Inefficiency in Agricultural Production: Do Information Frictions Matter? *

This version: August 16, 2024. Click here for the latest version.

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Abstract

Does information and communication technology (ICT) based provision of agricultural extension services help improve agricultural productivity in poor or developing countries? We answer this question in the case of rice production in rural Bangladesh. We exploit the spatiotemporal variation in the availability of village-level phone services and the temporal variation in the timing of an ICT-based intervention to identify the differential impact by input use, network centrality, and geographic proximity. We observe that, in the villages with access to phone service, there is a 50 percent reduction in plot-level inefficiency after the intervention, driven by plots that used rainfed water for cultivation. We provide evidence suggesting that these effects are due to increased input use by the farmers using rainfed farming. Our results also document that the intervention benefits geographically remote farmers differentially 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 spillovers through geographic ties.

JEL Codes: D83, O13, Q16.

Keywords: Agriculture, Inefficiency, Extension, ICT, Networks.

1 Introduction

A large and influential body of literature attributes differences in per-capita incomes between rich and poor countries to differences in their agricultural productivity (Gollin et al., 2002, 2004, 2007; Restuccia et al., 2008). Recent research shows that the inefficiency in agricultural production in poor countries is primarily due to non-geographical factors

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(Adamopoulos and Restuccia, 2022).[1] One of the main non-geographical factors that explain productivity gaps is the lack of adoption of new technology and the use of traditional agricultural practices (Suri, 2011; Magruder, 2018; Takahashi et al., 2019). Evidence shows that information inefficiencies can partly explain why farmers may not adopt new technology or may not use it effectively (Anderson and Feder, 2004; Jack, 2013).[2] Access to expert advice and extension services can play an important role in serving information needs and raising awareness about modern practices among farmers (Anderson and Feder, 2004). However, in-person agricultural extension services have limited outreach and are expensive to run and operate (Anderson and Feder, 2004; Magruder, 2018).

In this paper, we study the role of Information and Communication Technology (ICT) in reducing inefficiency in agricultural production. In particular, we look at the case of rice production in rural Bangladesh. Rice is a staple crop central to Bangladesh's overall economy and is cultivated throughout the country two to three times a year across all three agricultural seasons. Although Bangladesh's geography is amenable to rice cultivation, its farm productivity remains low compared to other major rice producers (Asian Development Bank, 2023). This low productivity, combined with the dominance of small-scale farming, threatens the food and livelihood security of the large agriculture-dependent rural population of the country (Asian Development Bank, 2023; Sarker et al., 2021). Despite the need and potential benefits of traditional extension services in this regard, the overall reach and effectiveness of such extension efforts remain low (Alam and Kijima, 2024).

Taking advantage of the growth of mobile phone technology in rural Bangladesh, the government launched *Krishi Call Centers* (Agricultural Call Centers) in 2014, wherein farmers could call and consult experts on various aspects of agriculture (Huber and Davis, 2017). The objective of the intervention was to provide timely, need-based, and farmer-specific services where farmers could consult experts at any stage of crop production. Using unique nationally representative household-level panel data, we study the effectiveness of this intervention in reducing agricultural inefficiency in Bangladesh. Our main dependent variable of interest is a plot-level measure of *inefficiency* in rice production, constructed as the gap between the actual yield and the potential yield corresponding to the geographical location of the plot and the reported input use.

[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).

Our results exploit the spatiotemporal variation in access to phone services and the temporal variation in the timing of the intervention to identify the differential impact by input use, network centrality, and geographic proximity. We observe that, in the villages with access to phone service, there is a 50 percent reduction in plot-level inefficiency after the intervention. We show that this impact is driven by those plots that used rainfed water supply for cultivation, and we find no statistically significant impact of ACCI on the plots that used high level of inputs on their plots as proxied by tractor usage. We present the robustness of our approach in two ways: first, by generating a placebo intervention in the period prior to the actual intervention, and second, by randomly shuffling input usage across households. Our results remain robust to both these variations. Our results remain robust to various other robustness checks that we document in the appendices.

In terms of the mechanism of these results, we find that, in villages with telephone service, farmers using rainfed water supply intensified the input use per hectare after the intervention. This included higher usage of both fertilizer and pesticide along with an increase in the amount of family labor used on farms post-ACCI. On the other hand, we find that farmers using tractors reduced their usage of both fertilizer and pesticide after the intervention though they increased the expenses on purchase of seeds.

We also investigate the role of social networks, to the extent spanned by geographical proximity, in moderating the impact of ACCI. In the villages with phone service, compared to better-connected households, the inefficiency of geographically remote households differentially decreased after the intervention, and at the same time, their actual yields increased. This impact is, however, not driven by any change in input use in terms of rainfed water supply and tractor usage. It suggests that the differential reduction in inefficiency is on account of the efficient use of existing inputs, not due to any changes in either cultivation input. In terms of the spillover effects of ACCI, we document that there were large cross-community spillovers. Using a dyadic regression framework, we find that the inefficiency of a household gets reduced differentially more, compared to a far-off household, if it is closer to another household that happened to be a part of the community that received the intervention. It indicates that the spillover effects get stronger with a decrease in the geographical distance from a community that benefited from the intervention.

Our paper makes three contributions to the existing literature. First, we contribute to the literature on inefficiency and misallocation in the agricultural sector. This literature 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). Using the high-resolution gridded micro-geography data made available by the Food and Agricultural Organization's (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 the quality of land between rich and poor countries.[3] This suggests that the higher agricultural inefficiency of poor countries is primarily due to non-geographical factors, which hinder farmers from achieving the full potential of their farmlands' natural endowments. Taking a cue from this misallocation literature, we construct a plot-level measure of *inefficiency* in rice production as the gap between the actual yield and the potential yield corresponding to the geographical location of the plot and the reported input use. The advantage of using this measure as the dependent variable as compared to actual yield is twofold. First, it captures and controls for the effect of variation in geographical endowments across plots. Second, it also differentiates between two agricultural plots that may be endowed with the same geographical factors but using different material inputs by comparing their actual yields to different potential yields. To the best of our knowledge, our study is the first to use this measure for plot-level analysis of agricultural production.

Our second contribution is to the literature on the role of extension services in productivity growth. A large body of literature has studied the role of Information and Communication Technology (ICT) in agriculture (see Aker (2011) and Aker et al. (2016) for an in-depth review). The findings, however, remain mixed. While some find positive productivity impacts of mobile phone-based interventions (Casaburi et al., 2014; Gupta et al., 2020), others find none (Fafchamps and Minten, 2012; Cole and Fernando, 2020). Aker and Ksoll (2016) find suggestive evidence that other concurrent market failures in developing countries may make such interventions ineffective. Gupta et al. (2020) show that heterogeneity and differences in local languages can create barriers for farmers in accessing such mobile-based extension interventions. Suri (2011), in general, highlights the importance of heterogeneous costs in the adoption of new technologies. Such heterogeneity can also be attributed to differences in micro-geography. Given the heterogeneity in local geography and natural conditions, we argue that the actual yield may not be the right measure to evaluate the impact of such interventions. We explicitly show the importance of heterogeneity in local geography by comparing the results from actual yields with the constructed inefficiency measure.

