

The importance of extension in reaching geographically remote households is well emphasized in the policy domain (Abate et al., 2020; Maulu et al., 2021; Lee et al., 2023). Whether an agricultural extension intervention is successful in reaching geographically remote households is an important indicator of the effectiveness of the intervention, and the role of ICTs is well recognized in this regard (Westermann et al., 2018; Fabregas et al., 2019b). The specification (5) captures this through the coefficient $\beta_5$. A negative value of this coefficient for the *Inefficiency* outcome variable would indicate that the intervention is successful in improving the efficiency of households living further from the central households (i.e., those living in the periphery of their networks). However,

any given network.[20] Also, denote the total number of geodesic paths from $i$ to $j$ to be $N_{ij}$ for the same network. Then, the betweenness centrality of node $k$ in that network is defined as:

$$\text{Betweenness Centrality}_k = \sum_{\forall i,j \ s.t. i \neq j \ and \ k \notin \{i,j\}}^{\infty} \left(\frac{N_{ij}^k}{N_{ij}}\right),$$

with $\frac{N_{ij}^k}{N_{ij}} = 0$ if $N_{ij} = 0$.

[21] Source: https://visiblenetworklabs.com/2022/09/30/network-science-a-reference-guide/.

the specification does not help us understand the potential spillovers of the intervention over network ties, which brings us to our next question.

**Do the effect of ACCI vary differentially by dyadic geographic distances?**
Finally, we use the dyadic data frame of the geographic networks to study the spillover effect of the intervention within geographic networks in the post-intervention period. Consider two households $i$ and $i'$. We want to capture how the impact of ACCI on the community $c'$ of household $i'$ post-intervention differentially affects household $i$'s inefficiency by the distance between the households.[22] We use the following specification for this purpose:

$$\begin{aligned}\text{Outcome}_{icdst} = \gamma_0 &+ \gamma_1 \text{Phone Service}_{c't} + \gamma_2 \text{Phone Service}_{c't} \times \text{Inverse Distance}_{ii'} \\ &+ \gamma_3 \text{Phone Service}_{c't} \times \text{Post ACCI}_t + \gamma_4 \text{Inverse Distance}_{ii'} \times \text{Post ACCI}_t \\ &+ \gamma_5 \text{Phone Service}_{c't} \times \text{Inverse Distance}_{ii'} \times \text{Post ACCI}_t \\ &+ \gamma_6 X_{ijcdt} + \sigma_{ii'} + \phi_s + \lambda_t + \psi_d \times \lambda_t + \nu_{icdst}, \qquad (6)\end{aligned}$$

where $Outcome_{icdst}$ captures the outcome in the use of all agricultural plots used by household $i$ from community $c$ of division $d$ at year $t$ for season $s$, $\textit{Phone Service}_{c't}$ is a dummy indicating whether the community $c'$ (the community of household $i'$) reported having phone service at year $t$, and Inverse Distance$_{ii'}$ represents the inverse of geographic distance between households $i$ and $i'$, captured at the baseline.

The specification includes $\sigma_{ii'}$, $\phi_s$, and $\lambda_t$, as pair, season, and year fixed effects, respectively. We also include the interaction of the fixed effect of division $\psi_d$ with the fixed effect of year $\lambda_t$ to control for the characteristics that vary over time at the level of division of the household $i$. Our coefficient of interest is $\gamma_5$, which captures how much the post-intervention impact of ACCI in the community of household $i'$ differentially affects the outcome of the household $i$, lower the distance between households $i$ and $i'$. We expect this coefficient to be negative for the *Inefficiency* outcome variable if the network spillovers of the program reduce inefficiency.

## 5.3 Results

Table 3 documents the potential for ACCI to reach agents in geographically remote areas. For this purpose, we use the specification (5), which exploits the variation in the centrality of households in the geographic network, in addition to the spatiotemporal variation in access to phone services and the temporal variation in the timing of the intervention. We causally interpret the coefficient on only the triple interaction terms.

[22] This analysis focuses on the balanced panel of households to avoid having the scenario where one of the households is not surveyed.

The results in columns (1) and (2) show that the agricultural inefficiency differentially decreased and the actual yield differentially increased for geographically remote farmers that have a lower betweenness centrality. However, columns (3) and (4) show that this impact is not driven by changes in the use of rainfed farming and tractors, as the associated coefficients are small and statistically insignificant. Given the variation in the *Inverse Betweenness Centrality* of farmers in the baseline (around 0.3 standard deviations), the differential impact of the intervention on the reduction of inefficiency in our sample is around 0.1 standard deviations. For the average farmer in our sample, this corresponds to a 13 percentage points (or 0.3 standard deviations) increase in actual yield.

Table 3: Differential Effect of the Agricultural Call Center Intervention by Geographic Network Centrality on Plot-level Agricultural Outcomes

| | (1) Inefficiency | (2) Actual Yield | (3) Used Rainfed Farming | (4) Used Tractor |
|---|---|---|---|---|
| Phone Service in the Village | -30.551 | -3.942 | -0.116* | -0.084 |
| | (22.565) | (272.676) | (0.064) | (0.069) |
| Phone Service in the Village × Post ACCI | 30.117 | -378.156* | -0.005 | -0.033 |
| | (19.934) | (201.094) | (0.049) | (0.054) |
| Inverse Betweenness Centrality × Phone Service in the Village | 31.452 | -197.648 | 0.124* | 0.082 |
| | (26.469) | (307.141) | (0.072) | (0.079) |
| Inverse Betweenness Centrality × Post ACCI | 24.934 | -442.374*** | 0.005 | -0.063 |
| | (17.624) | (151.379) | (0.036) | (0.043) |
| Inverse Betweenness Centrality × Phone Service in the Village × Post ACCI | -54.567** | 578.403** | 0.031 | 0.010 |
| | (22.727) | (226.715) | (0.056) | (0.059) |
| Mean Baseline Outcome | 29.625 | 3582.026 | 0.321 | 0.071 |
| (SD) | (208.816) | (1734.7) | (0.467) | (0.257) |
| Observations | 27064 | 27745 | 27745 | 27482 |
| $R^2$ | 0.400 | 0.630 | 0.673 | 0.558 |

*Notes:* * p<0.10, ** p<0.05, *** p<0.01. Robust standard errors clustered at the household level are in parentheses. *Phone Service in the Village* dummy measures whether the household's community reported having phone service in that year, and Post ACCI is the time dummy capturing whether the survey year is post introduction of the Agricultural Call Center Intervention. $Inverse\ Betweenness\ Centrality = \frac{1}{1+Betweenness\ Centrality}$ captures the inverse of geographic betweenness centrality for the household at the baseline, which is omitted at the level as the regressions include the household fixed effects. All regressions use data from plots that are within 2 kilometers of their respective household locations. All regressions include year and season-fixed effects, time-varying controls, household, crop type, and the interaction of the division with year-fixed effects. Time-varying controls include the dummy capturing whether the household owns the plot, a dummy capturing whether the household has an agricultural input subsidy card, and the weather of the household's village as reflected by the minimum and maximum temperature of the year (in °C) and average yearly rainfall (in mm).

The above results show that although the program was successful in reaching remote farmers, decreasing the inefficiency associated with their agricultural production and improving their yield, this is not driven by farmers adjusting their use of rainfed farming and tractors. Thus, the results appear to be driven by the more efficient use of the same mixture of rainfed farming and tractors. This indicates the importance of ACCI in communicating information on the efficient use of existing inputs and benefiting geographically remote farmers, who do not have access to such information otherwise.

Furthermore, Table 4 reports the potential amplification of the program's impacts through social spillovers. Using the specification (6), here we investigate whether the outcomes of household $i$ are differentially affected if the community of household $i'$ receives ACCI, as the distance between the pair of households decreases. It is important to note that this specification controls for *Phone Service in the Village of $i$* dummy measuring whether the community of household $i$ reported having phone service in the year interacted with the Post ACCI dummy. This control variable partials out the post-intervention impact of ACCI on the household $i$'s own community. Therefore, we can interpret the triple interaction terms as the cross-community spillover effect of the intervention.

Table 4: Differential Effect of the Agricultural Call Center Intervention by Dyadic Geographic Distances on Household-level Agricultural Outcomes

| | (1) Inefficiency | (2) Actual Yield | (3) Used Rainfed Farming | (4) Used Tractor |
|---|---|---|---|---|
| Phone Service in the Village of $i'$ | -63.407** | -96.802 | 0.026 | -0.090*** |
| | (24.589) | (597.956) | (0.032) | (0.034) |
| Phone Service in the Village of $i'$ × Post ACCI | 38.906* | -455.164 | -0.038* | -0.034* |
| | (20.630) | (536.658) | (0.022) | (0.020) |
| Inverse Distance between $i$ and $i'$ × Phone Service in the Village of $i'$ | 60.702 | -667.826 | -0.012 | 0.163 |
| | (45.190) | (1667.954) | (0.095) | (0.109) |
| Inverse Distance between $i$ and $i'$ × Post ACCI | 102.427*** | -3623.542** | -0.184*** | -0.033 |
| | (35.110) | (1563.588) | (0.042) | (0.038) |
| Inverse Distance between $i$ and $i'$ × Phone Service in the Village of $i'$ × Post ACCI | -119.823*** | 4161.021** | 0.144** | 0.086 |
| | (46.327) | (1912.950) | (0.064) | (0.054) |
| Mean Baseline Outcome | 29.625 | 3582.026 | 0.321 | 0.071 |
| (SD) | (208.816) | (1734.7) | (0.467) | (0.257) |
| Observations | 60724 | 60724 | 60724 | 60667 |
| $R^2$ | 0.243 | 0.875 | 0.658 | 0.597 |

*Notes:* * p<0.10, ** p<0.05, *** p<0.01. Robust standard errors multi-way clustered at the household $i$ and household $i'$ level are in parentheses. *Phone Service in the Village of* $i'$ dummy measures whether the community of household $i'$ reported having phone service in that year and *Post ACCI* is the time dummy capturing whether the survey year is post introduction of the Agricultural Call Center Intervention. *Inverse Distance between i and* $i' = \frac{1}{1+\textit{Distance between i and i'}}$ captures the inverse of geographic distance between households $i$ and $i'$ measured at the baseline, which is omitted at the level as the regressions include the pair fixed effects. All regressions use data from plots that are within 2 kilometers of their respective household locations. All regressions include year and season-fixed effects, time-varying controls, pair-fixed effects, and the interaction of the division of household $i$ with year-fixed effects. Time-varying controls include the total number of plots owned by $i$, the total number of plots operated by them, whether $i$ has an agricultural input subsidy card, the weather of household $i$'s village as reflected by the minimum and maximum temperature of the year (in °C) and average yearly rainfall (in mm), and *Phone Service in the Village of i* dummy measuring whether $i$'s community reported having phone service in the year interacted with the Post ACCI dummy.

Columns (1) and (2) show that the spillover significantly reduces inefficiency and increases actual yield, in line with our expectations. However, in terms of inputs, we only observe significant impacts on the use of rainfed farming and not on the use of tractors, as documented in columns (3) and (4). The average distance between each pair of households in our sample is around 3.8 kilometers (with a standard deviation of 2.8), which corresponds to around 0.3 units in our *Inverse Distance* measure (with a standard deviation of 0.2). Given these numbers, the differential impact of the intervention in the community of an average household $i'$ on the inefficiency of another average household $i$ in our sample is a decrease of approximately 0.2 standard deviations. For all farmers in our sample, this results in a 0.1 standard deviation decrease in inefficiency. The decrease also corresponds to a 0.7 standard deviation (or 33 percentage points) increase in actual yield and a 13 percentage points increase in the probability of adopting rainfed farming for an average farmer. These results document large cross-community spillovers of the intervention. These results are consistent with the evidence of community-based spillover effects in ICT-driven extension programs (Fabregas et al., 2019b,a).

# 6 Robustness Checks

We perform a series of robustness checks to ensure that the unobservables and peculiarities of the data do not drive our results. We summarize them below in three broad categories, postponing the detailed results to Appendix D for those interested.

## 6.1 Addressing Measurement Errors in the Inefficiency Variable

In subsection 3.2, we have noted that, in our data, many agricultural plots have an actual yield greater than the potential yield, resulting in a negative inefficiency measure. We discussed three possible reasons behind this phenomenon. First, farmers could potentially compensate for poorer natural endowments/lack of irrigation infrastructure/mechanization by overusing other inputs such as fertilizer and pesticides. Our results in Section 4.2 provide evidence in favor of this possibility. In the Appendix Table D.6, we address the associated concern by documenting the robustness of our estimates after controlling for other input usage.

The second reason for a negative inefficiency measure is the possible measurement error in capturing high-yielding input usage, which is proxied by tractor usage information in our analysis. To address this issue, we document the robustness of our estimates for the use of fertilizer instead of tractor usage as an indicator of high-yielding input. We report this in the Appendix Table D.5.

Finally, we also argued that there may be measurement errors in capturing the heterogeneity in land productivity using the average potential yield, as given in the GAEZ data. As noted in subsection 3.2, we check the robustness of our estimates to this error by measuring the plot-level inefficiency as the percentage difference between the actual and the 90th percentile plot-level potential yield drawn from a Frećhet distribution. Appendix Table D.7 documents the robustness of our results to this alternative measure of inefficiency.

## 6.2 Placebo and Falsification Tests

Although our benchmark estimates are encouraging, there is the possibility that they are correlated with other changes in the village during the post-intervention period. One way of testing the robustness of our estimates is to generate a placebo intervention. We do that by re-coding the post-ACCI dummy to be 1 for the second round and limiting the sample to only the first two rounds of the BIHS data. Given that the intervention was actually scaled up after June 2014, we should not see an effect prior to the intervention being fully implemented.[23]

[23]While the intervention was launched in June 2014, the recall period of the second round of the BIHS was from December 1, 2013, to November 30, 2014.

