Access to Information, Technology Adoption and Productivity: Large-Scale Evidence from Agriculture in India*

Apoorv Gupta† Jacopo Ponticelli‡ Andrea Tesei§

This draft: January 2021

We present large-scale evidence on the effects of access to information on agricultural technology adoption and crop yields in India. We combine geo-referenced data on the construction of new mobile phone towers with data on the location and content of 2.5 million phone calls made by farmers to a leading call center for agricultural advice. Exploiting language barriers between farmers and call center advisors, we show that while the expansion of the mobile phone network may lead to a long-term modernization of agriculture and increased productivity, this only happens in areas where farmers can access agricultural advice over the phone.

Keywords: Mobile phones, languages, agriculture, HYV Seeds, KCC, phone towers.
JEL Classification: G21, Q16, E51

* We received valuable comments from Siwan Anderson, Shawn Cole, Nicola Gennaioli, Doug Gollin, Sergei Guriev, Sabrina Howell, Dean Karlan, Marco Manacorda, Pepita Miquel, Imran Rasul, Gabriella Santangelo, Chris Udry and seminar participants at Columbia, Universidad de Los Andes, Universidad Javeriana, University of Zurich, University of Bonn, Lancaster University, NYU Stern, Bocconi University, Queen Mary University, University of Maryland, Northwestern University, Berkeley Haas, UBC, CUNY, Diego Portales University, University of Geneva, GATE-Lyon, BGSE Summer Forum, CAF, DFID UK, European Economic Association 2019, IPA 2019 Researcher Gathering and American Economic Association 2021. Ponticelli gratefully acknowledges financial support received for this project from the Cohen and Keenoy Faculty Research Fund and the Fama-Miller Center at the University of Chicago Booth School of Business. The project was developed while Andrea Tesei was visiting the Ford Motor Company Center for Global Citizenship at the Kellogg School of Management, Northwestern University, whose hospitality is gratefully acknowledged. Pierre Jaffard, Gursharan Bhue and Mark He provided excellent research assistance. We are grateful to the staff at GSMA for their help with the mobile phones data. The GSMA data used in this study are covered by a confidential license agreement. We also thank the staff at the Center for Development of Telematics, Department of Telecommunications of India, and the Department of Agriculture, Cooperation and Farmers Welfare for their help with data.

† Dartmouth College; contact: apoorv.gupta@dartmouth.edu.
‡ Northwestern University - Kellogg School of Management, NBER & CEPR; contact: jacopo.ponticelli@kellogg.northwestern.edu.
§ Queen Mary University of London, CEPR, CEP (LSE) & CESifo; contact: a.tesei@qmul.ac.uk.

1 Introduction

Nearly 80 percent of the world's extreme poor live in rural areas, with most relying on agriculture for their livelihoods (World Bank, 2019). These individuals are often trapped in a vicious circle of low yields, due to limited adoption of modern agricultural technologies capable of improving their productivity and raising their incomes. One of the main barriers to adoption is farmers' imperfect knowledge of these technologies and of the best practices associated with their use.[1]

Over the past two decades, the rapid diffusion of mobile phones and telecommunication services in rural areas of developing countries has raised expectations about their ability to reduce informational frictions, promote technology adoption and increase farmers' productivity. A number of recent randomized controlled trials have shown that access to mobile-based agricultural advice services may indeed affect agricultural practices (Cole and Fernando, 2020; Casaburi et al., 2019; Fabregas et al., 2019). Yet, several important questions remain unanswered. First, there is little empirical evidence on the distributional consequences of greater access to information. Does its expansion amplify or reduce productivity differences across farmers? Second, we have limited empirical evidence on its long-run consequences. Is the effect of access to information on agricultural practices and productivity temporary or long-lived? A key challenge to tackle these questions is that one needs to observe, for a large sample of farmers and over a long period of time, data on access to information about modern agricultural technologies, the actual adoption of these technologies, and the evolution of agricultural productivity. Furthermore, one needs to be able to separate the role of information from additional dimensions through which mobile phones can influence farmers' decisions to modernize their technologies.

In this paper we address these challenges using large-scale data from India. First, we exploit variation in the rollout of mobile phone coverage generated by the Shared Mobile Infrastructure Scheme (SMIS), a large government program launched in 2007 that financed the construction of about 7,000 mobile phone towers in previously unconnected areas of India. Second, we match the geographical coverage brought by new SMIS towers with data on the location and content of 2.5 million toll-free phone calls made by farmers to one of India's leading agricultural advice services, the Kisan Call Centers (KCC). This data allows us to observe farmers' questions about specific agricultural technologies and the answers they receive from agronomists. We exploit one feature of the KCC service – that agricultural advice is offered in a limited number of languages, effectively excluding farmers who do not speak any of these – to isolate the effect of access to information. Finally, we match data on mobile phone coverage and phone calls with detailed district-level survey data on crop yields and adoption of agricultural inputs – including seed

[1] On the constraints to the adoption of new technologies in agriculture in developing countries, see reviews in Jack (2013), Foster and Rosenzweig (2010) and Feder et al. (1985). On the role of information frictions see, among others, Foster and Rosenzweig (1995) and Conley and Udry (2010).

varieties, pesticides and herbicides – in an area covering around 19 million farmers.

The combination of these datasets allows us to map farmers' calls about specific agricultural technologies with their actual adoption. We observe data on agricultural inputs used by farmers 5 years after the introduction of the SMIS and annual agricultural yields for 10 years after the introduction of the SMIS, which allows to study the long-run effects of access to information.

Our empirical analysis proceeds in two steps. In the first step, we use an event-study design to document the evolution of farmers' calls to seek agricultural advice when new mobile phone towers are constructed in previously uncovered areas. Using high-frequency (monthly) variation, we document that the construction of the first mobile phone tower in a given area is followed by a significant increase in the number of farmers' calls. This is consistent with a large and underserved demand for agricultural advice in rural India.[2]

The event study also documents that linguistic differences can generate unequal gains in access to information. Although the government-sponsored agricultural advice is in principle available to all farmers with access to a phone, KCC agronomists answer calls only in one of the 22 official languages recognized by the Indian Constitution.[3] This effectively creates a language barrier for the over 40 million individuals whose main language belongs to the 100 non-official ones recorded in the Indian Census. Figure 1 shows an illustrative example of such barriers using data from the state of Odisha. The red outlined area in the southern part of the state is inhabited by a majority of local population speaking Kui, a Dravidian language without official status. While this area has experienced an expansion in mobile phone coverage similar to the rest of Odisha, phone calls by farmers to KCC from this area have been significantly lower. This is a robust finding across the whole country: calls for agricultural advice from areas where the majority of the local population speaks a non-official language only increase by 20 to 30 percent of the increase observed in areas where the majority speaks an official language. This is despite the fact that, within our sample, these areas are comparable in terms of initial socio-economic characteristics and pre-existing trends in agricultural performance.

In the second step of our analysis, we study the real effects of access to information on technology adoption and productivity. To account for the potentially endogenous location of SMIS mobile phone towers, we propose an identification strategy that compares – within each administrative district – locations where new SMIS towers were proposed and eventually constructed, with locations where they were also proposed but eventually

[2] As of 2003, 60 percent of Indian farmers in a nationally representative survey reported not having access to any source of information on modern technology to assist them in their farming practices (National Sample Survey, 2005).

[3] The 2011 Census identifies 121 languages spoken in India, 22 of which are part of the Eight Schedule of the Constitution, i.e. they are recognized as official languages of the Republic of India. The 22 officially-recognized languages are: Hindi, Bengali, Marathi, Telugu, Tamil, Gujarati, Urdu, Kannada, Odia, Malayalam, Punjabi, Assamese, Maithili, Santali, Kashmiri, Nepali, Sindhi, Dogri, Konkani, Manipuri, Bodo, and Sanskrit.

not constructed. We show that these two types of location are balanced on initial observable characteristics once we control for determinants of tower relocation such as terrain ruggedness and population covered, and that they experienced similar pre-existing trends in both technology adoption and agricultural yields in the 5 years preceding the introduction of new towers. In addition, we exploit variation in the spatial diffusion of non-official languages to capture the heterogeneous ability of farmers to access phone-based services for agricultural advice. We think of the combination of mobile phone coverage and absence of language barriers with agricultural advisors as a positive shock to information about agricultural practices for farmers.

Our measures of technology adoption include farmers' adoption of high-yielding variety (HYV) seeds, chemical fertilizers and pesticides, as well as artificial irrigation systems. HYV seeds are commercially developed to increase crop yields and are one of the most prominent innovations in modern agriculture.[4] Chemical fertilizers and reliable irrigation systems are key complementary inputs to maximize HYV potential. Data on the adoption of these technologies is sourced from the Agricultural Input Survey of India, which is carried out at 5-year intervals and whose last two waves were in 2007 and 2012.

Our estimates indicate that in areas where the entire population speaks an official language and can therefore access agricultural advice, a 1 s.d. larger increase in mobile phone coverage is associated to a 1.4 percentage points larger increase in area farmed with HYV seeds between 2007 and 2012. This effect corresponds to a 5.3 percent increase in land cultivated with HYV seeds for the average cell in our sample.[5] We find positive and significant effects also on the adoption of chemical fertilizers, pesticides and irrigation. Consistent with an information mechanism, we show that these areas also experienced a larger increase in farmers' calls seeking information on the adopted technologies. On the other hand, in areas where the population cannot access agricultural advice due to language barriers with KCC advisors, the impact of mobile phones on the modernization of agricultural technologies is significantly more limited. Our estimates indicate that, for any level of mobile phone coverage increase, a 1 s.d. increase in the share of non-official language speakers reduces the adoption of new agricultural technologies by 18 percent. This effectively represents the share of technology adoption attributable to access to information about agricultural practices.

Next, we study the effect of farmers' access to information on agricultural productivity, measured by average crop yields. Our estimates indicate a significant relative increase in yields in the years following the construction of a new SMIS tower in previously uncovered areas. We exploit the yearly frequency of the data to document the timing of this effect. While there are no pre-existing trends in agricultural yields in the 5 years prior to the

[4] On the impact of high-yielding varieties on agricultural productivity and economic development see, among others, Evenson and Gollin (2002, 2003).