Finally, this paper also contributes to the literature 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 literature also argues for ease of communication between agents who

[3]They find that the agricultural yield gap between rich and poor countries almost disappears from 214 percent to 5 percent if the crops were grown at the potential yield of their respective farmland. They use the potential yield corresponding to rainfed water supply and low input level usage for all countries. The top 10 percent and bottom 10 percent countries make up the rich and poor groups of countries, respectively.

live close to each other, making the 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 for being geographically central in terms of access to information. In this regard, we provide evidence that ACCI 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.

The rest of this paper is organized as follows. Section 2 provides the contextual background of our study and Section 3 discusses the empirical design along with the construction of key variables. We present our results in sections 4 and 5. Finally, section 6 summarises our main findings and concludes.

2 Background

2.1 Agriculture in Bangladesh

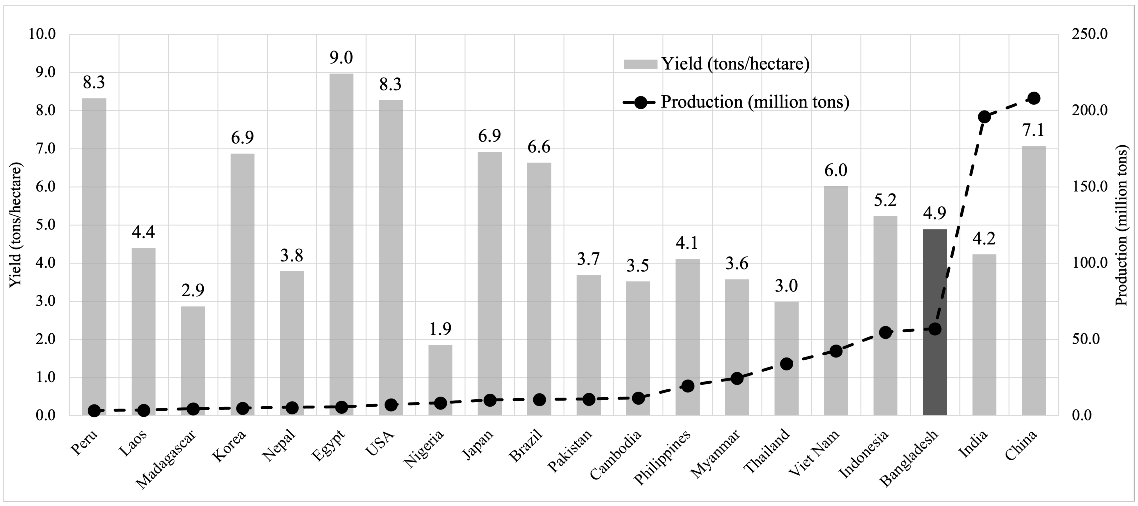


Figure 1: Rice yield of top 20 rice producers

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

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 cultivated almost the entire year across all three agricultural seasons: *Aman*, or the monsoon season; *Boro*, or the winter season; and *Aus*, the intermediated summer season. It is also the staple crop, accounting for around 80 percent of the cultivated area (Asian Development Bank, 2023).

While Bangladesh is the third largest producer of rice globally, in comparison to other major rice-producing countries, rice productivity in the country is relatively low at 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 farming, this low rice productivity threatens the food security and livelihoods of the large agriculture-dependent rural population in the country. Smallholder 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. 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).

2.2 Mobile Coverage and the Agricultural Call Center Intervention

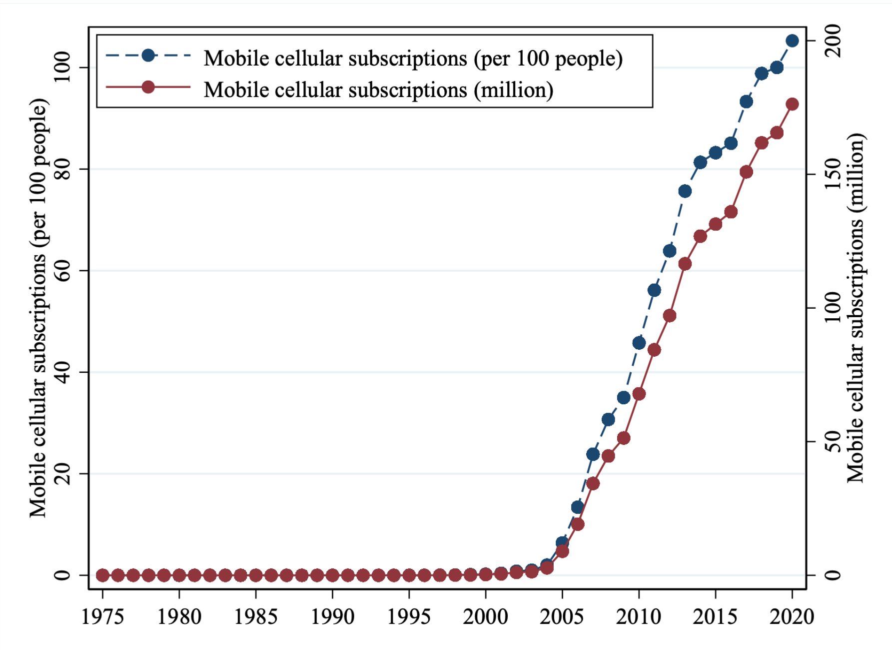


Figure 2: Trends in mobile phone coverage in Bangladesh

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

Like other developing countries around the world, Bangladesh has also seen a dramatic increase in mobile phone coverage in recent decades (Figure 2). From negligible cellular phone coverage in the early 2000s, almost all households in Bangladesh reported having access to a mobile phone in 2022 (Bangladesh Bureau of Statistics, 2022). The mobile revolution started in the late 1990s with the launch of the village phone program called GrameenPhone (Bayes, 2001). Recognizing the lack of telecommunication infrastructure as a major impediment to economic growth and development, the internationally recognized microlending institution, Grameen Bank of Bangladesh, introduced mobile phone services in some rural areas (Bayes, 2001). The GrameenPhone rapidly expanded its network and is now the largest mobile phone operator in the country.

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). The program was successful and reached over thirty thousand households within a year of its launch in 2014 (Huber and Davis, 2017). Farmers need for expert advice and the 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]

2.3 Potential for Telecommunication Extension Services

The inefficiency in agricultural production plays a huge role in keeping countries' agricultural productivity lower and, hence, their incomes low. Adamopoulos and Restuccia (2022) find that the rich-poor agricultural yield gap can be virtually closed from 214 percent to 5 percent if countries produce current crops according to potential yields.[5] The existing literature documents the potential positive impact of the adoption of modern practices on agricultural productivity (Bustos et al., 2016; Takahashi et al., 2019; Suri and Udry, 2022). Given the vulnerability of the agricultural sector to climate conditions and weather shocks (Gallic and Vermandel, 2020), the adoption of sustainable agricultural practices is also documented to be essential for adaptation to increasingly volatile weather due to climate change (Zilberman et al., 2012). The adoption can also lead to efficiency gains in production (Bustos et al., 2016; Bold et al., 2017; Foster and Rosenzweig, 2010), leading to a decrease in agricultural land misallocation (Adamopoulos and Restuccia, 2022).