Appendix Table D.1 presents the estimates from the placebo test. Estimates on the double interaction term in columns (1) and (2) are small in magnitude and statistically insignificant. Similarly, the estimates from the triple interactions are mostly statistically insignificant and of the opposite sign (columns (3) and (4)). More importantly, the estimates for the triple interactions for the outcome inefficiency (our main outcome of interest) are statistically insignificant. Hence, our main findings of this specification disappear when we use the placebo intervention, providing support in favor of the credibility of our approach. Similar results are documented in the Appendix Table D.13 and D.14, confirming the credibility of our network heterogeneity analysis through placebo tests.

We perform additional tests to see whether we can recreate the results we observe in the triple difference specification for the outcome variable *Inefficiency* in Table 3 if we randomly shuffle a household's rainfed farming and tractor use status. We do such a random shuffling 100 times, collecting the estimates from the triple difference specification each time. A widespread presence of statistically significant estimates with this shuffled input usage will signal that the triple-difference specification is picking up spurious effects, probably driven by other correlated factors. Appendix Figures D.1a and D.1b plot the estimates for the triple difference coefficients (with *Inefficiency* as the outcome variable) with 90% confidence intervals from this exercise. The figures show no systematic pattern in these coefficient estimates and most of them are statistically indistinguishable from zero.

We also performed a similar falsification exercise with randomly shuffled *Inverse Betweenness Centrality* and randomly shuffled *Inverse Distance* for specifications (5) and (6), respectively. As we document in the Appendix Figures D.2, such an exercise also does not show a systematic pattern in the estimated coefficients.

### 6.3 Verifying Results for Sub-samples

We perform a series of other robustness checks to ensure that several peculiarities of the data do not drive our results. First, we use household fixed effects in our preferred specifications. This choice is driven by the fact that many plots in our data are observed only once. As plot-fixed effects require the plot to be observed at least twice, using plot-fixed effects would drop those plots that are observed only once. However, using plot-fixed effects is probably better as it controls for all time-invariant observables and unobservables at the plot level, which is better than controlling for time-invariant observables and unobservables at the household level. Appendix Tables D.2 and D.9 document the robustness of our results using plot-fixed effects instead of the household fixed effects, restricting the sample only to plots that are observed at least twice in the data.

Second, in order to ensure that households that are surveyed only once or twice are not driving our results, we restrict our sample to households that are surveyed in all three rounds. Appendix Tables D.3 and D.10 document the robustness of our results with the balanced panel of households. Note that both this robustness check and the one using plot-fixed effects instead of household-fixed effects were not performed for regression (6), as it is a household-level regression that focuses on the balanced panel of households.

Third, in the data, the tractor use information has many missing values in year 1. One possible solution to this data issue is to use a separate indicator instead of using tractor usage as an indicator of high-yield input. As mentioned in Section 6.1, we have already done so by replacing tractor usage with higher than median fertilizer usage. Another solution is to impute the tractor usage of year 1, using the tractor usage in the following survey rounds. This is something we have done for our main analysis. If a plot has been observed in all three rounds and reported that it had used a tractor in both rounds 2 and 3, with a missing value of tractor usage in year 1, we have imputed the tractor usage of year 1 to be "yes." On the other hand, we have imputed the tractor usage of year 1 to be "no" if the plot has been observed in all three rounds and reported that it had not used a tractor in both rounds 2 and 3. To ensure that this imputation is not driving our results, we re-estimate our regressions using observations from survey years 2 and 3 only. Appendix Tables D.4, D.10, and D.11 document the robustness of our results excluding the observations from round 1.

Finally, to ensure that the change in community-level phone access after the introduction of the intervention is not endogenously driving our results, we also check the robustness of our results of our results fixing the community-level phone access at the baseline. Appendix Tables D.8, D.15, and D.16 document these results. Our results hold across all robustness checks and alternative specifications.

# 7 Summary and Concluding Remarks

Does ICT-based provision of agricultural extension services help improve agricultural productivity in poor or developing countries? Our paper tries to answer this question for rural Bangladesh, where the majority of the agriculture-dependent population is engaged in the production of rice crops. Although Bangladesh's geography is suitable for rice cultivation, yields are low in the country relative to other major rice producing countries. In this context, we investigate the role of an Agricultural Call Center Intervention (ACCI) in reducing the inefficiency in rice production due to non-geographical factors. The novelty of our approach lies in the fact that we look at the impact of this intervention after controlling for the effects of geographical factors by using a micro-geographic dataset.

We document that the intervention was effective in reducing plot-level inefficiency in rice production in those villages that had access to phone services. With the ability to provide farmer-specific and need-based extension services in the form of immediate expert advice, ACCI was able to help those farmers differentially more who were using rainfed water supply instead of irrigation. This reduction in inefficiency is found to be mediated by the increased intensity of the use of various inputs on farms.

We further assess the heterogeneity in the impact of ACCI by geographic network centrality of the households, as the need for extension services varies by the households' positions in the network. Absent any intervention, one would expect that more central and well-connected households could better access pertinent agricultural information, whereas access remains difficult for remotely located households. Therefore, any ICT-based extension service should enable remotely located households to access information. Our results provide support in favor of this intuitive prediction. We show that there was a differentially higher reduction in the inefficiency of remote households' production after the intervention.

Although our estimates are not directly comparable to existing experimental evidence, we find that our estimates are larger in magnitude. That could be either because we consider a different dependent variable that explicitly accommodates the heterogeneity in natural climatic conditions and micro-geography or because of spillovers. Evidence from the literature suggests that the spillover effects of ICT-based extension programs are important. We also provide evidence in support of such spillovers.

Given the robustness of our results to several robustness checks reported in Section 6 and Appendix D, we can confidently claim positive causal impacts of ICT-based extension services on small-scale farmers, who also happen to be more dependent on rainfed farming methods. Thus, policymakers can reliably use ICT-based extension services for their extension efforts in regions where mobile phone technologies have been widely disseminated. As suggested by our results, this can also increase access to information for remotely located or socially excluded households, increasing overall welfare.

Although we performed several robustness and falsification tests to assess the validity of our results, some limitations remain. First, our analysis captures only the average effects of the program, akin to an intention-to-treat (ITT) estimate. Although we have data on household-level mobile phone ownership, this variable is likely endogenous. Moreover, the survey reports the total number of mobile phones in the household, which may include devices owned by non-resident members working in areas with better network coverage. One potential refinement of our estimation strategy would involve taking advantage of the geographic and temporal expansion of Bangladesh's mobile tower network. However, we currently lack access to detailed location-specific time series data on tower deployment. We are actively pursuing this data and plan to explore this direction in future research.

Another limitation of our analysis is that for the purpose of documenting the role of networks in amplifying the impact of ACCI, we rely on geographic networks as a proxy for social networks. Although geography is documented to be an important factor driving social interactions (Kim et al., 2023), there is also evidence suggesting that physical proximity is not a good proxy for social connections in some contexts (Beaman et al. (2021)). Thus, it is important to interpret our results in terms of geographic proximity and not overemphasize its implications for social proximity. A detailed analysis of the importance of social interactions in driving the impact of ICT-based interventions remains beyond the scope of this paper.

This paper adds to our understanding of the role of information friction in keeping agricultural productivity low in poor and developing countries. Our analysis makes clear that the availability of ICT-based agricultural extension services can significantly alleviate inefficiency in agricultural production. Using different policy interventions placed in different institutional contexts, it will be interesting to measure the extent of inefficiency or misallocation caused by information frictions within the agricultural sector and between sectors in an economy. We leave it as a potential future research work in the burgeoning field of macro-development, which can build on our findings to study the direct and indirect productivity costs of information frictions.

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# Appendices

## A Global Agro-Ecological Zones Dataset

The GAEZ dataset is jointly prepared by the Food and Agriculture Organization of the United Nations (FAO) and the International Institute for Applied Systems Analysis (IIASA).[24] This dataset covers the entire land surface area of earth by dividing it into equal-sized grid cells at 5 arc-minute resolution.[25] It reports the *average* potential yield for a set of crops in each grid cell which is the maximum attainable yield given the natural inputs/endowments of the grid cell and the type of cultivation inputs assumed for growing the crop.[26] To calculate the potential yield, a crop-specific state-of-the-art agronomic model is fed with the natural inputs, which include the standardized soil, climate, and terrain conditions corresponding to the specific grid cell, and the type of cultivation inputs, which include the water supply and the level of complementary inputs usage.[27] Water supply and complementary input levels are of two types - rainfed and irrigated conditions for water supply, and low and high levels of complementary inputs usage. Low-level inputs correspond to traditional subsistence-based farm management. There is no usage of chemical fertilizers or pesticides, and there is no farm mechanization since all stages of production are labor-driven. Under high-level inputs, the farming system is market-oriented, i.e., there is usage of high-yielding variety seeds, fertilizers, pesticides, and machinery are used wherever possible. The labor intensity is low and nutrient application is optimal.[28] As a result, we know the potential yield of a set of crops for four input combinations – rainfed-low, rainfed-high, irrigated-low and irrigated-high – in each grid cell.

[24] Publicly available at `https://gaez.fao.org/`.

[25] The area of these cells map differently into sq-km. at different latitudes. For context, the average size of a grid cell is around 81 sq-km. at the equator, while it is around 78 sq-km. in Bangladesh.

[26] GAEZ dataset reports potential yield at a 5 arc-minutes resolution cell by taking average of the potential yields over 100 sub-cells at 30 arc-seconds resolution.

[27] Soil quality includes its depth, fertility, drainage, texture, and chemical composition. Climate conditions include temperature, sunshine hours, precipitation, humidity, and wind speed. And, terrain and topography include elevation and slope of the land surface (Adamopoulos and Restuccia, 2022).

[28] Though the GAEZ (v4) dataset provides potential yields for only two input levels - low and high, there is also a third level mentioned in the model documentation on its website. This is the intermediate level of inputs for which the potential yield information was also provided in the earlier versions of the GAEZ dataset. Under the intermediate level, the farming system is only partially market-oriented, with some focus still on subsistence production. Here, the farmers use some fertilizers, pesticides, mechanization (some preliminary hand/animal/machine tools), and adopt some conservation measures of weed control in contrast to minimum measures under low input level. We club together the low and intermediate levels of inputs, under the low category. So that we can segregate all input choices under only two levels - low and high.

# B Variation in potential yield within a GAEZ cell

The GAEZ dataset reports the average potential yield for each GAEZ cell at 5 arc-minute resolution by averaging the potential yield of 100 subfields at 30 arc-second resolution. Given the large size of a GAEZ cell, around 8000 hectares on average for Bangladesh, there is substantial variation in land productivity within a GAEZ cell. To account for this heterogeneity, we follow the approach adopted in Dasgupta and Rao (2022). Assume a continuum of parcels, indexed by $\omega$, spanning a GAEZ cell $i$ such that the potential productivity of parcel $\omega$ in producing rice under a given input combination $c$ is given by $A_{ic}(\omega)$. If the parcel-level potential yield follows an i.i.d Frećhet distribution, then the cdf is given by

$$Prob(A_{ic}(\omega) \leq a) = exp\Big( - \gamma^{\theta}(\overline{A}_{ic})^{\theta} a^{-\theta}\Big). \tag{7}$$

$\overline{A}_{ic}$ is the GAEZ-reported average potential yield for cell $i$ under input combination $c$, $\theta$ is the shape parameter which denotes the inverse of the degree of land heterogeneity in a GAEZ cell, and $\gamma$ is a mathematical Gamma function based normalization parameter which ensures that $\mathbb{E}[A_{ic}(\omega)] = \overline{A}_{ic}$. We adopt the calibrated value of shape parameter $\theta = 1.658$, as in Sotelo (2020).

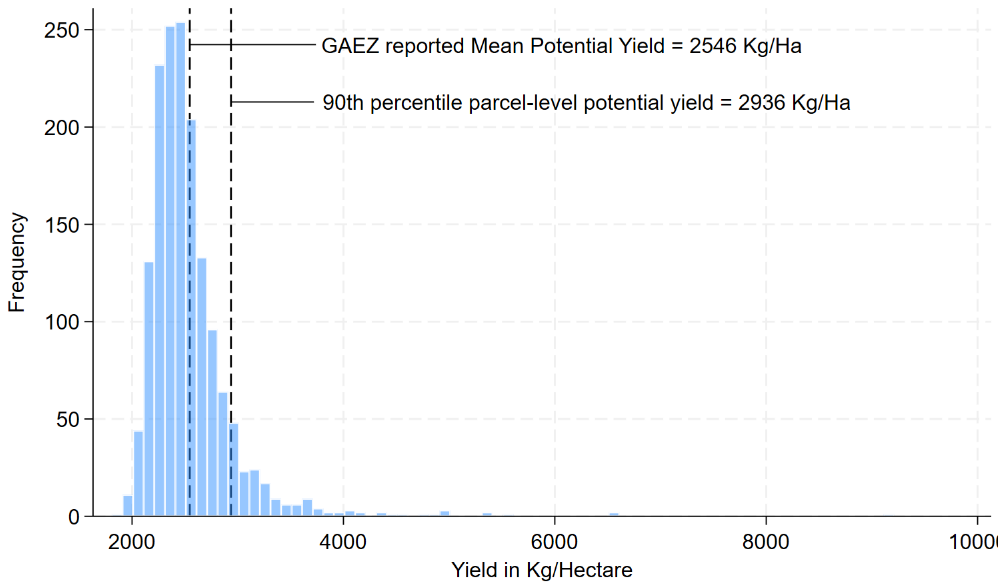



Figure B.1: Frequency distribution of parcel-level potential yields within a GAEZ cell of size 7971 hectares. The input combination corresponds to rainfed water supply and low level of complementary inputs. The parcel size is kept at 5 hectares. Two outlier observations greater than 10000 kg/ha are not shown in this plot.