[5] The units of observation are cells of 0.083×0.083 degree resolution, approximately corresponding to areas of $10{\times}10$ km at the equator.

launch of the program, the effect of new mobile phone towers materializes about one year after their construction and increases in magnitude for the first three years. We also show that this effect is persistent in the long run: areas that received a new SMIS tower and did not face language barriers to access agricultural advice still displayed higher agricultural yields in 2017, about a decade after the start of the program. As with technology adoption, however, the positive effects of mobile phones on agricultural productivity are strongly mitigated by the inability of farmers to access agricultural advice. Our estimates indicate that in areas where more than 50 percent of the population speaks a non-official language, the effect of mobile phone coverage on productivity is completely muted. We also show that these results, like the previous on technology adoption, are robust to controlling for the interaction between mobile coverage expansion and other factors, such as geographical isolation or income levels, that may potentially be correlated with the diffusion of non-official languages in a given area.

Finally, we show that the returns to mobile phone coverage and access to information are highly heterogeneous, depending on farmers' initial productivity. Within our sample of rural areas with no initial mobile phone coverage there is large variation in the baseline level of agricultural productivity. In 2007, the average yield of an area at the 75th percentile of the productivity distribution was around twice as large as the one observed at the 25th percentile. This is a yield gap similar to that observed in rice and wheat production between the richest 10 percent and the poorest 10 percent of countries (Gollin, Lagakos, and Waugh, 2014). Our results show that the effect of access to information is the largest for areas in the lowest productivity quartile. The estimates suggest that providing agricultural advice on mobile phones can close about 36 percent of the productivity gap between farmers in the 25th percentile of the productivity distribution and those in the 75th percentile.

The lower returns to mobile phone coverage in areas where farmers face language barriers with KCC advisors strongly suggest that access to agricultural advice plays a key role in the modernization of agriculture. However, we also discuss and test alternative mechanisms potentially linking mobile phone coverage with technology adoption and productivity. For one, previous evidence suggests that by providing detailed and timely information on prices, mobile phones can reduce price dispersion, favor a more efficient allocation of goods across markets and generate higher incomes for goods producers (Jensen, 2007). This, in turn, could help farmers pay the fixed cost of adopting new technologies. To account for this possibility, we also present estimates of the model where we include a full set of fixed effects for the closest agricultural market to each cell in our sample. This allows us to compare outcomes across farmers who plausibly face the same prices for their products and experience the same changes in local demand. All our main results are robust to this augmented specification.

A second alternative mechanism through which mobile phones could also affect technology adoption and productivity is social learning. Models of social learning suggest that individuals adopt new technologies once they have gathered enough evidence from previous adopters that the new technology is actually worthy of uptake.[6] In our context, the expansion of the mobile phone network could facilitate the diffusion of such information across farmers and encourage the modernization of agriculture, regardless of the availability of call centers for agricultural advice. A prediction of this interpretation is that social learning is more likely to happen in areas where individuals tend to speak the same language. We attempt to capture this potential channel in our main specification by controlling for the interaction between mobile phone diffusion and local linguistic fragmentation. We find that our main estimates on access to information are not significantly affected by the introduction of this additional interaction term.

Related Literature

Our paper is related to several strands of the literature. First, a growing literature analyzes the economic impacts of large infrastructure programs in developing countries. Recent empirical work has focused on transportation infrastructure (Faber 2014, Donaldson 2018, Asher and Novosad 2020), construction of dams (Duflo and Pande 2007) and rural electrification (Dinkelman 2011, Burlig and Preonas 2016, Lee, Miguel, and Wolfram 2020). Related papers have focused on how the expansion of telecommunication services by private operators affects price dispersion (Jensen 2007, Aker 2010) and estimated the welfare implications of this network good for individuals in rural areas (Björkegren 2019). We contribute to this literature by providing direct empirical estimates of the effects on agriculture of a large government program bringing telecommunications infrastructure to rural areas.

A separate body of literature uses randomized controlled trials to evaluate the impact of mobile phone-based agricultural extension programs on farmers' practices and yields, finding mixed results on their effectiveness. For example, Casaburi, Kremer, Mullainathan, and Ramrattan (2019) show that sending text messages containing agricultural advice has short-term positive effects on the yields of small sugarcane farmers in Kenya, but the increase dissipates over time. Cole and Fernando (2020) randomize access to a hot line for agricultural advice to households in the Indian state of Gujarat, finding evidence that the use of this phone service has a significant impact on agricultural practices, although not systematic positive impact on yields. Fafchamps and Minten (2012) study the impact of a text message-based agricultural information system providing market and weather information to Indian farmers and find non significant effects on cultivation practices or productivity. Relative to this literature, we use large administrative data to explore the long-run (5 to 10 years) effects of access to agricultural advice. The nature of the data

[6] See the review of the literature in Young (2009) and seminal empirical studies by Ryan and Gross (1943) and Griliches (1957) on innovation diffusion using data on adoption of hybrid corn in the US.

– which cover a large and geographically diverse sample of farmers – has the advantage to provide the statistical power necessary to detect even small effects, and to study how such effects change across farmers with different initial characteristics. Relative to the previous literature, we also document that language barriers between farmers and government employees can generate largely unequal gains from mobile phone based extension programs.[7]

More generally, our paper is also related to the micro-development literature investigating the role of modern agricultural technologies – such as high-yielding variety seeds – in the process of development. This literature has studied several potential frictions to the adoption of modern technologies by farmers, including credit constraints (Duflo, Kremer, and Robinson, 2004), missing insurance markets (Karlan, Osei, Osei-Akoto, and Udry, 2014), lack of access to high-quality inputs (Bold, Kaizzi, Svensson, and Yanagizawa-Drott, 2017). Among these frictions, the lack of information on new technologies or how to use them has received extensive attention. This literature includes work grounded on learning models of new technologies based on farmers' own experience or the experience of others in their social network (Foster and Rosenzweig, 1995; Conley and Udry, 2010; Munshi, 2004; Hanna, Mullainathan, and Schwartzstein, 2014; Beaman, BenYishay, Magruder, and Mobarak, 2018).[8]

Studies in this area have also highlighted the mixed record of traditional agricultural extension programs (Duflo, Kremer, and Robinson, 2011). In particular, researchers and policy makers have long identified the lack of timely and personalized information as obstacles to the effectiveness of the communication between farmers and extension workers (Anderson and Feder, 2004). A key characteristic of the mobile phone-based extension program in this paper is that it allows farmers to solicit information on the issues they face at any point during the agricultural production cycle. In addition, farmers receive information that is adapted to the specific agro-climatic characteristics of their area. Overall, our results are consistent with farmers valuing this service. In particular, farmers solicit more information when receiving mobile phone access, they request information on different issues and at different times of the year, and ask for more and more information over time.[9]

Finally, our paper is also related to an influential body of work documenting the existence of substantial differences in agricultural productivity across countries and investigated their determinants (e.g., Gollin, Lagakos, and Waugh, 2014). These differences are larger than those in aggregate labor productivity, suggesting that the productivity

[7] For recent reviews of the broader literature on the impact of mobile phones in developing countries see Aker, Ghosh, and Burrell (2016) and Fabregas, Kremer, and Schilbach (2019).

[8] The extent to which social networks represent a reliable source of information on agricultural practices and technologies is unclear, as neighboring farmers and agricultural input dealers may be either poorly informed or misinform farmers due to misaligned incentives (Anderson and Birner, 2007).

[9] The number of calls to Kisan Call Centers has been increasing steadily since its inception, from half a million yearly calls in the late 2000s to about four millions yearly calls a decade later.

gap in agriculture is particularly important for our understanding of income differences across countries (Caselli 2005, Restuccia, Yang, and Zhu 2008). Several potential explanations of this productivity gap have been proposed, including land misallocation, lack of insurance markets, or frictions in the reallocation of workers from agriculture to the non-agricultural sectors (Adamopoulos and Restuccia 2014, Lagakos and Waugh 2013, Donovan 2020). Relative to these studies, we emphasize and quantify the role played by information frictions.

The rest of the paper is organized as follows. Section 2 introduces the data used in the analysis, and provides institutional background on the diffusion of mobile phones in India and on the two government programs – the Shared Mobile Infrastructure Scheme and the Kisan Call Centers for agricultural advice – that are central to our empirical analysis. Section 3 presents our identification strategy and all the empirical results. Section 4 provides concluding remarks.

2 Data, Institutional Background, and Stylized Facts

In this section we describe the main datasets used in the empirical analysis, provide some institutional background for the government programs used for identification, and present a set of stylized facts that emerge from the raw data. The unit of observation in our empirical analysis are areas of 10×10 km, which we refer to as cells. We use a grid of 10×10 km cells to match information from the datasets presented below, which come at different levels of geographical aggregation, which could be an administrative division such as a village or a subdistrict, or a geo-referenced polygon in the case of mobile phone coverage data.[10]

2.1 Data on Mobile Phone Coverage and its Diffusion in India

We use data on the diffusion of mobile phone coverage in India provided by the Global System for Mobile Communication Association (GSMA), the association representing the interests of the mobile phone industry worldwide. The data is collected by GSMA directly from mobile operators and refers to the GSM network, which is the dominant standard in India with around 89 percent of the market share in 2012 (Telecom Regulatory Authority of India, 2012). The data licensed to us provide, for all years between 1998 and 2012,

[10] Overall, India can be split into 41,495 cells distributed over 524 districts. Since cell borders do not typically correspond to district administrative borders, we assign cells spanning over more than one district to the district which occupies the largest area. One challenge that we face is that Indian districts have been changing shape, or were created or dissolved during the period under study. In order to define districts consistently over time, we created minimum comparable areas (MCAs) encompassing one or more districts that cover the same geographical space between 1997 and 2012. The main source used to re-construct district changes over time is the Population Census Map, which contains a short history of how each district was created.

geo-located information on mobile phone coverage aggregated across all operators.[11] Our analysis focuses on the 2G technology, the generation of mobile phones available in India during the period under study, which allows for phone calls and text messaging.[12]

Figure 2 reports the geographical diffusion of 2G GSM mobile phone coverage in India at five-year intervals between 1997 and 2012. While the country had virtually no mobile phone coverage until 1997, the mobile phone network began to expand rapidly shortly afterwards, covering 22 percent of the population in 2002, 61 percent in 2007 and 89 percent in 2012.[13] Data from the World Bank (2014) indicate that mobile phone subscriptions per 100 people in India went from 0.08 in 1997 to 68.4 in 2012. Following a standard pattern of diffusion (Buys, Dasgupta, Thomas, and Wheeler, 2009; Aker and Mbiti, 2010), the spatial roll-out of mobile phone coverage started in urban areas and only later reached rural ones. We document this pattern in Figure C.1, which reports – at 5-year intervals between 1997 and 2012 – the average share of land covered by mobile phones across cells with different initial levels of urbanization. As a proxy for urbanization we use night light intensity in 1996. As shown, in 1997 there was virtually no mobile phone coverage in either urban or rural areas. By 2002, areas in the highest decile of night light intensity had, on average, 40 percent of their area covered by the mobile phone network, more than 80 percent in 2007, and close to full coverage by 2012. On the other hand, mobile phone coverage in the lowest decile was, on average, still almost non-existent in 2002, around 20 percent by 2007 and around 40 percent by 2012.