Agricultural production is a complex process and requires farmers to make several decisions during different stages of crop production (Aker and Ksoll, 2016). These decisions are dynamic in the sense that the entire input mix must be adjusted if the

[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.

[5]Rich and poor countries refer to top and bottom 10 percent countries by income, respectively.

farmers' assessment differs from the realized conditions (Aker et al., 2016). Farmers, therefore, would 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 would depend on the information set 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 in serving information needs and raising awareness about 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 usage of such inputs (Islam and Beg, 2021). Extension agents can help farmers guide in 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 (Magruder, 2018; Anderson and Feder, 2004). In addition, in-person extension services are primarily operated by the public sector and are fraught with inefficiencies (Aker, 2011; Alam and Kijima, 2024; Cole and Fernando, 2020).

The widespread access to mobile phones and telecommunication services provides a cheap and effective way to reach distant farmers (Magruder, 2018; Fabregas et al., 2019). 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 through 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 information delivery through extension services and the diffusion of the same via existing social networks (BenYishay and Mobarak, 2018). Studies have shown that extension agents can leverage this complementarity to design cost-effective interventions to deliver information to a broader set of agents with 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 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, there is thus a need to assess the ground-level impacts of large-scale ICT-based extension programs like Bangladesh's Agricultural Call Center Intervention (ACCI). Our study aims to serve this need by investigating the role of information provided through ACCI in effectively using agricultural inputs to reduce inefficiency in production. Our analysis focuses on understanding the heterogeneity in the effect of access to ACCI by input use. In addition, our analysis also strives to understand the role of social networks in amplifying the impact of ICT-based extension efforts by facilitating the diffusion of information obtained through such extension services. For the latter, we investigate the potential for ACCI to reach agents from geographically remote areas and the potential amplification of the program's impacts through social spillovers.

While there are studies that document the impact of a similar government-sponsored large-scale mobile phone-based extension program in India, none exists for Bangladesh.[6] 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., 2020). This can lead to a barrier if there is a mismatch between the official language and the language spoken and understood by sub-populations (Gupta et al., 2020). 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 Data Sources

We use data from several sources to construct the final dataset.

3.1.1 The Bangladesh Integrated Household Survey (BIHS)

Our primary data comes from the Bangladesh Integrated Household Surveys (BIHS).[7] The BIHS, funded and implemented by the United States Agency for International Development (USAID) and the International Food Policy Research Institute (IFPRI), col-

[6] See, for example, Gupta et al. (2020) for the evidence on the Indian mobile-phone-based extension program.

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

lects detailed information on all aspects of the social and economic lives of households in rural Bangladesh. The BIHS is based on a multi-stage stratified sampling procedure and is nationally representative as well as representative of the seven administrative divisions of rural Bangladesh.[8] 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 geocoded location of surveyed households. The harmonized survey data provides 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 inefficiency measures and the empirical strategy.

Our primary focus is the roaster of all land and waterbodies owned by the households and the agricultural module of the survey. The roaster provides us with 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 the cultivated crops, planted areas, variety, and types. It also collects detailed information on inputs used and the harvested quantity. Out of the total plots cultivated over the three rounds, households report cultivating paddy in 71 percent of the plots. Given that paddy is a major staple crop of Bangladesh and the dominant crop in BIHS, we focus only on paddy.

The BIHS also provides detailed information on households' access to agricultural extension services and various input subsidies provided by the government of Bangladesh. The extension module collects responses on extension agent visits, the type of advice given for different inputs, and whether it was useful. The module also records whether the household received a subsidy on inputs from the government.

Along with 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 selected villages. 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.[9] Our empirical framework will particularly focus on the timing of arrival of telephone and mobile services in the village.

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

[9] 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.

3.1.2 Potential Yields

The potential yield data is obtained from the Global Agro-Ecological Zones (GAEZ) dataset jointly prepared by the Food and Agriculture Organization of the United Nations (FAO) and the International Institute for Applied Systems Analysis (IIASA).[10] This dataset covers the entire land surface area of earth by dividing it into equal-sized grid cells at 5 arc-minute resolution. 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. 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.[11]

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.[12] Again, both 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.[13] 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.

To know more about this dataset, one can refer the detailed discussion done in Adamopoulos and Restuccia (2022). Some relevant details are also discussed below in section 3.3.

3.1.3 Weather Variables

We extract weather variables from the TerraClimate dataset.[14] TerraClimate provides global gridded monthly rainfall and temperature data from 1958 to 2020 at 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 survey years.

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

[11] 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.

[12] 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).

[13] This paper uses version 4 of the GAEZ dataset which reports potential yields for only two levels of inputs usage – low and high, whereas the earlier GAEZ versions also had an intermediate level of input usage for which potential yields were reported.

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

3.2 Empirical Strategy

In the following subsections, we describe the main empirical specifications that we use for our analysis. We describe these for the outcome variable agricultural inefficiency, which is our main outcome of interest. For the results in Sections 4 and 5, we provide results with the same specifications for different outcome variables as well. Here we describe the specifications for our main outcome variable of interest to discuss the expected signs of our coefficients of interest.

3.2.1 Difference-in-Differences

To identify the effect of information on agricultural inefficiency, we first examine the impact of the Agricultural Call Center Intervention (ACCI) on our agricultural inefficiency measure, post-intervention, using the following specification:

$$\begin{aligned}\text{Inefficiency}_{ijcdpst} =& a_0 + a_1 \text{Phone Service}_{cdt} + a_2 \text{Phone Service}_{cdt} \times \text{Post ACCI}_t \\ &+ a_3 X_{ijcdt} + \sigma_i + \delta_p + \phi_s + \lambda_t + \psi_d \times \lambda_t + \epsilon_{ijcdpst}, \end{aligned} \tag{1}$$

where $Inefficiency_{ijcdpst}$ is the inefficiency in the use of agricultural plot j by household i from community c of division d at year t for season s and crop-type p. $Phone\ Service_{cdt}$ is a dummy that measures whether the community c of division d reported having phone service at year t and $Post\ ACCI_t$ is the time dummy capturing whether the survey year t is post introduction of the Agricultural Call Center Intervention. The latter is omitted in its level as the regression includes year fixed-effects λ_t. The specification also includes σ_i, δ_p, and ϕ_s, as household, crop-type, season fixed-effects, respectively. It also includes the interaction of division fixed effect ψ_d with year fixed effect λ_t to control for time-varying characteristics at the division level. X_{ijcdt} are some time-variant observables, including weather. Finally, ϵ_{ijpst} is the random error in the regression. Our coefficient of interest here is a_2, which we expect to be negative if the intervention is successful in reducing agricultural inefficiency.