For our purpose, we operationalize the above by dividing each GAEZ cell into discrete parcels of equal size. To calculate parcel-level potential yields, we take an average of

500 independent draws from the above distribution in equation (7). Figure B.1 plots the frequency distribution of the potential yields at the parcel level in a GAEZ cell whose average potential yield for rainfed water supply and low complementary inputs was reported at 2546 kg per hectare in the GAEZ dataset, while its mean potential yield at the parcel level is around 2563 kg per hectare. It is important that the average parcel-level potential yield comes close to GAEZ-reported one so that our assumption of Frećhet distribution is justified. In our simulations, we find that to be the case. The $90^{th}$ percentile potential yield is 15% higher than the GAEZ-reported potential yield, and it is 34% higher than the $10^{th}$ percentile potential yield, capturing well the land heterogeneity discussed above.

# C Additional Results

Table C.1: Evolution of Phone Services by Division over the Survey Years

| Survey Year | Barisal | Chittagong | Dhaka | Khulna | Rajshahi | Rangpur | Sylhet | Observations |
|---|---|---|---|---|---|---|---|---|
| 2011 | 0.566 | 0.272 | 0.454 | 0.561 | 0.495 | 0.276 | 0.045 | 11661 |
| | (0.500) | (0.445) | (0.498) | (0.496) | (0.500) | (0.447) | (0.206) | |
| 2015 | 0.517 | 0.476 | 0.497 | 0.652 | 0.515 | 0.328 | 0.102 | 9417 |
| | (0.500) | (0.500) | (0.500) | (0.476) | (0.500) | (0.470) | (0.303) | |
| 2018 | 0.587 | 0.484 | 0.497 | 0.678 | 0.528 | 0.264 | 0.091 | 7689 |
| | (0.493) | (0.500) | (0.500) | (0.467) | ( 0.499) | (0.441) | (0.287) | |
| Observations | 1739 | 2266 | 9044 | 3336 | 6021 | 3571 | 2790 | **28767** |

*Notes: Based on the community survey module for the third round of BIHS. The table reports the means, with standard deviations in parentheses.*

Table C.2: Effect of the ACCI on Plot-level Agricultural Inefficiency for Different Agricultural Seasons

| | (1) All | (2) Boro | (3) Aman | (4) Aus |
|---|---|---|---|---|
| Phone Service in the Village | -5.640 | -6.100 | 14.251 | -267.305*** |
| | (11.410) | (9.134) | (14.798) | (59.057) |
| Phone Service in the Village × Post ACCI | -15.634** | 0.355 | -23.056*** | -57.171 |
| | (6.794) | (7.302) | (8.855) | (38.097) |
| Mean Baseline Inefficiency | 29.625 | -13.987 | 62.617 | 98.165 |
| (SD) | (208.816) | (112.529) | (248.972) | (313.016) |
| Observations | 27298 | 12407 | 12959 | 1326 |
| $R^2$ | 0.399 | 0.440 | 0.567 | 0.563 |

*Notes:* * p<0.10, ** p<0.05, *** p<0.01. Robust standard errors clustered at the community level are in parentheses. The dependent variable for all regressions is the *Inefficiency of Agricultural Yield*. *Phone Service in the Village* dummy measures whether the household's community reported having phone service in that year, and Post ACCI is the time dummy capturing whether the survey year is post introduction of the Agricultural Call Center Intervention. All regressions use data from plots that are within 2 kilometers of their respective household locations. All regressions include year fixed effects, time-varying controls, household, crop type, and the interaction of the division with year fixed-effects. Column (1) also includes the season-fixed effects. Time-varying controls include the dummy capturing whether the household owns the plot, a dummy capturing whether the household has an agricultural input subsidy card, and the weather of the household's village as reflected by the minimum and maximum temperature of the year (in °C) and average yearly rainfall (in mm). *Mean Baseline Inefficiency* represents the average inefficiency of all plots calculated in the baseline year (2011) using a total of 12901 observations (6058 from Boro, 5762 from Aman, and 1081 from Aus season).

Table C.3: Differential Effect of the ACCI by Input Use on Plot-level Agricultural Inefficiency for Different Agricultural Seasons

| | (1)<br>All | (2)<br>Boro | (3)<br>Aman | (4)<br>Aus |
|---|---|---|---|---|
| Phone Service in the Village | -8.381 | 1.822 | -7.613 | -238.158** |
| | (7.746) | (5.739) | (13.378) | (93.768) |
| Phone Service in the Village × Post ACCI | -1.963 | -1.618 | 4.123 | 13.386 |
| | (4.048) | (3.812) | (9.158) | (43.477) |
| Used Rainfed Farming | -0.423 | -6.672 | -33.982*** | -62.372 |
| | (7.245) | (10.609) | (9.186) | (40.998) |
| Used Tractor | 230.904*** | 149.831*** | 284.011*** | 302.257*** |
| | (11.984) | (9.047) | (23.275) | (37.980) |
| Used Rainfed Farming × Phone Service in the Village | 24.223** | 0.328 | 40.210*** | 127.860** |
| | (10.750) | (15.717) | (12.581) | (61.676) |
| Used Tractor × Phone Service in the Village | 16.643 | 5.204 | -12.475 | -59.311 |
| | (30.384) | (12.997) | (45.564) | (44.195) |
| Used Rainfed Farming × Post ACCI | -1.518 | -2.933 | 19.137 | 1.035 |
| | (9.273) | (13.369) | (13.102) | (41.723) |
| Used Tractor × Post ACCI | -63.520*** | -18.985 | -101.701*** | 33.067 |
| | (22.440) | (28.523) | (37.332) | (52.499) |
| Used Rainfed Farming × Phone Service in the Village × Post ACCI | -43.539*** | 1.369 | -49.974*** | -46.888 |
| | (12.223) | (19.988) | (17.216) | (62.714) |
| Used Tractor × Phone Service in the Village × Post ACCI | -15.905 | 31.728 | -11.730 | -60.479 |
| | (39.255) | (42.190) | (70.979) | (65.364) |
| Mean Baseline Inefficiency | 29.625 | -13.987 | 62.617 | 98.165 |
| (SD) | (208.816) | (112.529) | (248.972) | (313.016) |
| Observations | 27298 | 12407 | 12959 | 1326 |
| $R^2$ | 0.468 | 0.516 | 0.634 | 0.651 |

*Notes:* * p<0.10, ** p<0.05, *** p<0.01. Robust standard errors clustered at the household level are in parentheses. The dependent variable for all regressions is the *Inefficiency of Agricultural Yield*. *Phone Service in the Village* dummy measures whether the household's community reported having phone service in that year, and Post ACCI is the time dummy capturing whether the survey year is post introduction of the Agricultural Call Center Intervention. *Used Rainfed Farming* and *Used Tractor* dummies capture whether the household used rainfed farming and tractor in their plot, respectively. All regressions use data from plots that are within 2 kilometers of their respective household locations. All regressions include year fixed effects, time-varying controls, household, crop type, and the interaction of the division with year fixed-effects. Column (1) also includes the season-fixed effects. Time-varying controls include the dummy capturing whether the household owns the plot, a dummy capturing whether the household has an agricultural input subsidy card, and the weather of the household's village as reflected by the minimum and maximum temperature of the year (in °C) and average yearly rainfall (in mm).

Table C.4: Differential Effect of the ACCI by Geographic Network Centrality on Plot-level Agricultural Inefficiency for Different Agricultural Seasons

| | (1)<br>All | (2)<br>Boro | (3)<br>Aman | (4)<br>Aus |
|---|---|---|---|---|
| Phone Service in the Village | -30.551 | -29.350 | 19.319 | -268.568*** |
| | (22.565) | (24.220) | (38.955) | (70.980) |
| Phone Service in the Village $\times$ Post ACCI | 30.117 | 40.706** | 9.872 | -95.334 |
| | (19.934) | (17.835) | (33.480) | (106.663) |
| Inverse Betweenness Centrality $\times$ Phone Service in the Village | 31.452 | 30.563 | -5.512 | 0.000 |
| | (26.469) | (25.445) | (45.959) | (.) |
| Inverse Betweenness Centrality $\times$ Post ACCI | 24.934 | 15.204 | 15.082 | -70.142* |
| | (17.624) | (12.061) | (31.853) | (38.066) |
| Inverse Betweenness Centrality $\times$ Phone Service in the Village $\times$ Post ACCI | -54.567** | -47.466** | -40.114 | 51.438 |
| | (22.727) | (20.303) | (36.905) | (109.093) |
| Mean Baseline Inefficiency | 29.625 | -13.987 | 62.617 | 98.165 |
| (SD) | (208.816) | (112.529) | (248.972) | (313.016) |
| Observations | 27064 | 12274 | 12882 | 1308 |
| $R^2$ | 0.400 | 0.440 | 0.567 | 0.564 |

*Notes:* * p<0.10, ** p<0.05, *** p<0.01. Robust standard errors clustered at the household level are in parentheses. The dependent variable for all regressions is the *Inefficiency of Agricultural Yield*. *Phone Service in the Village* dummy measures whether the household's community reported having phone service in that year, and Post ACCI is the time dummy capturing whether the survey year is post introduction of the Agricultural Call Center Intervention. $Inverse\ Betweenness\ Centrality = \frac{1}{1+Betweenness\ Centrality}$ captures the inverse of geographic betweenness centrality for the household at the baseline, which is omitted at the level as the regressions include the household fixed effects. All regressions use data from plots that are within 2 kilometers of their respective household locations. All regressions include year fixed effects, time-varying controls, household, crop type, and the interaction of the division with year fixed-effects. Column (1) also includes the season-fixed effects. Time-varying controls include the dummy capturing whether the household owns the plot, a dummy capturing whether the household has an agricultural input subsidy card, and the weather of the household's village as reflected by the minimum and maximum temperature of the year (in °C) and average yearly rainfall (in mm). *Mean Baseline Inefficiency* represents the average inefficiency of all plots calculated in the baseline year (2011) using a total of 12901 observations (6058 from Boro, 5762 from Aman, and 1081 from Aus season).

Table C.5: Differential Effect of the ACCI by Dyadic Geographic Distances on Plot-level Agricultural Inefficiency for Different Agricultural Seasons

| | (1)<br>All | (2)<br>Boro | (3)<br>Aman | (4)<br>Aus |
|---|---|---|---|---|
| Phone Service in the Village of $i'$ | -63.407** | -17.071** | -107.001* | -260.613** |
| | (24.589) | (7.520) | (55.612) | (115.204) |
| Phone Service in the Village of $i'$ $\times$ Post ACCI | 38.906* | 27.073*** | 77.000 | -141.795 |
| | (20.630) | (10.382) | (53.077) | (123.533) |
| Inverse Distance between $i$ and $i'$ $\times$ Phone Service in the Village of $i'$ | 60.702 | 59.058** | 97.236 | 135.022 |
| | (45.190) | (23.313) | (85.562) | (215.601) |
| Inverse Distance between $i$ and $i'$ $\times$ Post ACCI | 102.427*** | 121.800*** | 142.425* | -71.996 |
| | (35.110) | (43.916) | (84.406) | (57.950) |
| Inverse Distance between $i$ and $i'$ $\times$ Phone Service in the Village of $i'$ $\times$ Post ACCI | -119.823*** | -141.057*** | -152.682 | 161.632 |
| | (46.327) | (49.001) | (107.831) | (382.763) |
| Mean Baseline Inefficiency | 29.625 | -13.987 | 62.617 | 98.165 |
| (SD) | (208.816) | (112.529) | (248.972) | (313.016) |
| Observations | 60724 | 29085 | 26670 | 1312 |
| $R^2$ | 0.243 | 0.523 | 0.423 | 0.731 |

*Notes:* * p<0.10, ** p<0.05, *** p<0.01. Robust standard errors multi-way clustered at the household $i$ and household $i'$ level are in parentheses. The dependent variable for all regressions is the *Inefficiency of Agricultural Yield for i*. *Phone Service in the Village of* $i'$ dummy measures whether the community of household $i'$ reported having phone service in that year and *Post ACCI* is the time dummy capturing whether the survey year is post introduction of the Agricultural Call Center Intervention. *Inverse Distance between i and* $i' = \frac{1}{1+Distance\ between\ i\ and\ i'}$ captures the inverse of geographic distance between households $i$ and $i'$ measured at the baseline, which is omitted at the level as the regressions include the pair fixed effects. All regressions use data from plots that are within 2 kilometers of their respective household locations. All regressions include year fixed effects, time-varying controls, pair fixed effects, and the interaction of the division of household $i$ with year fixed-effects. Column (1) also includes the season-fixed effects. Time-varying controls include the total number of plots owned by $i$, the total number of plots operated by them, whether $i$ has an agricultural input subsidy card, the weather of household $i$'s village as reflected by the minimum and maximum temperature of the year (in °C) and average yearly rainfall (in mm), and *Phone Service in the Village of i* dummy measuring whether $i$'s community reported having phone service in the year interacted with the Post ACCI dummy. *Mean Baseline Inefficiency* represents the average inefficiency of all plots calculated in the baseline year (2011) using a total of 12901 observations (6058 from Boro, 5762 from Aman, and 1081 from Aus season).