2.2 Construction of mobile phone towers under the SMIS Government Program

The Indian government played an important role in the expansion of the mobile phone network in rural areas, where market demand did not justify infrastructural investment by private telecommunication companies. In 2007, the government launched the Shared Mobile Infrastructure Scheme (SMIS), aimed at providing subsidies to telecom operators for the construction and maintenance of mobile towers in identified rural areas without existing mobile coverage. Under Phase-I of the program, a total of 7,871 sites across 500

[11] The extent of geographical precision of the original data submissions ranges between 1 km^2 on the ground for high-quality submissions based on GIS vector format, and 15-23 km^2 for submissions based on the location of antennas and their corresponding radius of coverage. The data have been used by Manacorda and Tesei (2020) to study the effects of mobile phone coverage on political mobilization in Africa.

[12] The 3G spectrum was allocated to private operators only at the end of 2010 and the roll-out of commercial operations was very slow. By 2015, 3G penetration was just 20 percent in urban areas and much lower in rural areas (Ericsson, 2015).

[13] We use data from the Gridded Population of the World, Version 4. We assume that population is uniformly distributed within each 10×10 km cell and we use information on the share of each cell's area that is covered by mobile phone technology to compute the fraction of individuals reached by the mobile phone signal in each cell/year. We then aggregate across cells to obtain the share of population covered by mobile phone signal in the country in a given year.

districts were initially identified as potential locations for new towers. Villages or cluster of villages not covered by the mobile phone network and with a population of at least 2,000 were prioritized. Telecom operators receiving government subsidies were responsible for installing and maintaining the towers between 2007 and 2013.[14] Of the 7,871 proposed towers under Phase-I, 7,353 were eventually constructed.

We obtained data on the towers constructed under SMIS from the Center for Development of Telematics (C-DoT) - the consulting arm of the Department of Telecommunications of India. The C-DoT provided us with the geographical coordinates of the location of the 7,871 initially proposed towers, the geographical coordinates of the location of the 7,353 effectively constructed towers, and the operational date of each tower. The latter is the date in which the construction of the tower is completed and the tower becomes operational. For simplicity, in the remainder of the paper we refer to this date as the date of construction. From the 7,353 towers constructed under Phase I of the SMIS program we remove 350 towers for which the construction date is missing. This leaves us with 7,003 mobile towers used in our empirical analysis. Figure 3 shows a timeline of construction of these towers by month. As shown, the construction of towers effectively started in January of 2008 and ended in May of 2010, with most towers being introduced between the second half of 2008 and the first half of 2009. To estimate the potential coverage of each tower, we assume a 5-km radius of coverage around the towers' location, based on information reported in tender documents obtained from the C-DoT officials responsible for the Phase I implementation (tender document No. 30-148/2006-USF).

2.3 Data on farmers' calls to Kisan Call Centers

To investigate the role of information on agricultural practices we use data on farmers' calls to Kisan Call Centers (KCC), which we obtained from the Department of Agriculture, Cooperation and Farmers Welfare. Calls are geo-located at the subdistrict (or block) level and we assign them proportionally to all cells whose centroid is contained in the subdistrict.[15]

---

[14] A second Phase of the scheme was also planned to be launched shortly after Phase-I to cover even more sparsely populated areas, but was never implemented.

[15] On average, there are 27 cells per subdistrict. Whenever information on the subdistrict from which the call is originated is missing, we use information on the district of the call and the crop for which the caller is seeking information to assign calls to a given cell. Our probabilistic assignment rule is described in the following equation:

$$Calls_{idt} = \sum_{c \in O_i} (Calls)_{cdt} \times \left(\frac{Area_{idc,t=2000}}{Area_{dc,t=2000}} \right)$$

The first element of the product captures the number of calls about a given crop c that are originated from district d, while the second element of the product captures the share of crop c that is farmed in cell i over the total area farmed with the same crop in district d (sourced from the FAO-GAEZ data). Thus, this assignment rule implies that if 10 percent of the area farmed with rice in district d is farmed in cell i, 10 percent of the calls about rice received from farmers located in district d will be assigned to cell i.

KCC were introduced in January 2004 by the Indian Ministry of Agriculture and were the first providers of general agricultural advice to farmers via mobile phone in India.[16] KCC are available in all Indian states and allow farmers to call a toll-free number to get answers to their questions. In total, during the 2006-2012 period, farmers made around 2.5 million calls to KCC. The number of calls increased substantially starting in 2009, reaching over half a million per year between 2009 and 2011, and over eight hundred thousands in 2012.[17]

For every call received in one of the 25 call centers that are part of the KCC network, the agronomist collects basic information on the farmer (name, location and contact information), date and time of the call, a brief description of the question, the crop for which the query is made, and the response provided.[18] The calls are answered by trained KCC agricultural graduates, who address the query based on their knowledge and on a database of previous answers to similar queries. Approximately 98 percent of the calls are answered using this database. In case the agronomist is unable to answer the question, the call is forwarded to a senior expert.[19]

Around 50 percent of the calls to KCC are about pests and how to deal with them. In the responses, farmers receive detailed advice on which pesticide (if any) they should use, as well as information on dosage and number of applications. The second most represented category is calls on how to improve yields or – more specifically – on which seed varieties to use to obtain higher yields (13 percent of calls). In these cases, farmers often receive suggestions on which HYV seeds to use based on crop, location, and irrigation system available. Other topics farmers consistently ask about are: fertilizers (10.5 percent of calls), weather conditions (5.7 percent), advice for field preparation (4.6 percent), market price information (3.6 percent), credit information (2.3 percent), and irrigation (1 percent).[20]

In Figure 4 we report the breakdown by month and topic of the call for the two largest

[16] Figure C.2 shows the timing of introduction of the largest Indian providers of agricultural advice via mobile phones. Other early development extensions, like aAQUA and NanoGanesh, established in 2003 and 2004 respectively, focused on SMS-based advice on agricultural practices and irrigation techniques, respectively. Until 2010, no other provider of general agricultural advice entered the market.

[17] The availability of this service has been largely advertised by the Indian government. The advertising campaign mostly took the form of TV ads. Ads were broadcasted in both public and private TV channels, and at times matching farmer's preferences in different states.

[18] The version of the data provided to us by the Department of Agriculture, Cooperation and Farmers Welfare does not contain farmers' names or contact information. Thus, we cannot identify farmers that call multiple times.

[19] According to an external evaluation of the KCC program, 84% of farmers expressed satisfaction with the advice received, 99% said they would call again if there was a problem, and 96% were willing to recommend the service to their friends.

[20] In Appendix A we provide a detailed description of the keywords that we use to categorize calls to KCC by topic. We classify calls by categories based on the description provided by the operator. Based on these descriptions, we are able to classify 93 percent of the calls to KCC between 2006 and 2012.

crops by cultivated area in India, rice – panel (a) – and wheat – panel (b). A number of patterns emerge. First, the distribution of calls reflects the different farming season of the two crops. Rice is mainly grown during the *kharif* season, where crops are grown between June and September and harvested between October and February. On the other hand, wheat is mainly grown in the *rabi* season, where crops are grown between October and November and harvested between December and the Spring months. Second, the composition of the calls is consistent with the agricultural calendar just described. For example, rice farmers mostly ask questions about which seeds to use in May and June – at the beginning of the growing season. Instead, when crops are fully grown, most of the calls are about how to defend the plants from pests. Similar patterns can be observed for wheat.

Finally, in Figure C.3 we report the overall distribution of calls to KCC by month, by time of the day and by crop. The figure shows that most calls are received during Summer months (panel a), that the peak number of calls is around late morning hours (panel b) and that most questions are about rice and wheat (panel c).

2.4 Data on Technology Adoption and Agricultural Productivity

Our measures of technology adoption come from the Agricultural Input Survey (AIS), conducted at five-year intervals by the Ministry of Agriculture in coincidence with the Agricultural Census to collect information on input use by Indian farmers. Our main empirical analysis focuses on the last two waves of the AIS, 2007 and 2012, while we use earlier survey waves to document pre-existing trends.[21] In the survey, all operational holdings from a randomly selected 7 percent sample of all villages in a sub-district are interviewed about their input use.[22] The AIS reports information on land farmed with these input technologies at the district-crop level. We compute the share of land farmed with a given agricultural technology k in a given cell i using the following neutral assignment rule:

$$\left(\frac{Area^k}{Area}\right)_{idt} = \sum_{c \in O_i} \left[\left(\frac{Area^k}{Area}\right)_{dct} \times \left(\frac{Area_{idc,t=2000}}{Area_{id,t=2000}}\right) \right] \tag{1}$$

The first element in the summation is the share of land farmed with technology k in district d among the land farmed with crop c. This variable captures the rate of technology adoption for a given crop in a given district and varies over time. The second element in the summation is the share of land farmed with crop c in cell i, which is observed at cell level in the FAO-GAEZ dataset and captures the initial allocation of land across crops

[21] The Agricultural Input Survey runs from 1^{st} July to June 30^{th} of the following year. In the paper, we use the terminology 2007 when referring to the survey carried out between July of 2006 and June of 2007.

[22] The AIS was not conducted in the states of Bihar and Maharastra before 2012. Thus, we exclude these states from our analysis.

in a given cell in the baseline year 2000.[23] Thus, the product of first and second element gives us an estimate of the share of land in cell i that is farmed under technology k and crop c. Summing across the set of crops farmed in cell i (O_i), we obtain an estimate of the share of land farmed with a given technology in a given cell.[24]

Effectively, the within-district variation generated by our assignment rule is driven by the baseline crop composition of each cell coupled with district-crop level variation in technology adoption. One potential concern with this assignment rule is that it may generate non-classical measurement error. This would happen if, for example, new SMIS towers are systematically constructed in cells (within a district) where farmers grow crops characterized by fast technology adoption. To address this concern, in section 3.6 we show that our treatment and control cells are balanced in terms of initial shares of area farmed with crops that experienced faster increase in HYV adoption at district level. In addition, in section 3.2, we show that treatment and control cells have similar trends in technology adoption in the five years before the introduction of the SMIS program, which rules out the concern that baseline crop composition captures long-term trends in adoption. Finally, in Appendix B, we validate our cell-level measure of technology adoption by using a sample of cells for which we observe actual adoption of HYV seeds and irrigation at the village level from publicly available surveys.