3.2.2 Triple-Differences

Although the difference-in-differences specification above helps us examine the effect of the ACCI on the agricultural inefficiency of the households, our main specifications use triple-differences that exploit a third difference, in addition to the differences in community-level exposure to phone services and the temporal variation in the introduction of the ACCI. We use this third difference in three different types of variations, namely: the variations in input use, the variation in geographic network centrality, and the variation in dyadic geographic distances.

Do the effect of ACCI vary differentially by input use?

To answer the above question, we exploit the 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:

$$\begin{aligned}\text{Inefficiency}_{ijcdpst} = \alpha_0 &+ \alpha_1 \text{Phone Service}_{cdt} + \alpha_2 \text{Input}_{ijcdt} + \alpha_3 \text{Phone Service}_{cdt} \times \text{Input}_{ijcdt} \\ &+ \alpha_4 \text{Phone Service}_{cdt} \times \text{Post ACCI}_t + \alpha_5 \text{Input}_{ijcdt} \times \text{Post ACCI}_t \\ &+ \alpha_6 \text{Phone Service}_{cdt} \times \text{Input}_{ijcdt} \times \text{Post ACCI}_t + \alpha_7 X_{ijcdt} \\ &+ \sigma_i + \delta_p + \phi_s + \lambda_t + \psi_d \times \lambda_t + \epsilon'_{ijcdpst}, \end{aligned} \tag{2}$$

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 α_6, which captures 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 usage of the input (one that reduces inefficiency). It would be positive in that case and negative otherwise. Hence, this is an empirical question that our results focus on answering.

Do the effect of ACCI vary differentially by geographic network centrality?

Our next triple-differences specification exploits the household-level variation in network centrality. Network centrality measures are used to capture the node's position in a network (Jackson, 2010). Betweenness centrality helps capture 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). We do not have data on social interactions, but we have the geographic location of the households, which we use to construct the geographic networks of households in our data. Using this network, we subsequently calculate the betweenness centrality of all households in our sample. We provide a detailed description of the network construction and the subsequent calculation of our betweenness centrality measure in the next sub-section. We use this centrality measure in the following triple-differences specification:

$$
\begin{aligned}
&\text{Inefficiency}_{ijcdpst} = \beta_0 + \beta_1 \text{Phone Service}_{cdt} + \beta_2 \text{Inverse Betweenness}_{icd} \\
&+ \beta_3 \text{Phone Service}_{cdt} \times \text{Inverse Betweenness}_{icd} + \beta_4 \text{Phone Service}_{cdt} \times \text{Post ACCI}_t \\
&+ \beta_5 \text{Inverse Betweenness}_{icd} \times \text{Post ACCI}_t \\
&+ \beta_6 \text{Phone Service}_{cdt} \times \text{Inverse Betweenness}_{icd} \times \text{Post ACCI}_t + \beta_7 X_{ijcdt} \\
&+ \sigma_i + \delta_p + \phi_s + \lambda_t + \psi_d \times \lambda_t + \mu_{ijcdpst},
\end{aligned} \tag{3}
$$

where $\textit{Inverse Betweenness}_{icd} = \frac{1}{1+\textit{Betweenness Centrality}_{icdt}}$ 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 intervention's effectiveness (cite), and the role of Information and Communication Technologies (ICTs) is well-recognized in this regard (Westermann et al., 2018; Fabregas et al., 2019).

The specification (3) captures this through the coefficient β_6. A negative value of this coefficient 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).

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. We provide details on the construction of this dyadic data frame in the next sub-section. Using this data frame, we explore the differential effect of ACCI post-intervention by dyadic geographic distances.

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. We use the following specification for this purpose:

$$\begin{aligned}\text{Inefficiency}_{icdst} = {} & \gamma_0 + \gamma_1 \text{Phone Service}_{c't} + \gamma_2 \text{Phone Service}_{c't} \times \text{Inverse Distance}_{ii'} \\ & + \gamma_3 \text{Phone Service}_{c't} \times \text{Post ACCI}_t + \gamma_4 \text{Inverse Distance}_{ii'} \times \text{Post ACCI}_t \\ & + \gamma_5 \text{Phone Service}_{c't} \times \text{Inverse Distance}_{ii'} \times \text{Post ACCI}_t \\ & + \gamma_6 X_{ijcdt} + \sigma_{ii'} + \phi_s + \lambda_t + \psi_d \times \lambda_t + \nu_{icdst}, \end{aligned} \tag{4}$$

where $Inefficiency_{icdst}$ captures the inefficiency in the use of all agricultural plots used by household i from community c of division d at year t for season s, $Phone\ Service_{c't}$ is a dummy indicating whether the community c' (the community of household i') reported having phone service at year t, and Inverse $\text{Distance}_{ii'}$ represents the inverse of geographic distance between households i and i', captured at the baseline. Our coefficient of interest is γ_5, which captures how much the post-intervention impact of ACCI in the community of household i' differentially affects the inefficiency of household i, lower the distance between households i and i'. We expect this coefficient to be negative if the network spillovers of the program reduce inefficiency.

3.3 Construction of Key Variables

The Inefficiency Measure

We have the households' location information (in latitude and longitude) in the BIHS dataset. We also have information on these households' input use on their plots. Using the GAEZ data, we first associate a household's location with a GAEZ plot and then derive the potential yield for different combinations of input use. Given the actual input use at each plot, we then compute a measure of potential yield for that plot. Comparing this potential yield with the actual yield (also available in the BIHS data), we construct our measure of inefficiency. It is basically the percentage difference between actual and potential yield as given below:

$$\text{Inefficiency} = \frac{\text{Potential Yield} - \text{Actual Yield}}{\text{Actual Yield}} \times 100 \tag{5}$$

It is important to note that the potential yield for growing the same crop could vary in two different ways. 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 the agricultural plots that lie within the same GAEZ grid cell but use different combinations of cultivation inputs. Because different cultivation inputs 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 the geographical location of agricultural plots and the actual input choices made by the farmers.

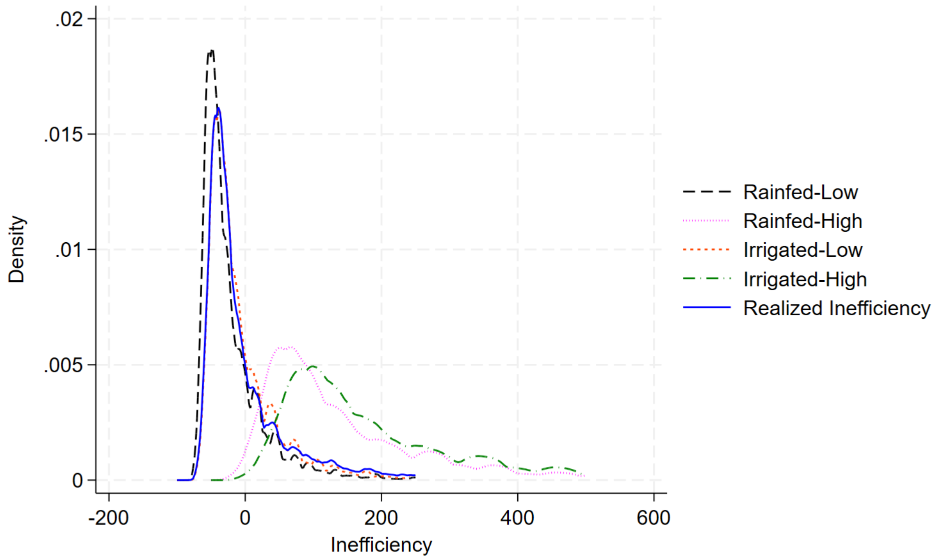


Figure 3: Variation in Inefficiency Densities

Notes: (1) The four possibilities for plot-level inefficiency correspond to the four possible input combinations compared with the actual yield, assuming 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 high level of complementary inputs 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 that 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.