Table C.6: Full set of Mechanism Results Capturing Differential Effect of the ACCI by Input Use on Plot-level Usage of Other Inputs

| | (1) Fertilizer Use | (2) Manure Use | (3) Pesticide Use | (4) Cost of Machine | (5) Cost of Seeds | (6) Cost of Labor | (7) Hours of Family Labor | (8) Hours of Hired Labor |
|---|---|---|---|---|---|---|---|---|
| Phone Service in the Village | 43.547* | -8.977 | 57.749 | -6.451 | 803.216*** | 3856.736*** | 46.802 | 124.407*** |
| | (22.381) | (155.354) | (180.487) | (280.558) | (288.203) | (1185.014) | (36.231) | (32.985) |
| Phone Service in the Village × Post ACCI | -16.291 | -77.934 | 380.081** | -194.848 | -254.891 | -1641.702 | -130.567*** | -36.402 |
| | (17.411) | (162.684) | (171.496) | (237.545) | (259.232) | (1078.967) | (26.046) | (23.333) |
| Used Rainfed Farming | -36.071*** | -81.624 | -140.951* | 42.505 | -179.767 | -494.567 | -31.699** | -25.283 |
| | (11.223) | (91.418) | (77.170) | (129.881) | (143.412) | (586.830) | (14.601) | (15.732) |
| Used Tractor | -24.559* | 398.817** | 9.501 | 30.628 | 135.675 | 954.827 | 7.039 | 11.930 |
| | (13.474) | (160.445) | (121.517) | (243.224) | (268.549) | (908.562) | (35.323) | (25.485) |
| Used Rainfed Farming × Phone Service in the Village | -60.970*** | -10.203 | -182.686* | -486.640** | -27.277 | -950.914 | -56.042** | -35.502* |
| | (13.736) | (130.563) | (108.858) | (209.162) | (199.981) | (739.682) | (23.585) | (19.594) |
| Used Tractor × Phone Service in the Village | 44.127** | 7.137 | 280.457 | 1182.682*** | -527.334 | 1272.350 | -95.265** | 23.766 |
| | (21.828) | (268.238) | (253.335) | (395.814) | (413.406) | (1573.772) | (48.274) | (42.940) |
| Used Rainfed Farming × Post ACCI | 2.062 | 303.336** | -287.783** | -887.387*** | -235.444 | -763.301 | 3.402 | 19.760 |
| | (14.188) | (128.041) | (135.234) | (225.110) | (211.487) | (922.012) | (20.962) | (20.076) |
| Used Tractor × Post ACCI | 6.992 | -337.445 | 323.397 | 588.253 | -449.932 | -1512.261 | -43.055 | -48.543 |
| | (20.465) | (299.071) | (256.035) | (437.837) | (431.043) | (1719.601) | (39.099) | (47.313) |
| Used Rainfed Farming × Phone Service in the Village × Post ACCI | 37.924* | 34.157 | 355.477* | 464.503 | 195.941 | 519.026 | 96.034*** | 28.395 |
| | (21.138) | (202.103) | (181.330) | (317.583) | (328.769) | (1179.358) | (33.553) | (25.688) |
| Used Tractor × Phone Service in the Village × Post ACCI | -72.066* | 324.259 | -798.231* | -600.474 | 1589.203** | 766.087 | 134.056* | -2.404 |
| | (40.901) | (484.019) | (413.868) | (775.285) | (702.558) | (2776.455) | (71.333) | (68.690) |
| Mean Baseline Outcome | 364.695 | 1019.461 | 1405.986 | 4933.866 | 5126.187 | 14364.99 | 457.979 | 467.584 |
| (SD) | (237.595) | (2532.455) | (1809.46) | (3128.249) | (4771.416) | (20649.26) | (543.823) | (664.411) |
| Observations | 20629 | 20629 | 20629 | 20629 | 27722 | 20629 | 20629 | 20629 |
| $R^2$ | 0.427 | 0.402 | 0.507 | 0.380 | 0.454 | 0.474 | 0.464 | 0.404 |

*Notes:* * p<0.10, ** p<0.05, *** p<0.01. Robust standard errors clustered at the household level are in parentheses. All dependent variables are in per-hectare terms. *Phone Service in the Village* dummy measures whether the household's community reported having phone service in that year, and Post ACCI is the time dummy capturing whether the survey year is post introduction of the Agricultural Call Center Intervention. *Used Rainfed Farming* and *Used Tractor* dummies capture whether the household used rainfed farming and tractor in their plot, respectively. All regressions use data from plots that are within 2 kilometers of their respective household locations. All regressions include year and season-fixed effects, time-varying controls, household, crop type, and the interaction of the division with year fixed-effects. Time-varying controls include the dummy capturing whether the household owns the plot, a dummy capturing whether the household has an agricultural input subsidy card, and the weather of the household's village as reflected by the minimum and maximum temperature of the year (in °C) and average yearly rainfall (in mm).

Table C.7: Full set of Mechanism Results Capturing Differential Effect of the ACCI by Input Use on Household-level Extension Activities

| | (1) Extension Access Dummy | (2) Extension Agent Visited | (3) Reached Out to Extension Services | (4) Extension Agent Advice Index | (5) Extension Seeking Advice Index |
|---|---|---|---|---|---|
| Phone Service in the Village | -0.013 | 0.018 | 0.018 | 0.034 | 0.032 |
| | (0.056) | (0.044) | (0.033) | (0.032) | (0.025) |
| Phone Service in the Village × Post ACCI | 0.034 | -0.023 | -0.041 | 0.016 | -0.032* |
| | (0.038) | (0.037) | (0.030) | (0.026) | (0.018) |
| Used Rainfed Farming | 0.005 | -0.002 | -0.000 | 0.006 | -0.007 |
| | (0.013) | (0.011) | (0.012) | (0.008) | (0.008) |
| Used Tractor | -0.060*** | 0.007 | -0.013 | -0.000 | 0.002 |
| | (0.022) | (0.021) | (0.022) | (0.015) | (0.015) |
| Used Rainfed Farming × Phone Service in the Village | -0.027 | -0.012 | -0.015 | -0.008 | 0.003 |
| | (0.020) | (0.018) | (0.016) | (0.013) | (0.010) |
| Used Tractor × Phone Service in the Village | 0.050 | 0.012 | -0.001 | -0.000 | -0.012 |
| | (0.039) | (0.047) | (0.030) | (0.032) | (0.019) |
| Used Rainfed Farming × Post ACCI | -0.038 | 0.016 | -0.015 | 0.009 | 0.004 |
| | (0.027) | (0.029) | (0.024) | (0.020) | (0.015) |
| Used Tractor × Post ACCI | 0.020 | -0.019 | 0.077 | 0.030 | 0.029 |
| | (0.052) | (0.070) | (0.058) | (0.053) | (0.042) |
| Used Rainfed Farming × Phone Service in the Village × Post ACCI | 0.123*** | 0.018 | 0.064* | 0.013 | 0.006 |
| | (0.041) | (0.040) | (0.034) | (0.031) | (0.021) |
| Used Tractor × Phone Service in the Village × Post ACCI | -0.047 | -0.028 | -0.009 | -0.074 | 0.038 |
| | (0.087) | (0.096) | (0.081) | (0.070) | (0.059) |
| Mean Baseline Outcome | 0.256 | 0.117 | 0.074 | 0.074 | 0.037 |
| (SD) | (0.437) | (0.321) | (0.261) | (0.230) | (0.157) |
| Observations | 27723 | 27689 | 27689 | 27723 | 27723 |
| $R^2$ | 0.541 | 0.534 | 0.555 | 0.544 | 0.559 |

*Notes:* * p<0.10, ** p<0.05, *** p<0.01. Robust standard errors clustered at the household level are in parentheses. Dependent variables in columns (1)-(3) represent dummies, whereas the dependent variables in columns (4)-(5) are indices that take values between 0 and 1. *Phone Service in the Village* dummy measures whether the household's community reported having phone service in that year, and Post ACCI is the time dummy capturing whether the survey year is post introduction of the Agricultural Call Center Intervention. *Used Rainfed Farming* and *Used Tractor* dummies capture whether the household used rainfed farming and tractor in their plot, respectively. All regressions use data from plots that are within 2 kilometers of their respective household locations. All regressions include year and season-fixed effects, time-varying controls, household, crop type, and the interaction of the division with year fixed-effects. Time-varying controls include the dummy capturing whether the household owns the plot, a dummy capturing whether the household has an agricultural input subsidy card, and the weather of the household's village as reflected by the minimum and maximum temperature of the year (in °C) and average yearly rainfall (in mm).

Table C.8: Full set of Mechanism Results Capturing Differential Effect of the ACCI by Geographic Network Centrality on Plot-level Usage of Other Inputs

| | (1) Fertilizer Use | (2) Manure Use | (3) Pesticide Use | (4) Cost of Machine | (5) Cost of Seeds | (6) Cost of Labor | (7) Hours of Family Labor | (8) Hours of Hired Labor |
|---|---|---|---|---|---|---|---|---|
| Phone Service in the Village | -9.848 | -837.797** | -236.470 | 124.111 | 2170.503** | 1989.598 | -12.997 | 61.115 |
| | (52.576) | (417.388) | (526.541) | (784.768) | (1031.336) | (4694.660) | (135.774) | (120.580) |
| Phone Service in the Village × Post ACCI | -9.430 | 188.332 | 370.718 | 255.773 | 1512.157** | -8108.527*** | -150.266** | -128.891** |
| | (48.162) | (502.040) | (420.349) | (784.843) | (680.294) | (2886.471) | (68.103) | (62.995) |
| Inverse Betweenness Centrality × Phone Service in the Village | 43.809 | 978.212** | 295.124 | -245.636 | -1506.220 | 2052.785 | 39.539 | 65.795 |
| | (59.926) | (471.208) | (590.164) | (867.180) | (1124.377) | (5096.286) | (147.155) | (131.586) |
| Inverse Betweenness Centrality × Post ACCI | -6.049 | 266.297 | 251.627 | 71.668 | 599.395 | -7656.718*** | -63.219 | -170.234*** |
| | (28.845) | (280.682) | (286.113) | (547.661) | (443.480) | (2074.349) | (44.196) | (43.984) |
| Inverse Betweenness Centrality × Phone Service in the Village × Post ACCI | -1.276 | -281.960 | 6.073 | -456.541 | -1868.282** | 8195.154** | 63.475 | 128.385* |
| | (50.801) | (549.451) | (445.008) | (846.425) | (774.557) | (3202.812) | (75.690) | (69.780) |
| Mean Baseline Outcome | 364.695 | 1019.461 | 1405.986 | 4933.866 | 5126.187 | 14364.99 | 457.979 | 467.584 |
| (SD) | (237.595) | (2532.455) | (1809.46) | (3128.249) | (4771.416) | (20649.26) | (543.823) | (664.411) |
| Observations | 20437 | 20437 | 20437 | 20437 | 27744 | 20437 | 20437 | 20437 |
| $R^2$ | 0.421 | 0.400 | 0.505 | 0.384 | 0.450 | 0.473 | 0.456 | 0.402 |

*Notes:* * p<0.10, ** p<0.05, *** p<0.01. Robust standard errors clustered at the household level are in parentheses. All dependent variables are in per-hectare terms. *Phone Service in the Village* dummy measures whether the household's community reported having phone service in that year, and Post ACCI is the time dummy capturing whether the survey year is post introduction of the Agricultural Call Center Intervention. $Inverse\ Betweenness\ Centrality = \frac{1}{1+Betweenness\ Centrality}$ captures the inverse of geographic betweenness centrality for the household at the baseline, which is omitted at the level as the regressions include the household fixed effects. All regressions use data from plots that are within 2 kilometers of their respective household locations. All regressions include year and season-fixed effects, time-varying controls, household, crop type, and the interaction of the division with year fixed-effects. Time-varying controls include the dummy capturing whether the household owns the plot, a dummy capturing whether the household has an agricultural input subsidy card, and the weather of the household's village as reflected by the minimum and maximum temperature of the year (in °C) and average yearly rainfall (in mm).

Table C.9: Full set of Mechanism Results Capturing Differential Effect of the ACCI by Dyadic Geographic Distances on Household-level Usage of Other Inputs

| | (1) Fertilizer Use | (2) Manure Use | (3) Pesticide Use | (4) Cost of Machine | (5) Cost of Seeds | (6) Cost of Labor | (7) Hours of Family Labor | (8) Hours of Hired Labor |
|---|---|---|---|---|---|---|---|---|
| Phone Service in the Village of $i'$ | -131.630* | -120.719 | -1954.914*** | -1249.654 | -4702.866*** | 5705.353* | 44.781 | 163.528** |
| | (79.097) | (561.571) | (629.847) | (858.945) | (1127.299) | (2964.037) | (71.718) | (72.950) |
| Phone Service in the Village of $i'$ $\times$ Post ACCI | 3.010 | -66.467 | 896.526*** | 424.581 | 939.336*** | 96.274 | 80.937** | -13.253 |
| | (35.437) | (213.180) | (215.787) | (390.342) | (314.656) | (1227.115) | (38.736) | (27.312) |
| Inverse Distance between $i$ and $i'$ $\times$ Phone Service in the Village of $i'$ | 322.911* | 1537.269* | 4999.876*** | -811.161 | 7076.539*** | -497.415 | -127.367 | -186.116 |
| | (177.700) | (924.152) | (1747.417) | (1017.570) | (2442.689) | (6358.196) | (228.589) | (167.093) |
| Inverse Distance between $i$ and $i'$ $\times$ Post ACCI | -26.559 | 110.937 | 24.001 | -696.752 | 45.398 | -4868.567*** | 135.105 | -52.408 |
| | (62.598) | (319.953) | (347.603) | (856.958) | (572.378) | (1724.110) | (84.465) | (37.950) |
| Inverse Distance between $i$ and $i'$ $\times$ Phone Service in the Village of $i'$ $\times$ Post ACCI | -58.452 | -738.580 | -1559.783*** | 1145.777 | -557.484 | 4635.532 | -170.227 | 51.939 |
| | (96.162) | (511.467) | (517.170) | (1038.316) | (845.857) | (3311.093) | (113.166) | (69.335) |
| Mean Baseline Outcome | 364.695 | 1019.461 | 1405.986 | 4933.866 | 5126.187 | 14364.99 | 457.979 | 467.584 |
| (SD) | (237.595) | (2532.455) | (1809.46) | (3128.249) | (4771.416) | (20649.26) | (543.823) | (664.411) |
| Observations | 38723 | 38723 | 38723 | 38723 | 38723 | 38723 | 38723 38723 | |
| $R^2$ | 0.506 | 0.503 | 0.653 | 0.563 | 0.616 | 0.721 | 0.665 | 0.718 |

*Notes:** $p<0.10$, ** $p<0.05$, *** $p<0.01$. Robust standard errors multi-way clustered at the household $i$ and household $i'$ level are in parentheses. All dependent variables are in per-hectare terms. *Phone Service in the Village of* $i'$ dummy measures whether the community of household $i'$ reported having phone service in that year and *Post ACCI* is the time dummy capturing whether the survey year is post introduction of the Agricultural Call Center Intervention. $\textit{Inverse Distance between i and } i' = \frac{1}{1+\textit{Distance between i and } i'}$ captures the inverse of geographic distance between households $i$ and $i'$ measured at the baseline, which is omitted at the level as the regressions include the pair fixed effects. All regressions use data from plots that are within 2 kilometers of their respective household locations. All regressions include year and season-fixed effects, time-varying controls, pair-fixed effects, and the interaction of the division of household $i$ with year-fixed effects. Time-varying controls include the total number of plots owned by $i$, the total number of plots operated by them, whether $i$ has an agricultural input subsidy card, the weather of household $i$'s village as reflected by the minimum and maximum temperature of the year (in °C) and average yearly rainfall (in mm), and *Phone Service in the Village of* $i$ dummy measuring whether $i$'s community reported having phone service in the year interacted with the Post ACCI dummy.