The AIS covers the following agricultural input technologies: seeds – distinguished between traditional and high-yielding varieties – chemical fertilizers, organic manures and pesticides, agricultural machinery and agricultural credit. Our preferred measure of technology adoption in agriculture is the share of land farmed with high-yielding varieties (HYV) of seeds. These are hybrid seeds developed via cross-breeding in order to increase crop yields. They combine desirable characteristics of different breeds, including improved responsiveness to fertilizers, dwarfness, and early maturation in the growing season. HYV seeds have been available in India since the Green Revolution (the IR8 rice, flagship of the Green Revolution, was introduced in 1966), but new varieties are constantly developed and introduced in the market. In the period between 2002 and 2013, 47 new varieties of different oilseeds, cereals and vegetables including rice, groundnut, wheat, millet, soy and cotton were introduced to the Indian market. Despite their early introduction and rapid adoption in many areas of the country, a large share of the Indian agricultural land is still not farmed using HYV seeds. The average share of HYV area across cells in our sample

[23] The GAEZ dataset reports information on the amount of land – expressed in hectares – farmed with a specific crop in a given cell. The data refers to the baseline year 2000. We focus on the 10 major crops by area harvested in India, namely: rice, wheat, maize, soybean, cotton, groundnut, rape, millet, sugar and sorghum. According to FAOSTAT, the area harvested with these 10 crops amounts to 135.5 million hectares and accounts for 76 percent of the total area harvested in India in 2000.

[24] As an example, suppose that in district d, 20 percent of land farmed with rice and 50 percent of land farmed with wheat are farmed using high-yielding variety seeds. Suppose also that 40 percent of land in cell i that is part of district d is farmed with rice, while the remaining 60 percent is farmed with wheat. Under our neutral assignment rule, we assign 38 percent of land in cell i to high-yielding varieties: $(0.2 \times 0.4) + (0.5 \times 0.6) = 0.38$.

in 2007 was 26 percent.

The data on agricultural productivity (yield) also come from the Ministry of Agriculture. The data provide yearly information on covered area and production for each crop at the district level. Our measure of agricultural productivity is crop yield, which is defined as the quantity of crop produced (in metric tons) in a given area divided by the land farmed with that crop (in hectares) in the same area. We construct our measure of crop yield similarly to Jayachandran (2006), who use a weighted average of normalized yields of the major crops farmed in India to generate a district-level measure of agricultural productivity. Agricultural productivity at the cell level is then computed with a neutral assignment rule similar to the one reported in equation (1) as follows:

$$\log yield_{idt} = \sum_{c \in O_i} \left[\log \left(\frac{\text{quantity produced}}{\text{area farmed}} \right)_{dct} \times \left(\frac{Area_{idc,t=2000}}{Area_{id,t=2000}} \right) \right] \tag{2}$$

Equation (2) defines yield in cell i as the weighted average of log crop yields for the ten major crops by area farmed, where the weights are the share of area farmed with a given crop in a cell at baseline.[25]

3 Empirics

Our empirical analysis proceeds in two steps. First, we use an event-study design to document the evolution of farmers' calls to KCC when new SMIS mobile phone towers are introduced in areas without previous coverage. This evidence relies on monthly-level variation in the number of farmers' calls originated from a given location, around the month of construction of the first tower in the area. The event-study also allows us to document the role of language barriers in the diffusion of information. In particular, we show that geographical differences in the diffusion of non-official languages among the rural population affect the spatial availability of agricultural advice provided by the KCC. We present these results in section 3.1.

Next, we study the real effects of access to information on technology adoption and agricultural productivity. Since technology adoption and productivity are not observed at the same high frequency as farmers' calls, we cannot use the event-study design just described for these outcomes.[26] Instead, we propose an identification strategy that compares locations where new mobile phone towers were proposed and constructed under the SMIS program with similar locations where new towers were proposed but eventually not constructed. We exploit variation in tower construction along with variation in local

[25] We first normalize the yield for each of the 10 major crops in India by the mean yield of that crop in each district (using the years 1998 to 2012 to construct the mean).

[26] Data on adoption of agricultural technologies is observed at 5-year intervals in the Agricultural Input Survey. Agricultural yields are instead observed at yearly level, which allows us to document the timing of the effect around the construction of new towers.

languages spoken by farmers to capture their ability to access phone-based services for agricultural advice. We focus on the change in technology adoption and productivity between 2007 and 2012, with 2007 being the last wave in the AIS *before* the SMIS program, and 2012 the first wave *after* the SMIS program. We discuss the identification strategy in section 3.2 and present the results in sections 3.3 to 3.5.

Finally, in section 3.6 we present a set of additional robustness tests on our main empirical results, while in section 3.7 we discuss and empirically test for alternative explanations to our results based on the impact of mobile phones on price dispersion and social learning.

3.1 Event-Study Evidence on Farmers' Access to Information

We estimate the evolution of farmers' calls to KCC around the introduction of new mobile phone towers using the following specification:

$$Ln\,(1 + Calls)_{it} = \alpha_i + \alpha_t + \sum_{k=-12}^{+36} \beta_k D_{it}^k + \varepsilon_{it} \tag{3}$$

The outcome variable in equation (3) is the natural logarithm of the total number of calls originated from cell i in month t. D_{it}^k is a dummy equal to 1 if month $t = k$ for cell i, and captures the time relative to the month of introduction of the first tower covering cell i, which we set at $k = 0$. We include the 12 months prior to the introduction of the first tower and the 36 months after. The specification has calendar time and cell fixed effects, denoted by α_t and α_i, respectively. Standard errors are clustered at the district level.

The objective of this exercise is to exploit the different timing of construction of mobile phone towers in different cells to document their impact on farmers' calls. Notice that we focus on cells that will eventually receive a mobile phone tower under the SMIS program described in section 2. Notice also that in this first analysis we focus on the number of calls, while the analysis of their content is discussed in detail in section 3.3.

Panel (a) of Figure 5 reports the estimated coefficients β_k along with their 95 percent confidence intervals. Several findings emerge. First, the coefficients are precisely estimated zeros in the months preceding the introduction of the first tower in a cell. This indicates that the timing of tower introduction is not correlated with pre-existing trends in calls.[27] Second, within 4 months of the construction of the first tower we observe a significant increase in calls for agricultural advice. The magnitude of the estimated coefficients indicates, on average, a 5 to 10 percent increase in the number of calls to KCC in the first year post tower construction. Third, this differential continues to grow over the next 18 months, reaching a 40 to 50 percent increase in calls three years after the construction of the first tower in a cell.

[27] Note that farmers can call KCC before the introduction of mobile phone towers using landlines, when available.

As discussed in section 2, KCC agricultural advice can in principle be accessed by any farmer with either a landline or a mobile phone connection. KCC agronomists, however, answer farmers' calls only in one of the 22 official languages recognized in the Indian Constitution.[28] This effectively creates a barrier to the service for around 40 million individuals, whose mother tongue is one of the about 100 additional non-official languages spoken in India. Thus, even among areas that receive similar mobile phone coverage via new SMIS towers, the ability of farmers to access dedicated information on agricultural practices might vary by local language. The heterogeneous impact of mobile coverage on calls depending on differences in local languages spoken by farmers is clearly visible in Figure 1, which we briefly presented in the introduction and that we discuss here in more detail. Panel (a) of Figure 1 shows in red the areas of the state of Odisha in which the majority of the local population speaks non-official languages. As shown in panels (b) and (c), the diffusion of non-official languages is not correlated with the diffusion of agriculture (captured by the share of farmed land) or the increase in mobile phone coverage experienced between 2007 and 2012. However, as shown in panel (d), the areas where the majority of the local population speaks a non-official language experienced significantly lower increase in phone calls made by farmers to KCC.

This example is illustrative of a strong statistical trend that we observe across all our sample. In panel (b) of Figure 5 we estimate equation (3) separately for cells where the majority of the local population speaks one of the 22 official languages and cells where the majority speaks one of the non-official languages.[29] The figure shows that, after the construction of the first mobile phone tower, calls to KCC increase in both groups. However, the increase is much more pronounced in areas where the majority of the local population speaks the same languages as KCC agronomists. Within 3 years from the construction of the first tower, calls in these cells increase by around 30 percentage points more than in those where the majority of the local population speaks a non-official language.

Since farmers' calls to KCC were extremely rare before the construction of SMIS towers in these areas, we also report the average number of calls per thousand farmers around the tower construction month. This is Figure C.6 in Appendix C. A few interesting stylized facts emerge from this figure. First, as shown in panel (a), there were almost no calls to KCC in the period before the construction of the first tower in a given cell. Second, there is a clear discontinuity in the number of calls per farmer around the date of tower construction.[30] Second, as shown in panel (b), the number of calls experienced an

[28] See `https://mkisan.gov.in/aboutkcc.aspx`. Agronomists answering in each KCC location answer calls in one (or more) of the official languages.

[29] Data on the share of local population speaking non-official languages is sourced from the 2011 Indian Census and available at the subdistrict level. To each cell whose centroid falls within a given subdistrict we assign the share of local population speaking non-official languages in that subdistrict.

[30] The figure shows how the sharp increase in calls occurs in the month before the first tower is reported to be constructed in a given cell, which is consistent with some delay in the reporting of the finalized

exponential increase in the years following the construction of the first tower in a given cell, reaching an average of about 20 calls per thousand farmers within five years from the first tower construction in cells with a majority of official language speakers.

Taken together, the evidence in Figure 5 suggests that the expansion of mobile phone coverage represents a large information shock to farmers, and that this shock has been largely heterogeneous depending on linguistic differences between farmers and government advisors working at KCC. In the next section, we study how differences in this shock to access to information map into technology adoption and agricultural yields among farmers.

3.2 The Real Effects of Access to Information - Identification Strategy

In this section, we present our identification strategy to study the effect of farmers' access to information on real outcomes, namely agricultural technology adoption and productivity. Our identification strategy relies on the two sources of cross-sectional variation that emerge as important determinants of farmers' calls in the event-study setting: availability of mobile phone coverage and share of local population speaking non-official languages. We think of the combination of mobile phone coverage and absence of language barriers with agricultural advisors as a positive shock to information about agricultural practices for farmers.