Figure 3 shows the distribution of our inefficiency measure under different *hypothetical* input choices. It demonstrates how the same set of agricultural plots can face different inefficiency levels due to differences in their corresponding input choices. The distribution of realized inefficiency corresponds to the actual input choices made by the farmers. This is the variable we use as the main dependent variable in our analysis. As evident in the figure, both the mean and spread of inefficiency are higher in case of high inputs usage. As discussed below, our choice of tractor-usage is a more conservative assumption to proxy high inputs, therefore the realized inefficiency distribution is closer to that of low inputs scenarios with a mean of 15 and a standard deviation of 167 percentage points, respectively.

Measuring Input Usage

We consider two broad categories of inputs, in line with the GAEZ dataset. First is the type of water supply used on the agricultural plot. This can be of two types - rainfed and irrigated (includes all forms of irrigation like groundwater, canal etc.). Second is the level of complementary inputs usage on the plot. This includes all things other than water supply like seeds, fertilizers, pesticides, modern machinery etc. Again, there are two levels that we consider here in line with GAEZ - low and high.

As per GAEZ, low level inputs correspond to traditional farm management which is mostly subsistence-based. There is no usage of chemical fertilizers or pesticides, and there is no farm mechanization since all stages of production are labor driven. Whereas, under high level inputs, the farming system is market-oriented. There is usage of high-yielding variety seeds, fertilizers, pesticides, and machinery is used wherever possible. The labor intensity is low and nutrient application is optimal.

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 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.

We consider the usage of the tractor as a proxy for high-level input usage on the plot. The reason is two-fold. First is the fact that a tractor is expensive agricultural machinery whose ownership or renting is justified only when the production is not only meant for subsistence purposes.[15] A tractor can be used at any or all stages of rice production - cultivating soil, planting rice seedlings, spraying, which enhances irrigation efficiency by reducing water and fertilizers usage, harvesting, digging out rice straw, and lastly transporting the produce to the market.

Second is the fact that, in data, we find that almost all plots used fertilizers (98.6 percent) or pesticides (86.66 percent) while only a few (8.35 percent) used tractors.[16] Many plots also used a powertiller (88.84 percent), which is a handheld machine used for purposes similar to those served by a tractor, but not all of them, and that too with lesser efficiency.[17]

Therefore, it seems from the data that most plots actually used intermediate level of inputs but only a few utilized high levels of inputs. Thus, while measuring inefficiency, the actual yield gets mostly compared against a lower potential yield corresponding to

[15]Price of a tractor ranged from 1 million to 2.2 million Takas in 2018, whereas the average income per capita was only 0.13 million Takas then. *Sources:* `https://www.thedailystar.net/business/news/tractor-sales-drop-1835503` and Bangladesh Bureau of Statistics (`http://nsds.bbs.gov.bd/en`).

[16]Percentage of plots that used a tractor by survey year - 7.13% in 2011, 7.93% in 2015, and 10% in 2018.

[17]Percentage of plots that used a powertiller by survey year - 88.93% in 2015, and 88.75% in 2018.

the low input level. This suggests that our inefficiency measure is a conservative one. Since the rainfed variable is directly reported in the survey, we believe that it contributes lesser distortion to our inefficiency measure.

Construction of Geographic Networks and Measuring Network Centrality

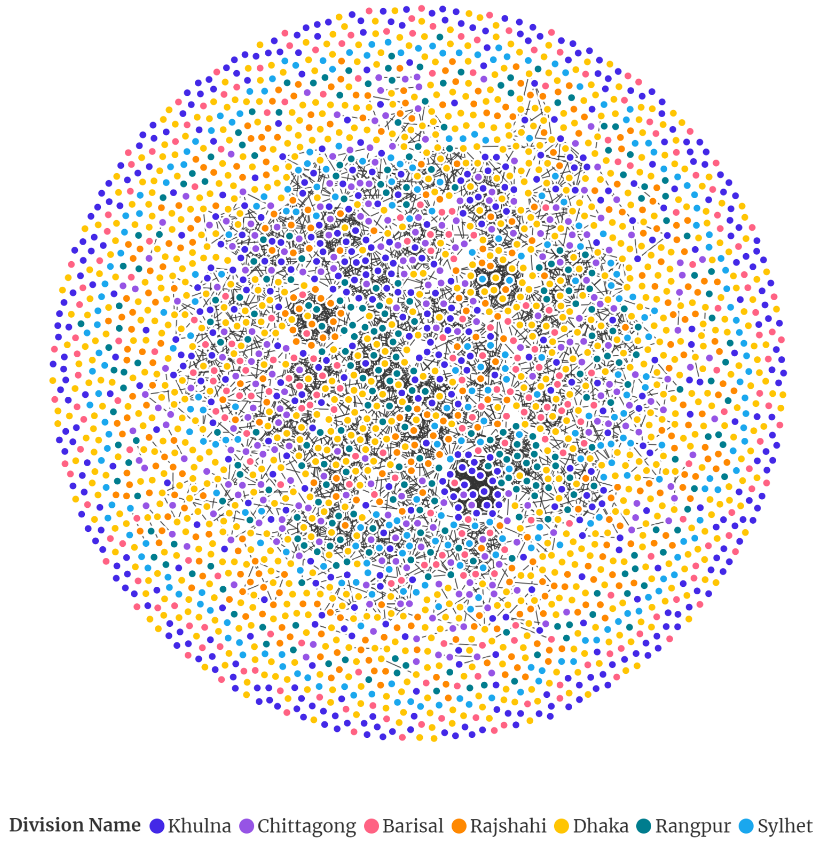


Figure 4: Geographic Distance Network

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.

To investigate the role of social networks in augmenting the effect of ICTs in the transmission of information related to the efficient use of resources, we need to first construct these networks. Ideally, data on social interactions are collected and used for this purpose.[18] 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

[18]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-`

to each other (Goldenberg and Levy, 2009; Helsley and Zenou, 2014; Kim et al., 2023). This is the approach 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 across communities.

Figure 4 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 edge 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. On the contrary, 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 the central households are already well-connected for them to benefit from the transmission of information from their social ties. However, most of the remote households lack the number of connections required for the effective diffusion of knowledge. [19] Thus, we expect the remote households to benefit more from the intervention. This is the hypothesis we test using the specification (3).