Table C.10: Full set of Mechanism Results Capturing Differential Effect of the ACCI by Geographic Network Centrality on Household-level Extension Activities

| | (1) Extension Access Dummy | (2) Extension Agent Visited | (3) Reached Out to Extension Services | (4) Extension Agent Advice Index | (5) Extension Seeking Advice Index |
|---|---|---|---|---|---|
| Phone Service in the Village | -0.105 | 0.005 | -0.134*** | -0.020 | -0.057** |
| | (0.125) | (0.069) | (0.046) | (0.043) | (0.025) |
| Phone Service in the Village × Post ACCI | 0.273*** | 0.118 | 0.067 | 0.142** | 0.027 |
| | (0.095) | (0.112) | (0.086) | (0.068) | (0.047) |
| Inverse Betweenness Centrality × Phone Service in the Village | 0.104 | 0.011 | 0.176*** | 0.061 | 0.105** |
| | (0.146) | (0.096) | (0.066) | (0.058) | (0.047) |
| Inverse Betweenness Centrality × Post ACCI | 0.145** | 0.083 | 0.025 | 0.103** | 0.028 |
| | (0.066) | (0.092) | (0.069) | (0.051) | (0.040) |
| Inverse Betweenness Centrality × Phone Service in the Village × Post ACCI | -0.244** | -0.167 | -0.115 | -0.158** | -0.069 |
| | (0.105) | (0.120) | (0.093) | (0.073) | (0.051) |
| Mean Baseline Outcome | 0.256 | 0.117 | 0.074 | 0.074 | 0.037 |
| (SD) | (0.437) | (0.321) | (0.261) | (0.230) | (0.157) |
| Observations | 27745 | 27714 | 27714 | 27745 | 27745 |
| $R^2$ | 0.541 | 0.533 | 0.552 | 0.542 | 0.555 |

*Notes:* * p<0.10, ** p<0.05, *** p<0.01. Robust standard errors clustered at the household level are in parentheses. Dependent variables in columns (1)-(3) represent dummies, whereas the dependent variables in columns (4)-(5) are indices that take values between 0 and 1. *Phone Service in the Village* dummy measures whether the household's community reported having phone service in that year, and Post ACCI is the time dummy capturing whether the survey year is post introduction of the Agricultural Call Center Intervention. $Inverse\ Betweenness\ Centrality = \frac{1}{1+Betweenness\ Centrality}$ captures the inverse of geographic betweenness centrality for the household at the baseline, which is omitted at the level as the regressions include the household fixed effects. All regressions use data from plots that are within 2 kilometers of their respective household locations. All regressions include year and season-fixed effects, time-varying controls, household, crop type, and the interaction of the division with year fixed-effects. Time-varying controls include the dummy capturing whether the household owns the plot, a dummy capturing whether the household has an agricultural input subsidy card, and the weather of the household's village as reflected by the minimum and maximum temperature of the year (in °C) and average yearly rainfall (in mm).

Table C.11: Full set of Mechanism Results Capturing Differential Effect of the ACCI by Dyadic Geographic Distances on Household-level Extension Activities

| | (1) Extension Access Dummy | (2) Extension Agent Visited | (3) Reached Out to Extension Services | (4) Extension Agent Advice Index | (5) Extension Seeking Advice Index |
|---|---|---|---|---|---|
| Phone Service in the Village of $i'$ | -0.044 | 0.148 | 0.150 | 0.025 | 0.123 |
| | (0.108) | (0.120) | (0.179) | (0.144) | (0.119) |
| Phone Service in the Village of $i'$ × Post ACCI | 0.023 | -0.013 | -0.068 | -0.025 | -0.014 |
| | (0.042) | (0.041) | (0.044) | (0.027) | (0.023) |
| Inverse Distance between $i$ and $i'$ × Phone Service in the Village of $i'$ | 0.274 | -0.193 | -0.095 | -0.182 | -0.093 |
| | (0.208) | (0.176) | (0.366) | (0.229) | (0.232) |
| Inverse Distance between $i$ and $i'$ × Post ACCI | 0.153** | 0.010 | 0.199** | -0.012 | 0.145** |
| | (0.060) | (0.065) | (0.097) | (0.038) | (0.072) |
| Inverse Distance between $i$ and $i'$ × Phone Service in the Village of $i'$ × Post ACCI | -0.202** | -0.089 | -0.236* | -0.022 | -0.180** |
| | (0.094) | (0.102) | (0.122) | (0.068) | (0.085) |
| Mean Baseline Outcome | 0.256 | 0.117 | 0.074 | 0.074 | 0.037 |
| (SD) | (0.437) | (0.321) | (0.261) | (0.230) | (0.157) |
| Observations | 38726 | 38548 | 38548 | 38726 | 38726 |
| $R^2$ | 0.586 | 0.616 | 0.613 | 0.638 | 0.603 |

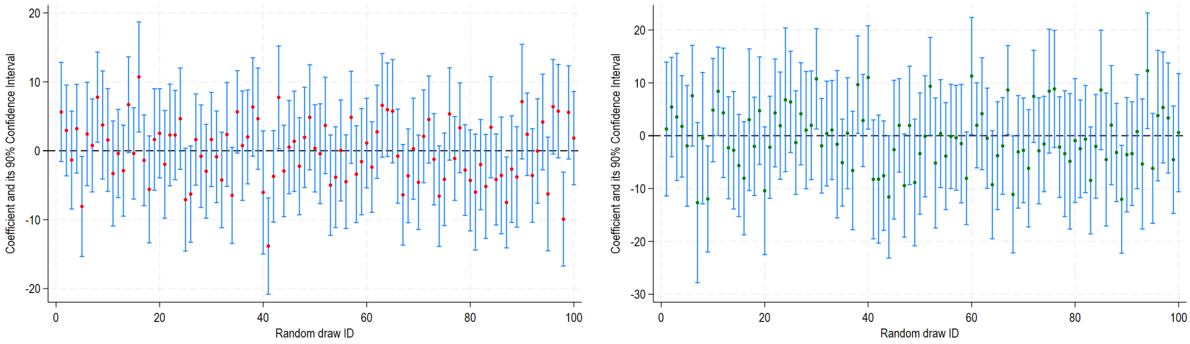
*Notes:* * p<0.10, ** p<0.05, *** p<0.01. Robust standard errors multi-way clustered at the household $i$ and household $i'$ level are in parentheses. Dependent variables in columns (1)-(3) represent dummies, whereas the dependent variables in columns (4)-(5) are indices that take values between 0 and 1. *Phone Service in the Village of $i'$* dummy measures whether the community of household $i'$ reported having phone service in that year and *Post ACCI* is the time dummy capturing whether the survey year is post introduction of the Agricultural Call Center Intervention. $Inverse\ Distance\ between\ i\ and\ i' = \frac{1}{1+Distance\ between\ i\ and\ i'}$ captures the inverse of geographic distance between households $i$ and $i'$ measured at the baseline, which is omitted at the level as the regressions include the pair fixed effects. All regressions use data from plots that are within 2 kilometers of their respective household locations. All regressions include year and season-fixed effects, time-varying controls, pair-fixed effects, and the interaction of the division of household $i$ with year-fixed effects. Time-varying controls include the total number of plots owned by $i$, the total number of plots operated by them, whether $i$ has an agricultural input subsidy card, the weather of household $i$'s village as reflected by the minimum and maximum temperature of the year (in °C) and average yearly rainfall (in mm), and *Phone Service in the Village of $i$* dummy measuring whether $i$'s community reported having phone service in the year interacted with the Post ACCI dummy.

# D Robustness Check Results

Table D.1: Placebo Intervention Effect of the Agricultural Call Center Intervention on Plot-level Agricultural Performances

| | (1)<br>Inefficiency | (2)<br>Actual Yield | (3)<br>Inefficiency | (4)<br>Actual Yield |
|---|---|---|---|---|
| Phone Service in the Village | -5.094 | -113.538 | -1.475 | -93.224 |
| | (14.057) | (135.591) | (9.473) | (118.973) |
| Phone Service in the Village × Placebo Post ACCI | -7.751 | 36.334 | -13.149* | 140.657* |
| | (9.346) | (133.069) | (6.711) | (83.189) |
| Used Rainfed Farming | | | -0.969 | -195.520*** |
| | | | (8.163) | (73.913) |
| Used Tractor | | | 253.207*** | -76.138 |
| | | | (15.392) | (74.331) |
| Used Rainfed Farming × Phone Service in the Village | | | 19.663 | -71.774 |
| | | | (13.247) | (92.964) |
| Used Tractor × Phone Service in the Village | | | -17.477 | 170.528 |
| | | | (33.301) | (132.920) |
| Used Rainfed Farming × Placebo Post ACCI | | | -6.613 | 235.266** |
| | | | (11.408) | (116.815) |
| Used Tractor × Placebo Post ACCI | | | -54.185*** | 148.211 |
| | | | (17.591) | (126.174) |
| Used Rainfed Farming × Phone Service in the Village × Placebo Post ACCI | | | 5.276 | -276.500** |
| | | | (18.814) | (132.715) |
| Used Tractor × Phone Service in the Village × Placebo Post ACCI | | | 47.589 | -237.195 |
| | | | (33.447) | (261.127) |
| Mean Baseline Outcome | 29.625 | 3582.026 | 29.625 | 3582.026 |
| (SD) | (208.816) | (1734.7) | (208.816) | (1734.7) |
| Observations | 20000 | 20621 | 20000 | 20354 |
| $R^2$ | 0.441 | 0.689 | 0.495 | 0.691 |

*Notes:* * p<0.10, ** p<0.05, *** p<0.01. All results report cluster robust standard errors in the parentheses. The clustering is at the community level for the results in columns (1)-(2) and at the household level for the results in columns (3)-(4). All regressions use data from the first two rounds of the Bangladesh Integrated Household Survey (BIHS 2011 & 2015). *Phone Service in the Village* dummy measures whether the household's community reported having phone service in that year, and Placebo Post ACCI is the time dummy capturing whether the survey year is 2015. *Used Rainfed Farming* and *Used Tractor* dummies capture whether the household used rainfed farming and tractor in their plot, respectively. All regressions use data from plots that are within 2 kilometers of their respective household locations. All regressions include year and season-fixed effects, time-varying controls, household, crop type, and the interaction of the division with year fixed-effects. Time-varying controls include the dummy capturing whether the household owns the plot, a dummy capturing whether the household has an agricultural input subsidy card, and the weather of the household's village as reflected by the minimum and maximum temperature of the year (in °C) and average yearly rainfall (in mm).

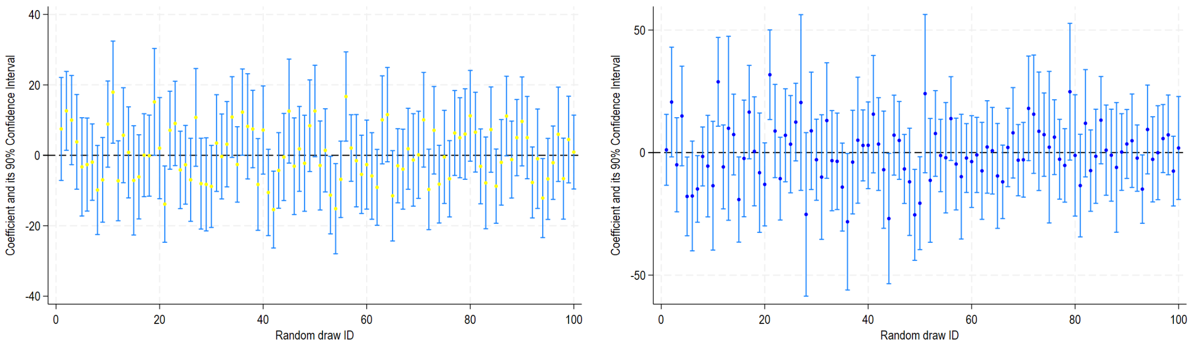



(a) By shuffled Rainfed Farming usage

(b) By shuffled Tractor usage

Figure D.1: Effect of the Agricultural Call Center Intervention by randomly shuffled input usage

*Notes:* The reported triple-difference coefficients for the specification (4), with input usage being captured by shuffled dummies on Rainfed Farming usage and Tractor usage. The coefficients for each draw are coming from the interaction of the respective (shuffled) input usage with the variables *Phone Service in the Village* and Post ACCI in the same regression. Each draw represents a random shuffling of both input usage from their respective distributions by survey year. *Phone Service in the Village* dummy measures whether the household's community reported having phone service in that year, and Post ACCI is the time dummy capturing whether the survey year is post introduction of the Agricultural Call Center Intervention.