Our identification strategy exploits variation in the construction of mobile phone towers under the Shared Mobile Infrastructure Scheme, or SMIS, described in section 2. In the initial phase of this program, the Department of Telecommunications identified 7,871 potential locations for the construction of mobile phone towers. All the locations in this initial list responded to certain specific criteria, including lack of existing mobile phone coverage and number of individuals potentially covered by the new tower. For identification purposes, we exploit the fact that not all the locations in the initial list eventually received a tower. In some cases, towers were either relocated or not constructed. Thus, we compare cells where towers were initially proposed and eventually constructed with cells in the same administrative district where towers were initially proposed but eventually not constructed.[31] Our final sample consists of 6,320 cells, of which 4,569 in the treatment group and 1,751 in the control group. The summary statistics for the main variables of interest are reported in Table 1. Figure 6 presents the geographical distribution of treatment (in red) and control (in blue) cells across India, while Figure C.5 zooms onto Rajasthan – the largest Indian state by area – superimposing the lattice of 10×10 km cells to show the level of geographical detail allowed by our data. On average,

construction.

[31] We compute coverage for each new tower based on its technical specifications, which corresponds to a 5 km coverage radius around its centroid. As discussed in Section 3.6, our analysis is robust to using the share of land covered by SMIS towers instead of an indicator variable. Figure C.4 provides a visual example of how we classify cells into treatment and control group based on proposed and actual tower location.

our sample includes 27 cells per district – 20 treated and 7 control. We further combine this variation with data on the share of local population speaking non-official languages. We report the geographical distribution of the share of local population speaking non-official languages in Figure 7.

The identification relies on the assumption that locations where a tower was proposed but eventually not constructed are a good control group for those that eventually received a tower. The main challenge to our identification is that, although all proposed locations had to meet specific criteria, the decision to relocate or cancel a tower is not random. For example, based on conversations with the C-DoT officials responsible for the implementation of the program, towers were sometimes relocated (or canceled) when, upon visiting the actual site, technicians realized that a relocation would increase the total population covered, or when they discovered logistical issues related to terrain characteristics or lack of an available connection to the electricity grid to power the tower. In what follows, we formally test for differences in the probability of receiving coverage from new SMIS towers based on cell observable characteristics and on pre-existing trends in technology adoption and productivity. We also perform this balance test across cells with different shares of the local population speaking a non-official language, conditional on receiving coverage from new SMIS towers.

The results of the balance tests are reported in Table 2. The outcome in columns (1) to (4) is an indicator variable – $\mathbb{1}\,(\text{Tower})$ – which is equal to 1 for cells where a new SMIS tower was proposed and eventually constructed, and 0 for cells where a new SMIS tower was proposed but eventually not constructed. Column (1) shows that, in line with the C-DoT officials' account, the conditional probability of eventually receiving a new tower is higher for cells with higher initial population and with flatter terrain, while it does not appear to depend on the availability of a connection to the power grid. Next, in column (2) we study whether pre-trends in agricultural technology adoption or productivity affect the probability of eventually receiving a SMIS tower. As shown, we find no significant differences in technology or productivity growth across treated and control cells in the 5 years preceding the tower construction program. In column (3) we then explore the correlation with a number of cell characteristics sourced from the Village Survey of the Population Census of India.[32] Treatment and control cells appear to be comparable along a large set of observable characteristics including: agricultural employment share, share of irrigated land, presence of a school, hospital or bank branch, availability of landline phone connections, night lights intensity, income and expense per capita. The only exception is average distance to the nearest town, which is shorter for the treatment group, although very small in terms of magnitude. In column (4) we

[32] We assign villages to 10×10 km cells based on the geographical coordinates for the centroid of the village. The coordinates are obtained from `http://india.csis.u-tokyo.ac.jp`. Village-level information is then aggregated to obtain cell-level characteristics.

consider all previous variables together. The main takeaway is that population and terrain ruggedness remain strong predictors of tower construction, while the other variables are by and large statistically insignificant. In the empirical analysis we add these controls to our specification and show that all our estimates are stable when including the observable cell characteristics reported in Table 2. Finally, in column (5) we condition on cells eventually receiving coverage from new SMIS towers, and explore the correlation between all observable cell characteristics and an indicator variable equal to one for cells where the majority of the population speaks a non-official language, and zero otherwise. As shown, among the treated cells in our sample, the distribution of non-official language speakers is uncorrelated with observable characteristics and pre-trends in technology adoption and productivity.

3.2.1 First Stage

Our first-stage regression is as follows:

$$\Delta Cover_{id} = \alpha_d + \gamma \, \mathbb{1}\,(\text{Tower})_{id} + \delta X_{id} + u_{id} \tag{4}$$

The outcome variable is the change in the share of land covered by the mobile phone network between 2007 and 2012 in cell i, district d. It is important to underline that this variable is constructed using actual mobile coverage data as reported by Indian telecommunication companies to GSMA, i.e. it is not the predicted increase in coverage constructed using SMIS tower location.[33] The coefficient of interest is γ, which captures the effect of tower construction under the SMIS program on the change in coverage in a given cell. X_{id} is a vector of initial cell-level controls, which includes all the cell characteristics reported in Table 2. We include in our specification district fixed effects (α_d) and we cluster standard errors at the district level. Finally, in all specifications we weigh each cell by its population at baseline (2001).

Table 3 reports the first-stage results. The estimated coefficient in column (1) indicates that cells covered by new SMIS towers experienced a 11 percentage points larger increase in the share of land covered by mobile phones between 2007 and 2012 relative to the control group. In column (2) we include the three main determinants of tower relocation according to C-DoT officials: population, availability of power supply and terrain ruggedness. The magnitude of the estimated coefficient decreases from 0.11 to 0.073, and remains highly statistically significant. Finally, in column (3) we add all the observable socio-economic cell characteristics. Consistent with the results presented in Table 2, the

[33] The tower construction program we use for identification is not the only driver of changes in mobile phone coverage in these areas. During the same period, private companies also built mobile phone towers across India to extend their services and expand their market shares. Thus, we do not expect tower construction under SMIS to be the sole source of variation in change in GSMA coverage, even in rural regions.

size of the point estimate is unaffected by including these additional controls. According to the specification in column (3), cells covered by new SMIS towers have, on average, 7.4 percentage points larger share of land covered by mobile phones in 2012 relative to the control group (recall that all these cells have no coverage at baseline). Below the regressions we report the Kleibergen and Paap (2006) first stage F-statistics for the validity of the instrument. We can safely reject that the first stage is weak.

3.2.2 Second Stage: Empirical Specifications

We start by modelling the overall effect of mobile phone coverage on the outcomes of interest – such as the number of calls for agricultural advice, the adoption of agricultural technologies or productivity. If we denote a generic cell by i, with $i \in d$, where d denotes a district, our regression model is:

$$\Delta y_{id} = \alpha_d + \beta \widehat{\Delta Cover}_{id} + \delta X_{id} + u_{id} \tag{5}$$

where Δy_{id} denotes the change in a given outcome between 2007 and 2012 and $\widehat{\Delta Cover}_{id}$ represents the change in the share of land covered by the mobile phone network over the same period, instrumented with the variable $\mathbb{1}$ (Tower) from equation (4). X_{id} is the vector of cell characteristics discussed in Table 2 and α_d are district fixed effects.

The main coefficient of interest is β, which will be positive if mobile phones have a positive impact on technology adoption and agricultural productivity. This coefficient subsumes different mechanisms linking mobile phone coverage with technology adoption and productivity. For example, the arrival of mobile phone coverage might promote local economic opportunities more generally, increasing local income and thus demand for agricultural products. Farmers might adopt new technologies to serve this increased demand.[34]

To make progress in the direction of isolating the role of information, we expand equation (5) to account for the share of population in the cell speaking a non-official language, hence with limited access to information about inputs and best agricultural practices provided by the KCC. We estimate the following augmented specification:

$$\Delta y_{id} = \alpha_d + \beta_1 \widehat{\Delta Cover}_{id} + \beta_2 \widehat{\Delta Cover_{id} \times} NOLang_{id} + \beta_3 NOLang_{id} + \delta X_{id} + u_{id} \tag{6}$$

where, compared to equation (5), we also include the share of population speaking a non-official language ($NOLang_{id}$) and its interaction with the change in mobile phone

[34] Previous studies have also shown that, by reducing transaction costs on money transfers, mobile phones can facilitate risk sharing among farmers (Jack and Suri 2014; Blumenstock et al. 2016). This might, in turn, incentivize them to experiment with newer but riskier technologies. See Feder, Just, and Zilberman (1985) for a discussion of the role of farmers' risk-aversion in adoption models. This mechanism is unlikely to be at play in our setting given the lack of mobile-based money transfer technologies in rural India during the period under study.

coverage.[35] The coefficient β_1 captures the effect of mobile coverage when the entire local population speaks an official language ($NOLang_{id} = 0$) and hence has full access to information about agricultural practices and inputs. The coefficient β_2 instead captures the differential impact of mobile phone coverage in cells with different shares of the population speaking a non-official language. The sum of the two coefficients β_1 and β_2 identifies the effect of mobile coverage on outcomes in the absence of access to a phone-based service for agricultural advice ($NOLang_{id} = 1$).

A potential concern with equation (6) is that the initial diffusion of non-official languages is not randomly assigned across locations. In section 3.6 we show that our results are robust to controlling for additional interaction terms of $\Delta\widehat{Cover}_{id}$ with other cell characteristics, including measures of agricultural intensity, geographical isolation and local income, that may potentially be correlated with the diffusion of non-official languages in a given area. Finally, in section 3.7 we further augment our baseline specification to take into account alternative potential mechanisms, such as the impact of mobile phones on price dispersion and social learning, that may link mobile phone expansion in areas with high prevalence of non-official languages to technology adoption and productivity, including.

3.3 The Effect of Access to Information on Farmers' Calls: By Topic of the Call

We start by documenting the effect of mobile phone coverage on farmers' calls for agricultural advice. In particular, we use the identification strategy described in section 3.2 to study farmers' access to information about specific technologies. Crucially for our purpose, the call-level data from KCC report the exact question asked by the farmer – as well as the answer provided by the agronomist. This allows us to distinguish between calls in which farmers seek advice regarding specific agricultural technologies such as new varieties of seeds, fertilizers, irrigation, or pesticides. Appendix A reports a detailed description of the keywords used to classify calls in different categories, as well as several examples. Documenting the type of information acquired by farmers is important in order to trace a link between access to information and actual adoption of agricultural technologies, which we study in the next section.