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). Let N_{ij}^k denote the number of geodesic paths between nodes i and j that pass through node k in 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:

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

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

[20] *Geodesic paths* between any pair of nodes represent paths with no more edges than any other paths between the same pair.

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

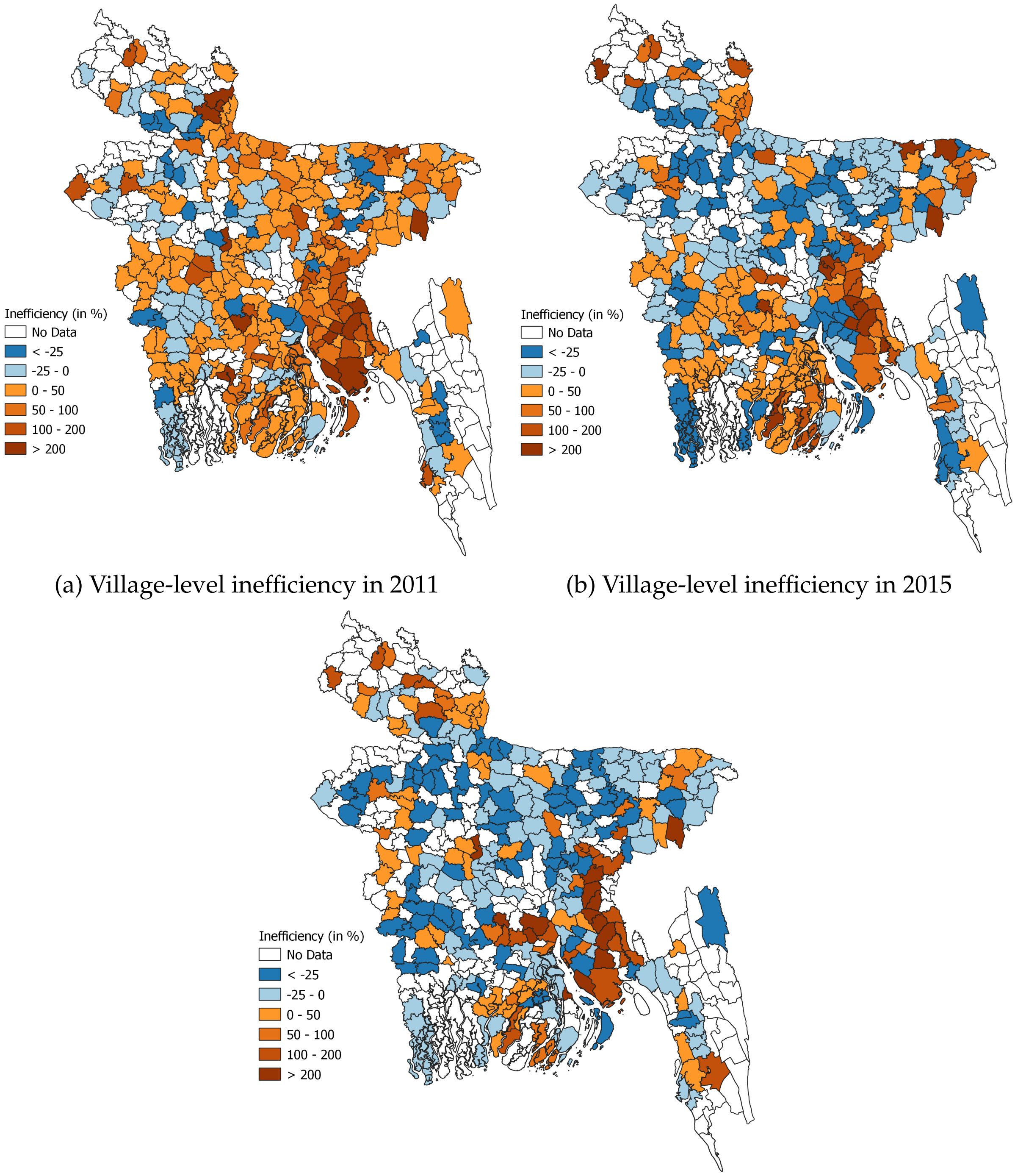
Betweenness Centrality is widely used in the literature on network-based interventions as a measure of the centrality of nodes (see, for example, Banerjee et al., 2013; Beaman and Dillon, 2018; Beaman et al., 2021). For our purpose, it is particularly useful as the nodes with higher betweenness centrality are often considered the gatekeepers of the 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.

3.4 Descriptive Statistics

Before getting into the impact of the ACCI intervention on plot-level inefficiency, it makes sense to look at the trend of inefficiency over time. In figure 5, we look at the inefficiency measure aggregated at the village level as the simple average of plot inefficiencies. Clearly, there is a declining trend of inefficiency over the years, with a greater number of villages falling in the lower inefficiency brackets over time. For instance, the share of villages with negative inefficiency (blue-colored) increase 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 across Bangladesh. One stark observation is that the villages along the eastern boundary and the coastal villages in the south-east have positive inefficiencies which don't go down in the post-ACCI period as well.

It might seem a bit puzzling that there are many plots where the actual yield is greater than the potential yield which results in negative inefficiency at the village level as well. This puzzle, however, can be understood in the following two ways (ignoring any data measurement errors). First, the plot might be using higher level of actual inputs resulting in higher actual yield than the potential yield corresponding to a lower input combination. For instance, a plot might get assigned rainfed-low input combination because they did not report using tractor in the survey, but it is possible that their production used all other inputs which qualify as a high inputs usage. So, in this case, the negative inefficiency is on account of the actual yield being compared to a lower potential yield. Second, even with the right assignment of inputs 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 GAEZ cell level. Given the large size of a GAEZ cell, there exists heterogeneity in land productivity (see footnote 11) 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

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



(a) Village-level inefficiency in 2011

(b) Village-level inefficiency in 2015

(c) Village-level inefficiency in 2018

Figure 5: 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 which were not a part of BIHS.

actual yield compared to the average GAEZ potential yield.

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)
Betweenness Centrality	2.938	3.832	3.322	3.332
	(19.048)	(26.667)	(26.531)	(23.817)
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. *Betweenness Centrality* and *Agricultural Subsidy Card* dummy are captured at the household level. Weather measures are captured at the village level. The *Betweenness Centrality* measure is calculated using baseline (2011) information on geographic locations for all households. The change in the average value of this measure over time is solely due to the change in the number of observations over time.

Table 1 presents the descriptive statistics of key variables for the three years of the survey. Overall, we observe a declining trend in the inefficiency measure and an increase in average rice yields in Bangladesh. These trends are consistent with figure 5. Around 44 percent of the villages in our sample report the availability of phone service. Figure 6 shows the trend in phone coverage in the BIHS villages over time.

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 inputs at government-subsidized prices. These statistics highlight that the average inefficiency in rice production has 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.