(a) By shuffled Inverse Betweenness Centrality

(b) By shuffled Inverse Distance

Figure D.2: Effect of the Agricultural Call Center Intervention by randomly shuffled Centrality and Distance measures

*Notes:* The reported triple-difference coefficients for the specifications (5) and (6), with *Inverse Betweenness Centrality* and *Inverse Distance between i and $i'$* being captured by shuffled values of the same variables at the baseline. Each draw represents a random shuffling of the corresponding variable from their respective distributions for the baseline. *Phone Service in the Village* dummy measures whether the household's community reported having phone service in that year, and Post ACCI is the time dummy capturing whether the survey year is post introduction of the Agricultural Call Center Intervention.

Table D.2: Post-Intervention Effect of the Agricultural Call Center Intervention on Plot-level Agricultural Performances (using plot fixed-effects instead of household fixed-effects)

| | (1) Inefficiency | (2) Actual Yield | (3) Inefficiency | (4) Actual Yield |
|---|---|---|---|---|
| Phone Service in the Village | -1.107 | -180.271 | -2.772 | -149.606 |
| | (10.414) | (110.602) | (8.707) | (107.295) |
| Phone Service in the Village × Post ACCI | -15.713** | 93.737 | 2.621 | 74.593 |
| | (7.542) | (109.443) | (4.964) | (92.521) |
| Used Rainfed Farming | | | -0.454 | -148.610* |
| | | | (8.339) | (83.749) |
| Used Tractor | | | 223.787*** | -50.612 |
| | | | (17.716) | (117.036) |
| Used Rainfed Farming × Phone Service in the Village | | | 23.654** | -199.533** |
| | | | (11.333) | (94.980) |
| Used Tractor × Phone Service in the Village | | | 54.787 | -60.480 |
| | | | (43.633) | (199.343) |
| Used Rainfed Farming × Post ACCI | | | -2.998 | 134.051 |
| | | | (10.866) | (100.239) |
| Used Tractor × Post ACCI | | | -52.812 | 241.116 |
| | | | (32.625) | (187.228) |
| Used Rainfed Farming × Phone Service in the Village × Post ACCI | | | -42.718*** | 131.552 |
| | | | (12.125) | (128.766) |
| Used Tractor × Phone Service in the Village × Post ACCI | | | -85.417 | 75.157 |
| | | | (57.015) | (354.660) |
| Mean Baseline Outcome | 29.625 | 3582.026 | 29.625 | 3582.026 |
| (SD) | (208.816) | (1734.7) | (208.816) | (1734.7) |
| Observations | 23520 | 24341 | 23520 | 23981 |
| $R^2$ | 0.492 | 0.706 | 0.532 | 0.707 |

*Notes:* * p<0.10, ** p<0.05, *** p<0.01. All results report cluster robust standard errors in the parentheses. The clustering is at the community level for the results in columns (1)-(2) and at the household level for the results in columns (3)-(4). *Phone Service in the Village* dummy measures whether the household's community reported having phone service in that year, and Post ACCI is the time dummy capturing whether the survey year is post introduction of the Agricultural Call Center Intervention. *Used Rainfed Farming* and *Used Tractor* dummies capture whether the household used rainfed farming and tractor in their plot, respectively. All regressions use data from plots that are within 2 kilometers of their respective household locations. All regressions include year and season-fixed effects, time-varying controls, plot, crop type, and the interaction of the division with year fixed-effects. Time-varying controls include the dummy capturing whether the household owns the plot, a dummy capturing whether the household has an agricultural input subsidy card, and the weather of the household's village as reflected by the minimum and maximum temperature of the year (in °C) and average yearly rainfall (in mm).

Table D.3: Post-Intervention Effect of the Agricultural Call Center Intervention on Plot-level Agricultural Performances (using the balanced panel of households)

| | (1) Inefficiency | (2) Actual Yield | (3) Inefficiency | (4) Actual Yield |
|---|---|---|---|---|
| Phone Service in the Village | 6.876 | -281.032** | 8.130 | -282.477** |
| | (11.642) | (133.078) | (9.367) | (115.513) |
| Phone Service in the Village × Post ACCI | -16.035** | 90.827 | 1.265 | 72.925 |
| | (7.644) | (111.925) | (4.883) | (94.388) |
| Used Rainfed Farming | | | -0.762 | -156.126 |
| | | | (9.581) | (99.376) |
| Used Tractor | | | 226.606*** | -61.350 |
| | | | (18.996) | (126.123) |
| Used Rainfed Farming × Phone Service in the Village | | | 21.490 | -168.309 |
| | | | (13.151) | (112.562) |
| Used Tractor × Phone Service in the Village | | | 48.814 | -27.378 |
| | | | (49.013) | (220.215) |
| Used Rainfed Farming × Post ACCI | | | 0.757 | 94.780 |
| | | | (11.785) | (106.637) |
| Used Tractor × Post ACCI | | | -56.228* | 233.830 |
| | | | (33.609) | (191.943) |
| Used Rainfed Farming × Phone Service in the Village × Post ACCI | | | -42.813*** | 128.107 |
| | | | (13.074) | (135.183) |
| Used Tractor × Phone Service in the Village × Post ACCI | | | -84.254 | 85.637 |
| | | | (61.862) | (372.900) |
| Mean Baseline Outcome | 29.625 | 3582.026 | 29.625 | 3582.026 |
| (SD) | (208.816) | (1734.7) | (208.816) | (1734.7) |
| Observations | 19191 | 19853 | 19191 | 19578 |
| $R^2$ | 0.476 | 0.696 | 0.524 | 0.697 |

*Notes:* * p<0.10, ** p<0.05, *** p<0.01. All results report cluster robust standard errors in the parentheses. The clustering is at the community level for the results in columns (1)-(2) and at the household level for the results in columns (3)-(4). *Phone Service in the Village* dummy measures whether the household's community reported having phone service in that year, and Post ACCI is the time dummy capturing whether the survey year is post introduction of the Agricultural Call Center Intervention. *Used Rainfed Farming* and *Used Tractor* dummies capture whether the household used rainfed farming and tractor in their plot, respectively. All regressions use data from plots that are within 2 kilometers of their respective household locations. All regressions include year and season-fixed effects, time-varying controls, household, crop type, and the interaction of the division with year fixed-effects. Time-varying controls include the dummy capturing whether the household owns the plot, a dummy capturing whether the household has an agricultural input subsidy card, and the weather of the household's village as reflected by the minimum and maximum temperature of the year (in °C) and average yearly rainfall (in mm).

Table D.4: Post-Intervention Effect of the Agricultural Call Center Intervention on Plot-level Agricultural Performances (excluding observations from round 1)

| | (1) Inefficiency | (2) Actual Yield | (3) Inefficiency | (4) Actual Yield |
|---|---|---|---|---|
| Phone Service in the Village | -21.688 | -393.063* | -22.906 | -288.744 |
| | (31.918) | (219.681) | (18.483) | (291.862) |
| Phone Service in the Village × Post ACCI | -14.971* | 145.814 | 1.365 | 80.457 |
| | (8.791) | (124.376) | (4.507) | (91.702) |
| Used Rainfed Farming | | | 1.447 | -252.161* |
| | | | (13.676) | (129.203) |
| Used Tractor | | | 191.687*** | 143.623 |
| | | | (14.437) | (162.345) |
| Used Rainfed Farming × Phone Service in the Village | | | 20.338 | -187.450 |
| | | | (19.323) | (145.435) |
| Used Tractor × Phone Service in the Village | | | 89.992 | -515.273* |
| | | | (62.049) | (304.394) |
| Used Rainfed Farming × Post ACCI | | | 2.395 | 50.367 |
| | | | (11.687) | (121.925) |
| Used Tractor × Post ACCI | | | -18.486 | 64.254 |
| | | | (15.607) | (177.703) |
| Used Rainfed Farming × Phone Service in the Village × Post ACCI | | | -37.391** | 171.553 |
| | | | (14.934) | (146.367) |
| Used Tractor × Phone Service in the Village × Post ACCI | | | -85.952 | 464.007 |
| | | | (60.006) | (364.352) |
| Mean Baseline Outcome | 29.625 | 3582.026 | 29.625 | 3582.026 |
| (SD) | (208.816) | (1734.7) | (208.816) | (1734.7) |
| Observations | 16016 | 16375 | 16016 | 16375 |
| $R^2$ | 0.498 | 0.657 | 0.551 | 0.660 |

*Notes:* * p<0.10, ** p<0.05, *** p<0.01. All results report cluster robust standard errors in the parentheses. The clustering is at the community level for the results in columns (1)-(2) and at the household level for the results in columns (3)-(4). *Phone Service in the Village* dummy measures whether the household's community reported having phone service in that year, and Post ACCI is the time dummy capturing whether the survey year is post introduction of the Agricultural Call Center Intervention. *Used Rainfed Farming* and *Used Tractor* dummies capture whether the household used rainfed farming and tractor in their plot, respectively. All regressions use data from plots that are within 2 kilometers of their respective household locations. All regressions include year and season-fixed effects, time-varying controls, household, crop type, and the interaction of the division with year fixed-effects. Time-varying controls include the dummy capturing whether the household owns the plot, a dummy capturing whether the household has an agricultural input subsidy card, and the weather of the household's village as reflected by the minimum and maximum temperature of the year (in °C) and average yearly rainfall (in mm).

Table D.5: Post-Intervention Effect of the Agricultural Call Center Intervention on Plot-level Agricultural Performances (using fertilizer usage, instead of tractor usage, as an indicator of high-yielding input)

| | (1) Inefficiency | (2) Actual Yield | (3) Inefficiency | (4) Actual Yield |
|---|---|---|---|---|
| Phone Service in the Village | 13.116 | -164.784 | -22.603* | 73.867 |
| | (11.636) | (101.555) | (12.881) | (109.574) |
| Phone Service in the Village × Post ACCI | -17.904** | 110.545 | 20.722* | -23.634 |
| | (8.685) | (99.436) | (11.311) | (113.221) |
| Used Rainfed Farming | | | -21.431** | -100.772 |
| | | | (10.477) | (89.011) |
| Above Median Fertilizer Usage | | | 157.367*** | 552.316*** |
| | | | (6.122) | (65.961) |
| Used Rainfed Farming × Phone Service in the Village | | | 44.144*** | -297.652*** |
| | | | (14.786) | (102.482) |
| Above Median Fertilizer Usage × Phone Service in the Village | | | 25.141** | -224.811*** |
| | | | (12.528) | (85.654) |
| Used Rainfed Farming × Post ACCI | | | 14.018 | 27.944 |
| | | | (11.093) | (103.688) |
| Above Median Fertilizer Usage × Post ACCI | | | 4.985 | -209.446** |
| | | | (9.315) | (91.655) |
| Used Rainfed Farming × Phone Service in the Village × Post ACCI | | | -60.155*** | 238.759* |
| | | | (16.276) | (138.106) |
| Above Median Fertilizer Usage × Phone Service in the Village × Post ACCI | | | -35.021** | 139.141 |
| | | | (14.883) | (125.604) |
| Mean Baseline Outcome | 91.717 | 3582.026 | 91.717 | 3582.026 |
| (SD) | (271.615) | (1734.7) | (271.615) | (1734.7) |
| Observations | 20254 | 27991 | 20254 | 20629 |
| $R^2$ | 0.332 | 0.631 | 0.448 | 0.644 |

*Notes:* * p<0.10, ** p<0.05, *** p<0.01. All results report cluster robust standard errors in the parentheses. The clustering is at the community level for the results in columns (1)-(2) and at the household level for the results in columns (3)-(4). *Phone Service in the Village* dummy measures whether the household's community reported having phone service in that year, and Post ACCI is the time dummy capturing whether the survey year is post introduction of the Agricultural Call Center Intervention. *Used Rainfed Farming* and *Above Median Fertilizer Usage* dummies capture whether the household used rainfed farming and above the median level of fertilizer in their plot, respectively. All regressions use data from plots that are within 2 kilometers of their respective household locations. All regressions include year and season-fixed effects, time-varying controls, household, crop type, and the interaction of the division with year fixed-effects. Time-varying controls include the dummy capturing whether the household owns the plot, a dummy capturing whether the household has an agricultural input subsidy card, and the weather of the household's village as reflected by the minimum and maximum temperature of the year (in °C) and average yearly rainfall (in mm).