In column (1) of Table 4 we estimate the effect of mobile phone coverage on the change in total number of calls to KCC between 2007 and 2012, as described by equation (5). The estimated coefficient suggests that cells with 1 s.d. larger increase in mobile phone coverage experienced a 23 percent larger increase in total calls by farmers. Next, in column (2), we report the results from the unrestricted model in equation (6), where we allow the effect of coverage to vary across areas facing different language barriers with KCC

[35] The latter is instrumented by the interaction of the share of population speaking a non-official language with the indicator variable for tower construction from equation (4).

advisors. We interpret the estimated coefficient β_1 as the combined effect of coverage and access to a phone-based service for agricultural advice on farmers' calls. Its magnitude suggests that a 1 s.d. increase in coverage in cells where all farmers speak an official language increases the number of calls by 26.6 percent. The coefficient β_2, on the other hand, indicates that calls for agricultural advice are less responsive to changes in coverage when the local population does not speak an official language. The sum of the estimated coefficients β_1 and β_2 (0.828 - 0.716 = 0.112) implies that, when the entire population does not speak an official language, the effect of a 1 s.d. increase in mobile phone coverage on calls is only 3.6 percent and not statistically different from zero.

Next, we focus on farmers' calls about specific agricultural technologies: seed varieties, fertilizers, irrigation, and pesticides. The results are shown in column (3) to (10). Odd columns refer to the average effect of mobile phone coverage, while even columns allow for the heterogeneous response to coverage depending on the share of non-official language speakers. The results are in line with those on the total number of calls and very similar for all agricultural technologies. An increase in mobile phone coverage is associated with more calls for agricultural advice on specific technologies, but the effect is limited by the existence of language barriers between the local population and the KCC advisors, as shown by the negative and statistically significant coefficients on the interaction terms in all specifications.

Overall, the results reported in Table 4 are consistent with the existence of an underserved demand for information on farming techniques by Indian farmers. To the extent that the information provided by call centers for agricultural advice is accurate, we can think of farmers acquiring mobile phone coverage and having access to a phone-based service for agricultural advice as receiving a positive shock to their information set on farming techniques. This allows to study the effect of such shock on the actual adoption of the technologies farmers ask about, as well as on local agricultural productivity. We focus on these two outcomes in the following sections.

3.4 The Effect of Access to Information on Technology Adoption

In this section we study the effect of farmers' access to information via call centers for agricultural advice on technology adoption. We focus in particular on those technologies farmers ask about in their phone calls to KCC, namely seed varieties, fertilizers, irrigation and pesticides.

To study the effect of mobile phone coverage on adoption of a given technology we estimate equations (5) and (6) using as outcome variable $\Delta\left(\frac{Area^k}{Area}\right)_{id}$, which is the change in the share of land farmed with a given technology k (e.g. HYV seeds) in cell i located in district d. Changes in outcomes are calculated using the last 2 waves of the AIS, which were run in 2007 and 2012.

Column (1) of Table 5 reports the results of estimating equation (5) when the outcome variable is the change in the share of land farmed with HYV seeds – as opposed to traditional seeds – in a given cell. The coefficient is positive and precisely estimated. Its magnitude indicates that cells with a 1 s.d. larger increase in mobile phone coverage experienced a 1.4 percentage points larger increase in the share of area farmed with HYV seeds. Among the cells in our sample, the average area farmed with HYV seeds in the baseline year 2007 was 26 percent. Thus, the 1.4 percentage point increase mentioned above corresponds to a 5.3 percent increase in land cultivated with HYV seeds for the average cell in our sample.

Column (2) reports the results of estimating equation (6), where we allow for the heterogeneous response to mobile phone coverage depending on the share of local population speaking non-official languages. The estimated coefficient β_1 captures the combined effect of coverage and access to a phone-based service for agricultural advice. Its magnitude indicates that areas with full coverage and where all farmers speak official languages experienced a 4.7 percentage points larger increase in share of land farmed with HYV seeds between 2007 and 2012, compared to areas with no coverage (corresponding to 28 percent of the share at baseline). The negative and statistically significant coefficient on the interaction term β_2 indicates that limited access to information about agricultural practices reduces the impact of mobile phones on technology adoption. For any level of mobile phone coverage increase, a 1 s.d. increase in the share of non-official language speakers reduces the adoption of new agricultural technologies by 18 percent.[36] This differential captures the portion of mobile phone impact that we attribute to access to information on agricultural practices.

In columns (3) and (4) we focus on the share of land under chemical fertilizers as an additional measure of technology adoption. One important characteristic of HYV seeds is that they are highly respondent to fertilizers (Dalrymple, 1974). Thus, we expect adoption of HYV seeds by farmers to increase their demand for these complementary inputs of production. Column (4) shows that cells with larger increase in mobile phone coverage and no language barriers experienced an increase in area farmed with chemical fertilizers of similar magnitude as the increase documented for HYV seeds. The negative coefficient on the interaction term, although less precisely estimated compared to column (2), suggests that language barriers with agricultural advisors limit the impact of mobile phone coverage on adoption of fertilizers.

Next, we test for the effect of access to information on adoption of artificial irrigation. Farming with HYV seeds does not necessarily require more water than farming with traditional seeds. However, in order for HYV seeds to attain their full potential, they do require a reliable source of irrigation (Dalrymple, 1974). Thus, we expect adoption of HYV seeds by farmers to also increase their demand for irrigation. We study the effect on irrigated area in columns (5) and (6), and find results that are similar, although smaller

[36] This is the result of (-0.041×0.212) divided by the level effect of mobile phone coverage, 0.047.

in magnitude, to the ones documented for chemical fertilizers.[37] Finally, columns (7) and (8) show a positive and significant effect of mobile coverage combined with access to a phone-based service for agricultural advice on the share of land under chemical pesticides. As in the previous columns, the point estimate on the interaction term suggests that the impact of mobile phones on technology adoption is limited by the presence of language barriers to obtain information about agricultural practices.

Overall, the results presented in Tables 4 and 5 are consistent with a positive and significant effect of mobile phone coverage, coupled with access to a service for agricultural advice, on technology adoption via the diffusion of information about new technologies. We can use the estimates to calculate the implied elasticity of technology adoption to access to information about a given technology. To compute this elasticity we divide the estimated percentage increase in area farmed with a given technology by the estimated percentage increase in farmers' calls regarding that same technology for a given information shock. For HYV seeds, the obtained elasticity indicates that a 1 percent increase in mobile phone calls about this technology translates into a 0.78 percent increase in its actual adoption. Similarly, we find elasticities of 0.64 for chemical fertilizers, 1.1 for chemical pesticides and 3 for irrigation.

3.5 The Effect of Access to Information on Productivity

In this section we study the effect of farmers' access to information via new mobile phone towers on agricultural productivity.

We start by studying the effects of access to information on productivity using the same specification used to study its effects on technology adoption. The results are reported in Table 6. Column (1) shows a positive but insignificant effect of mobile phone coverage on the change in agricultural productivity between 2007 and 2012. Column (2) shows that the impact of mobile phones varies significantly across areas, depending on farmers' access to agricultural advice. In areas where the entire population speaks an official language, a 1 s.d. increase in mobile phone coverage leads to a 1.3 percent larger increase in productivity, an effect 40 percent larger than the average. On the contrary, in areas where 50 percent or more of the population speaks a non-official language the positive effect of mobile phone coverage on productivity is completely offset, as implied by the magnitude of the negative and significant coefficient on the interaction term β_2.

In the remaining columns of Table 6, we investigate the differential returns to mobile phone coverage and access to information across areas with different initial levels of agri-

[37] The Agricultural Input Survey reports the use of fertilizers and irrigation by land farmed with HYV vs traditional seeds. In Table C.6 we estimate our main specifications splitting fertilizers and irrigation use in land farmed with HYV seeds and with traditional seeds. As shown, the effects of mobile coverage coupled with the availability of services for agricultural advice on fertilizers and irrigation are concentrated in areas farmed with HYV seeds. This is consistent with the complementarity between these inputs described above.

cultural productivity. In our sample of rural areas with no initial mobile phone coverage, there is large variation in the baseline level of agricultural productivity. In 2007, the average yield of a cell at the 75th percentile was almost twice as large as the one observed in a cell at the 25th percentile. This gap in yield is similar to the one documented in rice and wheat production between the top decile and the bottom decile of countries in the world income distribution (Gollin, Lagakos, and Waugh 2014). We test for heterogeneous effects across farmers with different initial productivity in columns (3) to (6), where we estimate equation (6) separately for each quartile of initial productivity. The results indicate that the effect of access to information is largest – and most precisely estimated – for farmers with the lowest initial level of productivity. The point estimate on β_1 for this group is 0.052, around 30 percent larger than the average effect reported in column (2). The effect is positive but small for farmers in the middle of the initial productivity distribution and large but extremely noisy for farmers in the top quartile. The estimate obtained for the lowest quartile indicates that providing access to information to farmers at the 25th percentile of the productivity distribution can close up to 36 percent of the productivity gap with farmers at the 75th percentile.

The nature of the agricultural yield data, which are available at the yearly level for the period until 2017, allows us to further characterize the relationship between mobile phone coverage, access to information and productivity. First, we explore the timing of the impact. To this end, we exploit the staggered introduction of SMIS towers among our treatment cells, estimating an event-study equation similar to (3). Notice that in this specification we focus exclusively on cells initially selected for the SMIS program and that eventually received a tower at some point between 2007 and 2010. The results are reported in Figure 8, which plots the estimated coefficients β_k on years relative to tower construction along with their 95 percent confidence intervals. We find no pre-existing trends in agricultural yields in the 4 years before the construction of the first tower in a cell. The effect of new mobile phone towers on productivity materializes about one year after their construction and increases in magnitude for the first three years. The magnitude of the estimated coefficients indicates, on average, a 2 to 4 percent increase in agricultural yields in the first five year post tower construction. The timing of the effect is consistent with a permanent and long-lived shift in productivity.