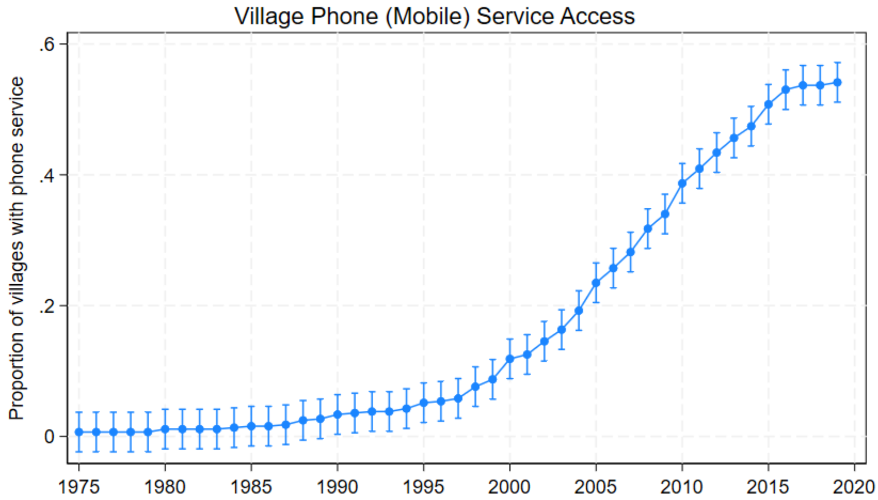


Figure 6: Telephone (or mobile phone) coverage in the surveyed villages

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

4 Results

4.1 Main Results

Table 2 presents estimates from the baseline difference-in-differences (regression (1)) and triple-difference (regression (2)) specifications that document the post-intervention effect of the ACCI on plot-level agricultural outcomes and the heterogeneity of these effects by input use. For comparison, we present estimates with both plot level inefficiency and actual yield as the dependent variables.

Looking at columns (1) and (2) we observe that the arrival of phone service in the village by itself does not influence inefficiency or actual paddy yields. As hypothesized, the availability of village phone service reduces inefficiency only after the intervention. In terms of magnitude, the intervention led to a 50 percent reduction in the average baseline inefficiency, as documented in column (1). Though the estimates with actual yield are in the expected direction, they are statistically insignificant.

To see how our baseline estimates vary based on irrigation choice and tractor usage, columns (3) and (4) present estimates from the triple difference specification. We causally interpret the coefficient on only the triple interaction terms. We find that the impact of the intervention on inefficiency is driven primarily by rainfed farming. Although the

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

	(1) Inefficiency	(2) Actual Yield	(3) Inefficiency	(4) Actual Yield
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)
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. 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. *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 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).

triple interaction of tractor use, village telephone service, and post-ACCI has a negative coefficient estimate, it's statistically insignificant.

4.2 Robustness Checks

4.2.1 Robustness with respect to placebo intervention between 2011 and 2015

While our benchmark estimates are encouraging, there is a 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 implemented in full force.[22]

[22]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.

Table 3: Placebo Intervention Effect of the Agricultural Call Center Intervention on Plot-level Agricultural Outcomes

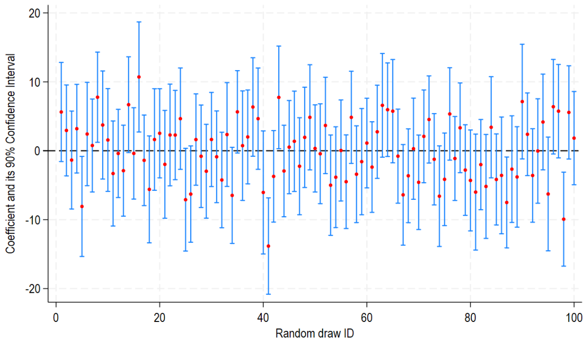
	(1) Inefficiency	(2) Actual Yield	(3) Inefficiency	(4) Actual Yield
Phone Service in the Village	-5.094 (14.057)	-113.538 (135.591)	-1.475 (9.473)	-93.224 (118.973)
Phone Service in the Village × Placebo Post ACCI	-7.751 (9.346)	36.334 (133.069)	-13.149* (6.711)	140.657* (83.189)
Used Rainfed Farming			-0.969 (8.163)	-195.520*** (73.913)
Used Tractor			253.207*** (15.392)	-76.138 (74.331)
Used Rainfed Farming × Phone Service in the Village			19.663 (13.247)	-71.774 (92.964)
Used Tractor × Phone Service in the Village			-17.477 (33.301)	170.528 (132.920)
Used Rainfed Farming × Placebo Post ACCI			-6.613 (11.408)	235.266** (116.815)
Used Tractor × Placebo Post ACCI			-54.185*** (17.591)	148.211 (126.174)
Used Rainfed Farming × Phone Service in the Village × Placebo Post ACCI			5.276 (18.814)	-276.500** (132.715)
Used Tractor × Phone Service in the Village × Placebo Post ACCI			47.589 (33.447)	-237.195 (261.127)
Mean Baseline Outcome (SD)	29.625 (208.816)	3582.026 (1734.7)	29.625 (208.816)	3582.026 (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. Robust standard errors clustered at the household level are in parentheses. 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 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).

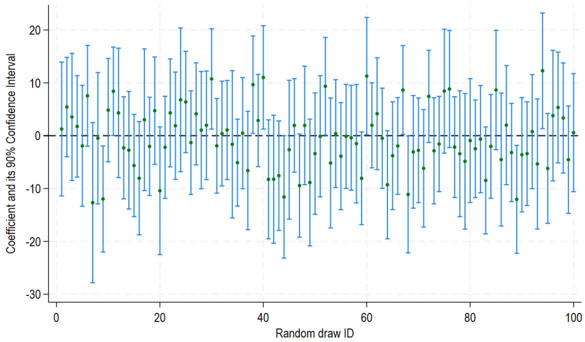
Table 3 presents the estimates from the placebo test. Estimates on the double interaction term in columns (1) and (2) are small in magnitude and statistically insignificant. Similarly, the estimates from the triple interactions are mostly statistically insignificant and of the opposite sign (columns (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 from this specification disappear when we use the placebo intervention, providing support in favor of the credibility of our approach.