Table D.6: Post-Intervention Effect of the Agricultural Call Center Intervention on Plot-level Agricultural Performances (controlling for other input usage)

| | (1) Inefficiency | (2) Actual Yield | (3) Inefficiency | (4) Actual Yield |
|---|---|---|---|---|
| Phone Service in the Village | -8.486 | -140.377 | -11.204 | -69.685 |
| | (15.121) | (104.101) | (9.668) | (102.927) |
| Phone Service in the Village × Post ACCI | -18.436** | 122.106 | -0.204 | 87.948 |
| | (7.894) | (104.237) | (4.311) | (80.944) |
| Used Rainfed Farming | | | 0.127 | -163.045* |
| | | | (8.800) | (89.411) |
| Used Tractor | | | 216.930*** | 4.475 |
| | | | (10.466) | (88.419) |
| Used Rainfed Farming × Phone Service in the Village | | | 25.202* | -195.873* |
| | | | (13.391) | (100.800) |
| Used Tractor × Phone Service in the Village | | | 35.782 | -36.531 |
| | | | (34.471) | (161.531) |
| Used Rainfed Farming × Post ACCI | | | -4.162 | 106.126 |
| | | | (9.897) | (96.935) |
| Used Tractor × Post ACCI | | | -39.108** | 175.589 |
| | | | (15.362) | (138.445) |
| Used Rainfed Farming × Phone Service in the Village × Post ACCI | | | -47.315*** | 151.544 |
| | | | (13.161) | (121.893) |
| Used Tractor × Phone Service in the Village × Post ACCI | | | -47.678 | 65.131 |
| | | | (40.772) | (262.413) |
| Mean Baseline Outcome | 29.625 | 3582.026 | 29.625 | 3582.026 |
| (SD) | (208.816) | (1734.7) | (208.816) | (1734.7) |
| Observations | 20254 | 20629 | 20254 | 20629 |
| $R^2$ | 0.417 | 0.645 | 0.484 | 0.647 |

*Notes:* * p<0.10, ** p<0.05, *** p<0.01. All results report cluster robust standard errors in the parentheses. The clustering is at the community level for the results in columns (1)-(2) and at the household level for the results in columns (3)-(4). *Phone Service in the Village* dummy measures whether the household's community reported having phone service in that year, and Post ACCI is the time dummy capturing whether the survey year is post introduction of the Agricultural Call Center Intervention. *Used Rainfed Farming* and *Used Tractor* dummies capture whether the household used rainfed farming and tractor in their plot, respectively. All regressions use data from plots that are within 2 kilometers of their respective household locations. All regressions include year and season-fixed effects, time-varying controls, household, crop type, and the interaction of the division with year fixed-effects. Time-varying controls include the dummy capturing whether the household owns the plot, a dummy capturing whether the household has an agricultural input subsidy card, and the weather of the household's village as reflected by the minimum and maximum temperature of the year (in °C) and average yearly rainfall (in mm). All regressions also control for fertilizer use (kilograms per hectare), manure use (taka per hectare), pesticide use (taka per hectare), cost of the machine (taka per hectare), cost of seeds (taka per hectare), cost of labor (taka per hectare), family labor hours (per hectare), and hired labor hours (per hectare).

Table D.7: Post-Intervention Effect of the Agricultural Call Center Intervention on Plot-level Agricultural Performances (using simulation-based potential yield at the 90th percentile)

| | (1)<br>Inefficiency | (2)<br>Actual Yield | (3)<br>Inefficiency | (4)<br>Actual Yield |
|---|---|---|---|---|
| Phone Service in the Village | -6.330 | -164.784 | -9.492 | -111.050 |
| | (12.978) | (101.555) | (8.801) | (96.423) |
| Phone Service in the Village × Post ACCI | -17.658** | 110.545 | -2.178 | 87.096 |
| | (7.718) | (99.436) | (4.599) | (80.204) |
| Used Rainfed Farming | | | -0.660 | -161.954** |
| | | | (8.227) | (73.481) |
| Used Tractor | | | 262.588*** | -5.803 |
| | | | (13.649) | (70.683) |
| Used Rainfed Farming × Phone Service in the Village | | | 27.675** | -222.761*** |
| | | | (12.176) | (85.864) |
| Used Tractor × Phone Service in the Village | | | 18.670 | 43.134 |
| | | | (34.279) | (131.907) |
| Used Rainfed Farming × Post ACCI | | | -1.718 | 87.067 |
| | | | (10.539) | (92.611) |
| Used Tractor × Post ACCI | | | -72.464*** | 257.615* |
| | | | (25.654) | (147.503) |
| Used Rainfed Farming × Phone Service in the Village × Post ACCI | | | -49.476*** | 163.653 |
| | | | (13.877) | (120.209) |
| Used Tractor × Phone Service in the Village × Post ACCI | | | -17.249 | -82.591 |
| | | | (44.461) | (252.435) |
| Mean Baseline Outcome | 29.625 | 3582.026 | 29.625 | 3582.026 |
| (SD) | (208.816) | (1734.7) | (208.816) | (1734.7) |
| Observations | 27298 | 27991 | 27298 | 27723 |
| $R^2$ | 0.399 | 0.631 | 0.468 | 0.633 |

*Notes:* * p<0.10, ** p<0.05, *** p<0.01. All results report cluster robust standard errors in the parentheses. The clustering is at the community level for the results in columns (1)-(2) and at the household level for the results in columns (3)-(4). *Phone Service in the Village* dummy measures whether the household's community reported having phone service in that year, and Post ACCI is the time dummy capturing whether the survey year is post introduction of the Agricultural Call Center Intervention. *Used Rainfed Farming* and *Used Tractor* dummies capture whether the household used rainfed farming and tractor in their plot, respectively. All regressions use data from plots that are within 2 kilometers of their respective household locations. All regressions include year and season-fixed effects, time-varying controls, plot, crop type, and the interaction of the division with year fixed-effects. Time-varying controls include the dummy capturing whether the household owns the plot, a dummy capturing whether the household has an agricultural input subsidy card, and the weather of the household's village as reflected by the minimum and maximum temperature of the year (in °C) and average yearly rainfall (in mm).

Table D.8: Post-Intervention Effect of the Agricultural Call Center Intervention on Plot-level Agricultural Performances (fixing the *Phone Service in the Village* at the baseline)

| | (1) Inefficiency | (2) Actual Yield | (3) Inefficiency | (4) Actual Yield |
|---|---|---|---|---|
| Phone Service in the Village × Post ACCI | -13.052* | 95.124 | 4.017 | 47.984 |
| | (6.703) | (98.833) | (4.187) | (81.080) |
| Used Rainfed Farming | | | -0.736 | -156.781* |
| | | | (9.242) | (95.095) |
| Used Tractor | | | 214.205*** | -4.381 |
| | | | (11.432) | (95.258) |
| Used Rainfed Farming × Phone Service in the Village | | | 31.015** | -317.568*** |
| | | | (13.654) | (106.130) |
| Used Tractor × Phone Service in the Village | | | 36.440 | 6.699 |
| | | | (30.402) | (153.942) |
| Used Rainfed Farming × Post ACCI | | | -1.198 | 56.643 |
| | | | (10.070) | (100.624) |
| Used Tractor × Post ACCI | | | -35.909** | 169.468 |
| | | | (15.826) | (144.333) |
| Used Rainfed Farming × Phone Service in the Village × Post ACCI | | | -51.810*** | 239.646* |
| | | | (13.228) | (124.537) |
| Used Tractor × Phone Service in the Village × Post ACCI | | | -50.456 | 65.841 |
| | | | (37.657) | (266.225) |
| Mean Baseline Outcome | 29.625 | 3582.026 | 29.625 | 3582.026 |
| (SD) | (208.816) | (1734.7) | (208.816) | (1734.7) |
| Observations | 27283 | 27976 | 20246 | 20621 |
| $R^2$ | 0.399 | 0.630 | 0.482 | 0.637 |

*Notes:* * p<0.10, ** p<0.05, *** p<0.01. All results report cluster robust standard errors in the parentheses. The clustering is at the community level for the results in columns (1)-(2) and at the household level for the results in columns (3)-(4). *Phone Service in the Village* dummy measures whether the household's community reported having phone service in the baseline, and Post ACCI is the time dummy capturing whether the survey year is post introduction of the Agricultural Call Center Intervention. *Used Rainfed Farming* and *Used Tractor* dummies capture whether the household used rainfed farming and tractor in their plot, respectively. All regressions use data from plots that are within 2 kilometers of their respective household locations. All regressions include year and season-fixed effects, time-varying controls, household, crop type, and the interaction of the division with year fixed-effects. Time-varying controls include the dummy capturing whether the household owns the plot, a dummy capturing whether the household has an agricultural input subsidy card, and the weather of the household's village as reflected by the minimum and maximum temperature of the year (in °C) and average yearly rainfall (in mm).

Table D.9: Differential Effect of the Agricultural Call Center Intervention by Geographic Network Centrality on Plot-level Agricultural Outcomes (using plot fixed-effects instead of household fixed-effects)

| | (1) Inefficiency | (2) Actual Yield | (3) Used Rainfed Farming | (4) Used Tractor |
|---|---|---|---|---|
| Phone Service in the Village | -29.307 | -97.127 | -0.148* | -0.097 |
| | (23.591) | (297.499) | (0.082) | (0.078) |
| Phone Service in the Village × Post ACCI | 40.603 | -332.128 | 0.024 | -0.020 |
| | (27.909) | (222.526) | (0.055) | (0.058) |
| Inverse Betweenness Centrality × Phone Service in the Village | 33.777 | -98.676 | 0.172* | 0.086 |
| | (28.416) | (338.923) | (0.088) | (0.086) |
| Inverse Betweenness Centrality × Post ACCI | 40.071 | -417.238** | 0.016 | -0.048 |
| | (26.975) | (170.934) | (0.042) | (0.042) |
| Inverse Betweenness Centrality × Phone Service in the Village × Post ACCI | -67.122** | 508.025** | 0.002 | -0.010 |
| | (30.948) | (252.068) | (0.064) | (0.064) |
| Mean Baseline Outcome | 29.625 | 3582.026 | 0.321 | 0.071 |
| (SD) | (208.816) | (1734.7) | (0.467) | (0.257) |
| Observations | 23334 | 24141 | 24141 | 23791 |
| $R^2$ | 0.492 | 0.706 | 0.701 | 0.746 |

*Notes:* * p<0.10, ** p<0.05, *** p<0.01. Robust standard errors clustered at the household level are in parentheses. *Phone Service in the Village* dummy measures whether the household's community reported having phone service in that year, and Post ACCI is the time dummy capturing whether the survey year is post introduction of the Agricultural Call Center Intervention. $Inverse\ Betweenness\ Centrality = \frac{1}{1+Betweenness\ Centrality}$ captures the inverse of geographic betweenness centrality for the household at the baseline, which is omitted at the level as the regressions include the household fixed effects. All regressions use data from plots that are within 2 kilometers of their respective household locations. All regressions include year and season-fixed effects, time-varying controls, plot, crop type, and the interaction of the division with year fixed-effects. Time-varying controls include the dummy capturing whether the household owns the plot, a dummy capturing whether the household has an agricultural input subsidy card, and the weather of the household's village as reflected by the minimum and maximum temperature of the year (in °C) and average yearly rainfall (in mm).

Table D.10: Differential Effect of the Agricultural Call Center Intervention by Geographic Network Centrality on Plot-level Agricultural Outcomes (using the balanced panel of households)

| | (1) Inefficiency | (2) Actual Yield | (3) Used Rainfed Farming | (4) Used Tractor |
|---|---|---|---|---|
| Phone Service in the Village | -28.483 | -52.351 | -0.099 | -0.095 |
| | (31.260) | (286.219) | (0.100) | (0.108) |
| Phone Service in the Village × Post ACCI | 33.327 | -440.795** | -0.006 | -0.032 |
| | (20.271) | (206.694) | (0.051) | (0.055) |
| Inverse Betweenness Centrality × Phone Service in the Village | 34.050 | -228.029 | 0.118 | 0.096 |
| | (35.575) | (324.254) | (0.108) | (0.117) |
| Inverse Betweenness Centrality × Post ACCI | 28.267 | -462.630*** | -0.000 | -0.069 |
| | (17.806) | (154.146) | (0.037) | (0.044) |
| Inverse Betweenness Centrality × Phone Service in the Village × Post ACCI | -60.301*** | 666.110*** | 0.031 | 0.014 |
| | (23.106) | (232.812) | (0.058) | (0.060) |
| Mean Baseline Outcome | 29.625 | 3582.026 | 0.321 | 0.071 |
| (SD) | (208.816) | (1734.7) | (0.467) | (0.257) |
| Observations | 21466 | 22021 | 22021 | 21807 |
| $R^2$ | 0.338 | 0.615 | 0.655 | 0.544 |

*Notes:* * p<0.10, ** p<0.05, *** p<0.01. Robust standard errors clustered at the household level are in parentheses. *Phone Service in the Village* dummy measures whether the household's community reported having phone service in that year, and Post ACCI is the time dummy capturing whether the survey year is post introduction of the Agricultural Call Center Intervention. $Inverse\ Betweenness\ Centrality = \frac{1}{1+Betweenness\ Centrality}$ captures the inverse of geographic betweenness centrality for the household at the baseline, which is omitted at the level as the regressions include the household fixed effects. All regressions use data from plots that are within 2 kilometers of their respective household locations. All regressions include year and season-fixed effects, time-varying controls, household, crop type, and the interaction of the division with year fixed-effects. Time-varying controls include the dummy capturing whether the household owns the plot, a dummy capturing whether the household has an agricultural input subsidy card, and the weather of the household's village as reflected by the minimum and maximum temperature of the year (in °C) and average yearly rainfall (in mm).

Table D.11: Differential Effect of the Agricultural Call Center Intervention by Geographic Network Centrality on Plot-level Agricultural Outcomes (excluding observations from round 1)

| | (1) Inefficiency | (2) Actual Yield | (3) Used Rainfed Farming | (4) Used Tractor |
|---|---|---|---|---|
| Phone Service in the Village | -235.256* | 868.769 | 0.055 | -0.708* |
| | (142.104) | (569.248) | (0.064) | (0.385) |
| Phone Service in the Village × Post ACCI | 27.811 | -511.326** | -0.052 | -0.011 |
| | (23.415) | (217.478) | (0.061) | (0.064) |
| Inverse Betweenness Centrality × Phone Service in the Village | 243.206 | -1435.240** | -0.071 | 0.729* |
| | (148.948) | (691.347) | (0.106) | (0.405) |
| Inverse Betweenness Centrality × Post ACCI | 24.983 | -657.915*** | -0.017 | -0.071 |
| | (19.498) | (165.015) | (0.043) | (0.051) |
| Inverse Betweenness Centrality × Phone Service in the Village × Post ACCI | -51.350* | 786.412*** | 0.059 | -0.010 |
| | (27.349) | (245.779) | (0.069) | (0.070) |
| Mean Baseline Outcome | 29.625 | 3582.026 | 0.321 | 0.071 |
| (SD) | (208.816) | (1734.7) | (0.467) | (0.257) |
| Observations | 15852 | 16204 | 16204 | 16204 |
| $R^2$ | 0.498 | 0.658 | 0.692 | 0.724 |

*Notes:* * p<0.10, ** p<0.05, *** p<0.01. Robust standard errors clustered at the household level are in parentheses. *Phone Service in the Village* dummy measures whether the household's community reported having phone service in that year, and Post ACCI is the time dummy capturing whether the survey year is post introduction of the Agricultural Call Center Intervention. $Inverse\ Betweenness\ Centrality = \frac{1}{1+Betweenness\ Centrality}$ captures the inverse of geographic betweenness centrality for the household at the baseline, which is omitted at the level as the regressions include the household fixed effects. All regressions use data from plots that are within 2 kilometers of their respective household locations. All regressions include year and season-fixed effects, time-varying controls, household, crop type, and the interaction of the division with year fixed-effects. Time-varying controls include the dummy capturing whether the household owns the plot, a dummy capturing whether the household has an agricultural input subsidy card, and the weather of the household's village as reflected by the minimum and maximum temperature of the year (in °C) and average yearly rainfall (in mm).