Next, we expand our analysis of long-term effects by investigating the impact of access to information 10 years after the introduction of the SMIS program. To this end, we replicate the results presented in Table 6 using as outcome variable the decadal change in agricultural yields between 2007 and 2017 (the latest year in our productivity data). The results are reported in Table 7. Comparing the magnitudes of the estimated coefficients with those in Table 6 suggests that the differential in productivity between areas covered or not by mobile phones, and between areas with and without access to agricultural advice, increases over time. Column 1 shows that the average effect of mobile phones on productivity over the ten-year horizon is positive and precisely estimated: a 1. s.d. larger increase in mobile phone coverage is associated with a 1.7 percent larger increase in productivity. Column (2) shows that, over ten years, a 1 s.d. increase in mobile phone coverage in areas with full access to agricultural advice leads to a 2.2 percent larger increase in productivity. This represents an additional 65 percent increase respect to the differential observed over the period 2007-2012. The negative and significant coefficient on the interaction term in column (2) also confirms the absence of effect of mobile phones on productivity in areas where the share of population speaking a non-official language exceeds 60 percent. Finally, the results in columns (3) to (6) display a pattern similar to what observed in Table 6 with regard to the effect at different levels of initial productivity. The estimates suggest that the returns to access to mobile phones and agricultural advice are the largest for farmers in the initially least productive areas.

Overall, the results in this subsection show that increased access to information can set rural areas on a different path of agricultural development, encouraging the adoption of modern technologies that generate higher yields. This effect manifests rapidly and persists over time. At the same time, the results indicate that language barriers between agricultural advisors and local communities represent an obstacle to widespread access to information, potentially increasing disparities between areas and significantly hampering the returns of telecommunications infrastructure programmes designed to include rural areas in the mobile phone network.

3.6 Robustness Checks

Our empirical model interprets the differential impact of mobile phone coverage in areas with different diffusion of official languages as the effect of language barriers between farmers and KCC agricultural advisors. A potential concern with this interpretation is that the share of local population speaking non-official languages may not be randomly assigned across geographical areas. In particular, it may be the case that areas with a greater share of non-official language speakers are also characterized by different levels of agricultural intensity, are more geographically isolated or simply poorer. In this case, one would load on the interaction term between local languages and mobile phone coverage also variation driven by other local conditions.

In section 3.2 we showed that, among the treated cells in our sample, the distribution of non-official language speakers is uncorrelated with observable characteristics and pre-trends in technology adoption and productivity. In Table C.7 we bring this analysis one step further, by presenting estimates of the parameters of a model that includes, in addition to the baseline interaction of mobile phone coverage with the share of population speaking non-official languages (column 1), also the interaction of coverage with measures of: agricultural intensity (share of irrigated land and of population employed in agriculture, column 2); geographical isolation (terrain ruggedness and distance from closest city, column 3); cell income (average income per capita and night lights intensity, column 4); as well as a fully saturated specification that includes all these interaction terms (column 5). The upper panel of the table refers to calls to KCC, the central panel to technology adoption and the lower panel to productivity. Irrespective of the outcome considered, the inclusion of additional interaction terms makes virtually no difference to our results. If anything, estimates of the parameters of interest become slightly larger compared to our baseline specification. These results strongly support our interpretation of the key role played by the (lack of) language barriers to access information, in explaining the positive effect of mobile phones on technology adoption and productivity.

In section 2 we discuss the neutral assignment rule that we use to construct our cell-level measures of technology adoption and productivity. A potential concern with this assignment rule is that it may generate non-classical measurement error if new SMIS towers are systematically constructed in cells where farmers grow crops characterized by fast technology adoption. To investigate this concern, in Table C.8 we report the correlation between tower placement and the initial share of land cultivated with crops that experienced the highest increase in HYV adoption at district level. As shown, treatment and control cells are balanced in terms of their initial shares of area cultivated with the three crops that the experienced the highest increase in HYV adoption within each district.

Another potential concern with our specification has to do with the roll-out of mobile phone coverage, which could generate spatial correlation in the data and lead to incorrect computation of the standard errors. To address this concern, we implement the Conley (1999) correction for cross-sectional spatial correlation. We allow the radius of the spatial kernel to vary between 50 km and 500 km. The results are reported in Table C.9. Accounting for spatially correlated standard errors does not significantly affect the results. Compared to the baseline specification that clusters the standard errors at the district level, the estimates typically become slightly more precise and the coefficients of interest remain statistically significant at conventional levels across all specifications.

Finally, we show that all our results are robust to using as an instrument for mobile phone coverage the share of land covered by a new SMIS tower, instead of the indicator variable used in the main analysis. Table C.10 presents the results from this analysis. The first-stage estimates in column (1) suggest that to a 50 percent increase in the share of land covered by a SMIS tower corresponds a 7.5 percent increase in mobile phone coverage. Column (2) to (6) confirm that higher mobile phone coverage leads to a higher number of calls to KCC about agricultural technologies, and that the effect is mitigated by the presence of language barriers to access agricultural advice. Similarly, columns (7) to (11) confirm the positive and significant effect of mobile phone coverage on technology adoption and productivity in areas where the entire population can access agricultural advice, whereas the effect is more limited - when not entirely offset - in areas where the majority of the population does not have access to the agricultural advice provided by the KCC.

3.7 Alternative Mechanisms: Price Information and Social Learning

The goal of our empirical analysis is to test whether the arrival of mobile phone coverage, coupled with the availability of phone-based services for agricultural advice, favored farmers' adoption of modern technologies and – thus – increased agricultural productivity via an information mechanism. The underlying assumption is that farmers might lack information about the existence of a new technology or how to use it productively. This is consistent with what we observe in the call data, where questions from farmers suggest that they often do not know which new seed varieties best meet their specific needs, or which are the best practices associated with their use.

Mobile phones, however, promote access to information above and beyond the information on agricultural practices provided by the KCC. Jensen (2007) and Aker (2010), for example, document that mobile phone diffusion reduced price dispersion in, respectively, fishing markets in the Indian state of Kerala and grain markets in Niger. In the same way, by allowing farmers to share information on crop prices in different markets, mobile phones could have facilitated a more efficient allocation of goods across markets in our sample and generated higher incomes for farmers, potentially helping them to pay the fixed cost of technology adoption. While we do not observe prices at local agricultural markets, we do observe the precise location of these markets. To assess the importance of better access to price information in our context, we therefore augment our main specification with agricultural market fixed effects. This allows us to compare outcomes across farmers who are differently exposed to changes in mobile phone coverage and access to agricultural advice, but that plausibly serve the same local market and therefore face the same prices for their products.

We collect data on the latitude and longitude of agricultural markets in rural India from the AGMARKNET service of the Ministry of Agriculture of India. We assign each cell in our sample to its closest agricultural market, based on minimum geographical distance within the same state.[38] This gives us a total of 1,017 agricultural markets, each serving on average six cells in our sample. The inclusion of this additional battery of market fixed effects makes this a very demanding specification. Nonetheless, as shown in Table C.11, the main results of this augmented specification are in line with our baseline estimates. In terms of outcomes, we focus on the adoption of the four agricultural technologies studied in section 3.4, and on agricultural productivity. The point estimates on the coefficient β_1, which captures the combined effect of mobile coverage and availability of phone-based services for agricultural advice, are similar in magnitude to those presented in Tables 5 and 6. Also the negative coefficient on the interaction term β_2 is similar in magnitude to

[38] Evidence from India suggests that the probability of farmers selling their produces to a given market decreases in travel time from the village to the market (Shilpi and Umali-Deininger, 2008).

our baseline estimates, although less precisely estimated. Overall, these results confirm that, even within narrowly defined areas where farmers face the same local demand and price variations, access to information on agricultural practices is important to determine the degree of modern technology adoption and productivity.

Another relevant mechanism linking mobile phone coverage to technology adoption is social learning. Existing empirical work has shown that farmers can adopt new technologies through social interactions or by observing their peers (Bandiera and Rasul 2006, Munshi 2004, Conley and Udry 2010). In our context, mobile phones may have facilitated the diffusion of shared knowledge among farmers and fostered the modernization of agricultural technologies, regardless of the agricultural advice from KCC agronomists that we emphasize in our analysis. One threat to the consistency of our estimates is, in particular, that areas with a higher proportion of non-official language speakers may also be characterized by lower social learning, and for this reason do not adopt new technologies.

While the level of aggregation of our data does not allow us to directly observe farmers' social networks, in Table C.12 we provide suggestive evidence that our results are robust to accounting for indirect measures of social learning. Specifically, we augment our baseline empirical model with additional interactions of mobile phone diffusion and observable characteristics associated with easier social learning. In particular, we focus on the degree of language concentration in a cell, since arguably what matters for social learning is the extent to which individuals speak the same language, rather than the nature of the language itself (official or non-official). The magnitude and precision of the coefficients of interest are unchanged when we account for language concentration and its interaction with mobile phone coverage.

To the extent that social networks span multiple cells, mobile phone coverage might have spillover effects on nearby areas that are not directly covered by new towers. For example, Cole and Fernando (2020) document that information provided through mobile phones spread within farmers' network, amplifying the effect of the agricultural extension program. To test for this mechanism of information diffusion, in Table C.13 we study the effect of mobile coverage in cells that are geographically adjacent to the treatment cells, and compare them to the control cells using our main specification (6). Specifically, we define the catchment area for a treatment cell as composed of all its adjacent cells, with the exclusion of those that were themselves originally included in the treatment or control group. Outcomes are then averaged across cells in this catchment area. The results are reported in Table C.13. Overall, the evidence does not support a relevant role of geographical spillovers within our sample, either across regions speaking official languages or non-official languages.

4 Concluding Remarks

In this paper, we provide large-scale evidence of the effects of accessing information via mobile phones on the adoption of modern agricultural technologies and crop yields in rural India, using detailed geo-referenced data on the construction of new mobile phone towers, farmers' calls for agricultural advice and the prevalence of local languages across fine geographical areas. Our results indicate that mobile phones can have long-lasting effects on farmers' productivity by facilitating the adoption of modern technologies. Our findings also suggest that the effects are larger for farmers with the lowest initial level of productivity, highlighting the potential of mobile phones to reduce the large productivity gap between farmers in India.

Access to mobile phones, however, is not in itself sufficient to foster this transition. A key element is the ability of farmers to access high-quality agricultural advice on their phones. We show that the benefits of mobile phone coverage are much more limited, when not entirely absent, for farmers facing language barriers with agricultural advisors. Our results imply that, in areas where 50 percent of more of the population cannot access agricultural advice, an increase in mobile phone coverage does not lead to a modernization of agricultural practices and technologies, nor to increased productivity for farmers.

As the number of mobile-based agricultural advisory services worldwide increases steadily (GSMA, 2020), our results therefore provide a tale of cautious optimism about their effectiveness. On the one hand, the ability to connect with farmers in hard-to-reach rural areas and to provide continuous and personalized advice during the agricultural cycle can make mobile-based agricultural extensions such as the KCC an effective tool to lift farmers out of poverty. On the other hand, however, the design and specific features of these programs – such as the language in which agricultural advice is provided – may generate an uneven access to information and exacerbate disparities among farmers, thus creating winners and losers from their introduction. In the context of our study, this highlights the importance of expanding the KCC service to the 40 million Indian farmers who do not speak any officially-recognized language.