4.2.2 Robustness with respect to shuffled values of input usage

We do another test to see whether we are able to re-create the results we observe in the triple difference specification for the outcome variable *Inefficiency* in Table 1 if we randomly shuffle a household's rainfed farming and tractor use status. The 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. We do such a random shuffling 100 times, collecting the estimates from the triple difference specification each time. Figures 7a and 7b plot the estimates



(a) By shuffled Rainfed Farming usage



(b) By shuffled Tractor usage

Figure 7: Effect of the Agricultural Call Center Intervention by randomly shuffled input usage

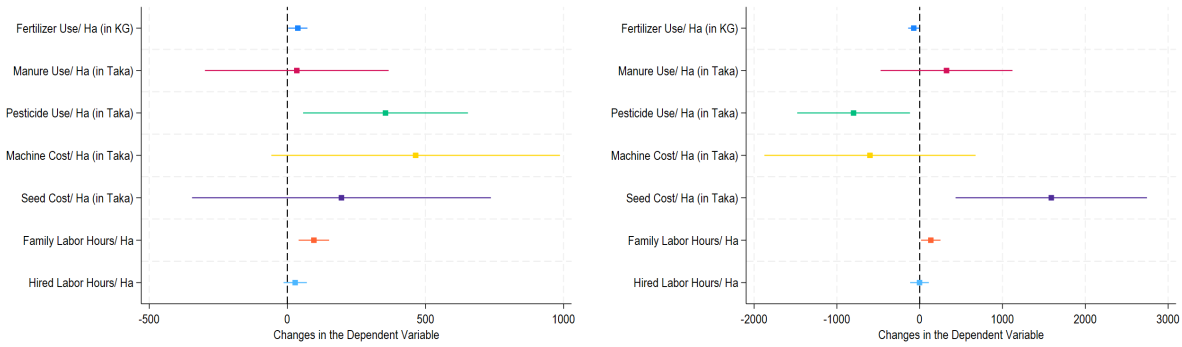
Notes: The reported triple-difference coefficients for the specification (2), with input usage being captured by shuffled dummies on Rainfed Farming usage and Tractor usage. The coefficients for each draw are coming from the interaction of the respective (shuffled) input usage with the variables *Phone Service in the Village* and Post ACCI in the same regression. Each drawing 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.

for the triple difference coefficients (with *Inefficiency* as the outcome variable) with confidence intervals from this exercise. The figures show that there is no systematic pattern in these coefficient estimates, and most of them are statistically indistinguishable from zero.

4.3 Mechanisms

To investigate the possible mechanisms behind the effects observed in the previous section, we estimate the triple difference specification with input use per hectare as dependent variables. 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 villages with telephone service, farmers using rainfed farming differentially increased the use of fertilizer and pesticides, and the farmers using tractors differentially reduced fertilizer and pesticide use after the intervention.

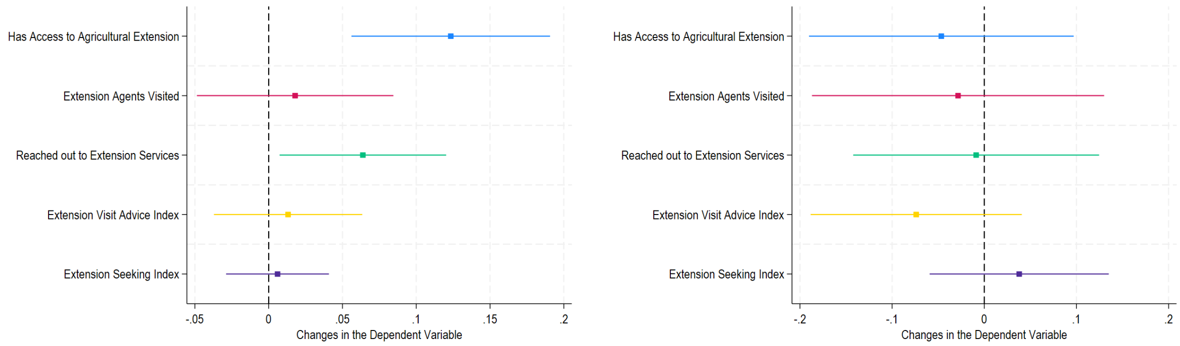
These findings are consistent with the fact that incorrect fertilizer use (for example, urea) can be easily diagnosed by the color of leaves, and the remedies can be easily and quickly disbursed by experts from agricultural call centers (Islam and Beg, 2021). Similarly, pest infestation is easily visually 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, figure 8 shows that farmers



(a) By Rainfed Farming Usage (b) By Tractor Usage

Figure 8: Effect of Agricultural Call Center Intervention on Other Input Uses

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 the farms.



(a) By Rainfed Farming Usage (b) By Tractor Usage

Figure 9: Effect of Agricultural Call Center Intervention on Interaction with Extension Services

Our data also records information on in-person extension services. We use this information to test whether the effects are driven by improved extension services in villages with phone service after the ACCI. 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 any statistically significant effects on the likelihood of an extension visit or whether the farmer actively seeks advice from an agent.

5 Heterogeneity Analysis: The Role of Networks

We now turn to our results that focus on understanding the role of social networks in amplifying the impact of ACCI. Table 4 documents the potential for ACCI to reach agents from geographically remote areas. For this purpose, we use specification (3), which exploits the variation in the geographic network centrality of the households, 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. The results in columns (1) and (2) show that the agricultural inefficiency differentially decreased and actual yield differentially increased for geographically remote farmers that have low 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.

Table 4: 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. $\textit{Inverse Betweenness Centrality} = \frac{1}{1+\textit{Betweenness Centrality}}$ 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 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 the farmers adjusting their use of rainfed farming and tractors. Thus, the results seem to be driven by the more efficient use of the same mix of rainfed farming and tractors. This indicates the importance of ACCI in communicating information regarding the efficient use of existing inputs and benefiting geographically remote farmers, who do not have access to such information otherwise.

Furthermore, Table 5 reports the potential amplification of the program's impacts through social spillovers. Using the specification (4), here we investigate whether the outcomes for household i get 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 community of household i reported having phone service in the year interacted with the Post ACCI dummy. This partials out the post-intervention impact of ACCI on household i's own community. Therefore, we can interpret the triple interaction terms as the cross-community spillover effect of the intervention.

Table 5: 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'* 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 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 expectation. However, in terms of the 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). These results document large cross-community spillovers of the intervention.

6 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 important question. The context of our investigation is rural Bangladesh, where the majority of its agriculture-dependent population is engaged in the production of rice crops. Even though its geography is amenable to rice cultivation, the yields are low in Bangladesh 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 called GAEZ.

The single word answer to the above question is a *yes*. The intervention was effective in reducing the plot-level inefficiency in rice production in those villages that had access to phone services. With the ability to provide need-based and farmer-specific 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. And, this reduction in inefficiency is found to be mediated by the increased usage-intensity of various inputs on the farms. Since our results remain robust to various checks that we perform in this paper, it is meaningful to suggest that the policymakers can reliably use ICT-based extension services to support small-scale farmers who also happen to be more dependent upon rainfed based farming methods.

Next, we assessed the heterogeneity in the impact of ACCI on plot-level inefficiency, as the importance of households varied in their respective social networks. Here, we looked at the role played by geography-based social networks on moderating the impact of the above intervention. One would expect that more central and well-connected households will better be able to access pertinent agricultural information, while it will be more difficult for a remotely located household to access such information. And, that any ICT-based extension service should enable those farmers more who were otherwise relatively unable to access information through their social networks. Our results affirm this intuition since there was a differentially higher reduction in the production inefficiency of remote households after the intervention. Again, at the risk of overstepping the scope of our analysis, we believe that there should be availability of ICT-based agricultural extension services, which could lend more help to the remotely located or socially excluded households who would otherwise find it difficult to obtain relevant information.

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 it clear that the availability of ICT-based agricultural extension services can significantly alleviate the inefficiency in agricultural production. By 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 agriculture 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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