Table D.12: Differential Effect of the Agricultural Call Center Intervention by Dyadic Geographic Distances on Household-level Agricultural Outcomes (excluding observations from round 1)

| | (1) Inefficiency | (2) Actual Yield | (3) Used Rainfed Farming | (4) Used Tractor |
|---|---|---|---|---|
| Phone Service in the Village of $i'$ | -51.837 | -2575.994** | 0.158* | -0.076 |
| | (51.059) | (1182.204) | (0.087) | (0.092) |
| Phone Service in the Village of $i'$ $\times$ Post ACCI | 63.271* | -736.776 | -0.045* | -0.016 |
| | (37.363) | (586.391) | (0.024) | (0.025) |
| Inverse Distance between $i$ and $i'$ $\times$ Phone Service in the Village of $i'$ | 103.320 | 3453.561* | -0.379* | 0.162 |
| | (79.955) | (1873.143) | (0.222) | (0.222) |
| Inverse Distance between $i$ and $i'$ $\times$ Post ACCI | 148.393** | -4266.983** | -0.167*** | -0.012 |
| | (62.835) | (1664.085) | (0.047) | (0.045) |
| Inverse Distance between $i$ and $i'$ $\times$ Phone Service in the Village of $i'$ $\times$ Post ACCI | -184.272** | 5059.340** | 0.157** | 0.069 |
| | (88.375) | (2072.056) | (0.072) | (0.065) |
| Mean Baseline Outcome | 29.625 | 3582.026 | 0.321 | 0.071 |
| (SD) | (208.816) | (1734.7) | (0.467) | (0.257) |
| Observations | 38726 | 38726 | 38726 | 38726 |
| $R^2$ | 0.362 | 0.902 | 0.687 | 0.691 |

*Notes:* * p<0.10, ** p<0.05, *** p<0.01. Robust standard errors multi-way clustered at the household $i$ and household $i'$ level are in parentheses. *Phone Service in the Village of* $i'$ dummy measures whether the community of household $i'$ reported having phone service in that year and *Post ACCI* is the time dummy capturing whether the survey year is post introduction of the Agricultural Call Center Intervention. *Inverse Distance between i and* $i' = \frac{1}{1+Distance\ between\ i\ and\ i'}$ captures the inverse of geographic distance between households $i$ and $i'$ measured at the baseline, which is omitted at the level as the regressions include the pair fixed effects. All regressions use data from plots that are within 2 kilometers of their respective household locations. All regressions include year and season-fixed effects, time-varying controls, pair fixed effects, and the interaction of the division of household $i$ with year fixed-effects. Time-varying controls include the total number of plots owned by $i$, the total number of plots operated by them, whether $i$ has an agricultural input subsidy card, the weather of household $i$'s village as reflected by the minimum and maximum temperature of the year (in °C) and average yearly rainfall (in mm), and *Phone Service in the Village of i* dummy measuring whether $i$'s community reported having phone service in the year interacted with the Post ACCI dummy.

Table D.13: Differential Effect of the Agricultural Call Center Intervention by Geographic Network Centrality on Plot-level Agricultural Outcomes (with respect to placebo intervention between 2011 and 2015)

| | (1) Inefficiency | (2) Actual Yield | (3) Used Rainfed Farming | (4) Used Tractor |
|---|---|---|---|---|
| Phone Service in the Village | -46.395* | -228.411 | -0.088 | -0.069 |
| | (26.834) | (335.691) | (0.090) | (0.072) |
| Phone Service in the Village $\times$ Post ACCI | -3.005 | 330.303 | 0.076 | -0.018 |
| | (22.678) | (222.396) | (0.055) | (0.037) |
| Inverse Betweenness Centrality $\times$ Phone Service in the Village | 50.387 | 136.747 | 0.012 | 0.033 |
| | (33.643) | (389.413) | (0.099) | (0.086) |
| Inverse Betweenness Centrality $\times$ Post ACCI | -22.797 | 516.034*** | 0.054* | 0.015 |
| | (19.102) | (191.100) | (0.032) | (0.027) |
| Inverse Betweenness Centrality $\times$ Phone Service in the Village $\times$ Post ACCI | -3.135 | -377.318 | -0.038 | 0.022 |
| | (26.096) | (246.921) | (0.060) | (0.042) |
| Mean Baseline Outcome | 29.625 | 3582.026 | 0.321 | 0.071 |
| (SD) | (208.816) | (1734.7) | (0.467) | (0.257) |
| Observations | 19836 | 20445 | 20445 | 20183 |
| $R^2$ | 0.442 | 0.689 | 0.716 | 0.605 |

*Notes:* * p<0.10, ** p<0.05, *** p<0.01. Robust standard errors clustered at the household level are in parentheses. *Phone Service in the Village* dummy measures whether the household's community reported having phone service in that year, and Post ACCI is the time dummy capturing whether the survey year is post introduction of the Agricultural Call Center Intervention. $Inverse\ Betweenness\ Centrality = \frac{1}{1+Betweenness\ Centrality}$ captures the inverse of geographic betweenness centrality for the household at the baseline, which is omitted at the level as the regressions include the household fixed effects. All regressions use data from plots that are within 2 kilometers of their respective household locations. All regressions include year and season-fixed effects, time-varying controls, household, crop type, and the interaction of the division with year fixed-effects. Time-varying controls include the dummy capturing whether the household owns the plot, a dummy capturing whether the household has an agricultural input subsidy card, and the weather of the household's village as reflected by the minimum and maximum temperature of the year (in °C) and average yearly rainfall (in mm).

Table D.14: Differential Effect of the Agricultural Call Center Intervention by Dyadic Geographic Distances on Household-level Agricultural Outcomes (with respect to placebo intervention between 2011 and 2015)

| | (1) Inefficiency | (2) Actual Yield | (3) Used Rainfed Farming | (4) Used Tractor |
|---|---|---|---|---|
| Phone Service in the Village of $i'$ | -44.988** | -336.568 | 0.012 | -0.094** |
| | (20.069) | (782.428) | (0.037) | (0.041) |
| Phone Service in the Village of $i'$ × Post ACCI | -52.104 | 473.667 | 0.035 | -0.023 |
| | (43.278) | (608.213) | (0.022) | (0.023) |
| Inverse Distance between $i$ and $i'$ × Phone Service in the Village of $i'$ | 23.838 | 1830.899 | -0.101 | 0.024 |
| | (80.126) | (3189.722) | (0.117) | (0.148) |
| Inverse Distance between $i$ and $i'$ × Post ACCI | -125.722 | 724.803 | 0.020 | -0.022 |
| | (89.192) | (997.452) | (0.039) | (0.029) |
| Inverse Distance between $i$ and $i'$ × Phone Service in the Village of $i'$ × Post ACCI | 173.922 | -1711.449 | -0.089 | 0.048 |
| | (135.452) | (1679.774) | (0.064) | (0.053) |
| Mean Baseline Outcome | 29.625 | 3582.026 | 0.321 | 0.071 |
| (SD) | (208.816) | (1734.7) | (0.467) | (0.257) |
| Observations | 40284 | 40284 | 40284 | 40212 |
| $R^2$ | 0.313 | 0.878 | 0.715 | 0.700 |

*Notes:* * p<0.10, ** p<0.05, *** p<0.01. Robust standard errors multi-way clustered at the household $i$ and household $i'$ level are in parentheses. *Phone Service in the Village of $i'$* dummy measures whether the community of household $i'$ reported having phone service in that year and *Post ACCI* is the time dummy capturing whether the survey year is post introduction of the Agricultural Call Center Intervention. $\textit{Inverse Distance between i and } i' = \frac{1}{1+\textit{Distance between i and } i'}$ captures the inverse of geographic distance between households $i$ and $i'$ measured at the baseline, which is omitted at the level as the regressions include the pair fixed effects. All regressions use data from plots that are within 2 kilometers of their respective household locations. All regressions include year and season-fixed effects, time-varying controls, pair fixed effects, and the interaction of the division of household $i$ with year fixed-effects. Time-varying controls include the total number of plots owned by $i$, the total number of plots operated by them, whether $i$ has an agricultural input subsidy card, the weather of household $i$'s village as reflected by the minimum and maximum temperature of the year (in °C) and average yearly rainfall (in mm), and *Phone Service in the Village of i* dummy measuring whether $i$'s community reported having phone service in the year interacted with the Post ACCI dummy.

Table D.15: Differential Effect of the Agricultural Call Center Intervention by Geographic Network Centrality on Plot-level Agricultural Outcomes (fixing the *Phone Service in the Village* at the baseline)

| | (1) Inefficiency | (2) Actual Yield | (3) Used Rainfed Farming | (4) Used Tractor |
|---|---|---|---|---|
| Phone Service in the Village × Post ACCI | 35.417* | -457.967** | -0.023 | -0.022 |
| | (19.679) | (196.915) | (0.049) | (0.054) |
| Inverse Betweenness Centrality × Post ACCI | 25.993 | -471.246*** | 0.004 | -0.057 |
| | (17.423) | (148.817) | (0.035) | (0.043) |
| Inverse Betweenness Centrality × Phone Service in the Village × Post ACCI | -57.415** | 652.454*** | 0.050 | 0.000 |
| | (22.452) | (222.166) | (0.056) | (0.059) |
| Mean Baseline Outcome | 29.625 | 3582.026 | 0.321 | 0.071 |
| (SD) | (208.816) | (1734.7) | (0.467) | (0.257) |
| Observations | 27049 | 27730 | 27730 | 27467 |
| $R^2$ | 0.400 | 0.630 | 0.673 | 0.558 |

*Notes:* * p<0.10, ** p<0.05, *** p<0.01. Robust standard errors clustered at the household level are in parentheses. *Phone Service in the Village* dummy measures whether the household's community reported having phone service in the baseline, and Post ACCI is the time dummy capturing whether the survey year is post-introduction of the Agricultural Call Center Intervention. $\textit{Inverse Betweenness Centrality} = \frac{1}{1+\textit{Betweenness Centrality}}$ captures the inverse of geographic betweenness centrality for the household at the baseline, which is omitted at the level as the regressions include the household fixed effects. All regressions use data from plots that are within 2 kilometers of their respective household locations. All regressions include year and season-fixed effects, time-varying controls, household, crop type, and the interaction of the division with year fixed-effects. Time-varying controls include the dummy capturing whether the household owns the plot, a dummy capturing whether the household has an agricultural input subsidy card, and the weather of the household's village as reflected by the minimum and maximum temperature of the year (in °C) and average yearly rainfall (in mm).

Table D.16: Differential Effect of the Agricultural Call Center Intervention by Dyadic Geographic Distances on Household-level Agricultural Outcomes (fixing the *Phone Service in the Village of $i'$* at the baseline)

| | (1) Inefficiency | (2) Actual Yield | (3) Used Rainfed Farming | (4) Used Tractor |
|---|---|---|---|---|
| Phone Service in the Village of $i'$ $\times$ Post ACCI | 29.836* | -300.765 | -0.031 | -0.035* |
| | (15.389) | (513.859) | (0.021) | (0.018) |
| Inverse Distance between $i$ and $i'$ $\times$ Post ACCI | 91.516*** | -3488.111** | -0.144*** | -0.008 |
| | (30.185) | (1405.068) | (0.043) | (0.037 |
| Inverse Distance between $i$ and $i'$ $\times$ Phone Service in the Village of $i'$ $\times$ Post ACCI | -105.736** | 4509.938** | 0.049 | 0.045 |
| | (41.666) | (1843.254) | (0.070) | (0.056) |
| Mean Baseline Outcome | 29.625 | 3582.026 | 0.321 | 0.071 |
| (SD) | (208.816) | (1734.7) | (0.467) | (0.257) |
| Observations | 60724 | 60724 | 60724 | 60667 |
| $R^2$ | 0.243 | 0.875 | 0.658 | 0.596 |

*Notes:* * p<0.10, ** p<0.05, *** p<0.01. Robust standard errors multi-way clustered at the household $i$ and household $i'$ level are in parentheses. *Phone Service in the Village of $i'$* dummy measures whether the community of household $i'$ reported having phone service in the baseline and *Post ACCI* is the time dummy capturing whether the survey year is post introduction of the Agricultural Call Center Intervention. *Inverse Distance between i and* $i' = \frac{1}{1+\textit{Distance between i and i'}}$ captures the inverse of geographic distance between households $i$ and $i'$ measured at the baseline, which is omitted at the level as the regressions include the pair fixed effects. All regressions use data from plots that are within 2 kilometers of their respective household locations. All regressions include year and season-fixed effects, time-varying controls, pair fixed effects, and the interaction of the division of household $i$ with year fixed-effects. Time-varying controls include the total number of plots owned by $i$, the total number of plots operated by them, whether $i$ has an agricultural input subsidy card, the weather of household $i$'s village as reflected by the minimum and maximum temperature of the year (in °C) and average yearly rainfall (in mm), and *Phone Service in the Village of i* dummy measuring whether $i$'s community reported having phone service in the year interacted with the Post ACCI dummy.