Our results refer to a period when the only available technology in India was effectively 2G. In recent years, the country has made advancements towards the expansion of 3G/4G mobile services and the universal availability of broadband Internet. These improvements have been contemporaneously met with the rise of social media, online information-sharing websites and smart-phone applications. These digital platforms can further help the diffusion of information among farmers but they can also further exacerbate the gap between those who can and cannot access agricultural advice. This will make it increasingly important to ensure universal access to mobile phones and information in the years to come.

References

Adamopoulos, T. and D. Restuccia (2014). The Size Distribution of Farms and International Productivity Differences. *American Economic Review 104*(6), 1667–97.

Aker, J. C. (2010). Information from Markets Near and Far: Mobile Phones and Agricultural Markets in Niger. *American Economic Journal: Applied Economics 2*(3), 46–59.

Aker, J. C., I. Ghosh, and J. Burrell (2016). The Promise (and Pitfalls) of ICT for Agriculture Initiatives. *Agricultural Economics 47*(S1), 35–48.

Aker, J. C. and I. M. Mbiti (2010). Mobile Phones and Economic Development in Africa. *Journal of Economic Perspectives 24*(3), 207–32.

Anderson, J. and R. Birner (2007). How to Make Agricultural Extension Demand-Driven? : The Case of India's Agricultural Extension Policy. *IFPRI Discussion Paper 00729*.

Anderson, J. R. and G. Feder (2004). Agricultural Extension: Good Intentions and Hard Realities. *The World Bank Research Observer 19*(1), 41–60.

Asher, S. and P. Novosad (2020). Rural Roads and Local Economic Development. *American Economic Review 110*(3), 797–823.

Bandiera, O. and I. Rasul (2006). Social Networks and Technology Adoption in Northern Mozambique. *The Economic Journal 116*(514), 869–902.

Beaman, L., A. BenYishay, J. Magruder, and A. M. Mobarak (2018). Can Network Theory-based Targeting Increase Technology Adoption? Technical report, National Bureau of Economic Research.

Björkegren, D. (2019). The Adoption of Network Goods: Evidence from the Spread of Mobile Phones in Rwanda. *The Review of Economic Studies 86*(3), 1033–1060.

Blumenstock, J. E., N. Eagle, and M. Fafchamps (2016). Airtime Transfers and Mobile Communications: Evidence in the Aftermath of Natural Disasters. *Journal of Development Economics 120*, 157–181.

Bold, T., K. C. Kaizzi, J. Svensson, and D. Yanagizawa-Drott (2017). Lemon Technologies and Adoption: Measurement, Theory and Evidence from Agricultural Markets in Uganda. *The Quarterly Journal of Economics 132*(3), 1055–1100.

Burlig, F. and L. Preonas (2016). Out of the Darkness and into the Light? Development Effects of Rural Electrification.

Buys, P., S. Dasgupta, T. S. Thomas, and D. Wheeler (2009). Determinants of a Digital Divide in Sub-Saharan Africa: A Spatial Econometric Analysis of Cell Phone Coverage. *World Development 37*(9), 1494–1505.

Casaburi, L., M. Kremer, S. Mullainathan, and R. Ramrattan (2019). Harnessing ICT to Increase Agricultural Production: Evidence from Kenya. *Harvard University*.

Caselli, F. (2005). Accounting for Cross-country Income Differences. *Handbook of Economic Growth 1*, 679–741.

Cole, S. A. and A. Fernando (2020). Mobile-izing Agricultural Advice: Technology Adoption, Diffusion and Sustainability. *The Economic Journal*.

Conley, T. (1999). GMM Estimation with Cross Sectional Dependence. *Journal of Econometrics 92*(1), 1 – 45.

Conley, T. G. and C. R. Udry (2010). Learning about a New Technology: Pineapple in Ghana. *American Economic Review 100*(1), 35–69.

Dalrymple, D. G. (1974). Development and Spread of High-yielding Varieties of Wheat and Rice in the Less Developed Nations. Technical report, United States Department of Agriculture, Economic Research Service.

Dinkelman, T. (2011). The Effects of Rural Electrification on Employment: New Evidence from South Africa. *American Economic Review 101*(7), 3078–3108.

Donaldson, D. (2018). Railroads of the Raj: Estimating the Impact of Transportation Infrastructure. *American Economic Review 108*(4-5), 899–934.

Donovan, K. (2020). The Equilibrium Impact of Agricultural Risk on Intermediate Inputs and Aggregate Productivity. *Working Paper*.

Duflo, E., M. Kremer, and J. Robinson (2004). Understanding Technology Adoption: Fertilizer in Western Kenya, Preliminary Results from Field Experiments. *Unpublished manuscript, Massachusetts Institute of Technology*.

Duflo, E., M. Kremer, and J. Robinson (2011). Nudging Farmers to Use Fertilizer: Theory and Experimental Evidence from Kenya. *American Economic Review 101*(6), 2350–90.

Duflo, E. and R. Pande (2007). Dams. *The Quarterly Journal of Economics 122*(2), 601–646.

Ericsson (2015). *The Changing Mobile Broadband.*

Evenson, R. E. and D. Gollin (2002). *Crop Variety Improvement and its Effect on Productivity.* CABI Pub.

Evenson, R. E. and D. Gollin (2003). Assessing the Impact of the Green Revolution, 1960 to 2000. *Science 300*(5620), 758–762.

Faber, B. (2014). Trade Integration, Market Size, and Industrialization: Evidence from China's National Trunk Highway System. *The Review of Economic Studies 81*(3), 1046–1070.

Fabregas, R., M. Kremer, M. Lowes, R. On, and G. Zane (2019). SMS-extension and Farmer Behavior: Lessons from Six RCTs in East Africa. Technical report, Working paper.

Fabregas, R., M. Kremer, and F. Schilbach (2019). Realizing the Potential of Digital Development: The Case of Agricultural Advice. *Science 366*(6471).

Fafchamps, M. and B. Minten (2012). Impact of SMS-based Agricultural Information on Indian Farmers. *The World Bank Economic Review 26*(3), 383–414.

Feder, G., R. E. Just, and D. Zilberman (1985). Adoption of Agricultural Innovations in Developing Countries: A Survey. *Economic Development and Cultural Change 33*(2), 255–298.

Foster, A. D. and M. R. Rosenzweig (1995). Learning by Doing and Learning from Others: Human Capital and Technical Change in Agriculture. *Journal of Political Economy 103*(6), 1176–1209.

Foster, A. D. and M. R. Rosenzweig (2010). Microeconomics of Technology Adoption. *Annual Review of Economics 2*(1), 395–424.

Gollin, D., D. Lagakos, and M. E. Waugh (2014). The Agricultural Productivity Gap. *The Quarterly Journal of Economics 129*(2), 939–993.

Griliches, Z. (1957). Hybrid Corn: An Exploration in the Economics of Technological Change. *Econometrica, Journal of the Econometric Society*, 501–522.

GSMA (2020). Digital Agriculture Maps: 2020 State of the Sector in Low and Middle-Income Countries. *London: GSMA.*

Hanna, R., S. Mullainathan, and J. Schwartzstein (2014). Learning Through Noticing: Theory and Evidence from a Field Experiment. *The Quarterly Journal of Economics 129*(3), 1311–1353.

Jack, B. K. (2013). Constraints on the Adoption of Agricultural Technologies in Developing Countries. *Literature review, Agricultural Technology Adoption Initiative, J-PAL (MIT) and CEGA (UC Berkeley).*

Jack, W. and T. Suri (2014). Risk Sharing and Transactions Costs: Evidence from Kenya's mobile money revolution. *American Economic Review 104*(1), 183–223.

Jayachandran, S. (2006). Selling Labor Low: Wage Responses to Productivity Shocks in Developing Countries. *Journal of Political Economy 114*(3), 538–575.

Jensen, R. (2007). The Digital Provide: Information (Technology), Market Performance, and Welfare in the South Indian Fisheries Sector. *The Quarterly Journal of Economics 122*(3), 879–924.

Karlan, D., R. Osei, I. Osei-Akoto, and C. Udry (2014). Agricultural Decisions After Relaxing Credit and Risk Constraints. *The Quarterly Journal of Economics 129*(2), 597–652.

Lagakos, D. and M. E. Waugh (2013). Selection, Agriculture, and Cross-country Productivity Differences. *American Economic Review 103*(2), 948–80.

Lee, K., E. Miguel, and C. Wolfram (2020). Experimental Evidence on the Economics of Rural Electrification. *Journal of Political Economy 128*(4), 1523–1565.

Manacorda, M. and A. Tesei (2020). Liberation Technology: Mobile Phones and Political Mobilization in Africa. *Econometrica 88*(2), 533–567.

Munshi, K. (2004). Social Learning in a Heterogeneous Population: Technology Diffusion in the Indian Green Revolution. *Journal of Development Economics 73*(1), 185–213.

National Sample Survey (2005). Report No. 499: Situation Assessment Survey of Farmers: Access to Modern Technology For Farming. Technical report, Government of India. Ministry of Statistics and Programme Implementation.

Restuccia, D., D. T. Yang, and X. Zhu (2008). Agriculture and Aggregate Productivity: A Quantitative Cross-country Analysis. *Journal of Monetary Economics 55*(2), 234–250.

Ryan, B. and N. C. Gross (1943). The Diffusion of Hybrid Seed Corn in Two Iowa Communities. *Rural Sociology 8*(1), 15.

Shilpi, F. and D. Umali-Deininger (2008). *Where to Sell? Market Facilities and Agricultural Marketing.* The World Bank.

World Bank (2014). *World Development Indicators 2014.* World Bank Publications.

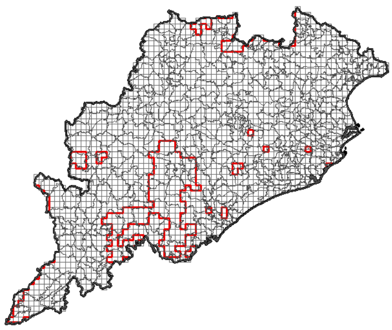
World Bank (2019). *Harvesting Prosperity: Technology and Productivity Growth in Agriculture.* The World Bank.

Young, H. P. (2009). Innovation Diffusion in Heterogeneous Populations: Contagion, Social Influence, and Social Learning. *American Economic Review 99*(5), 1899–1924.

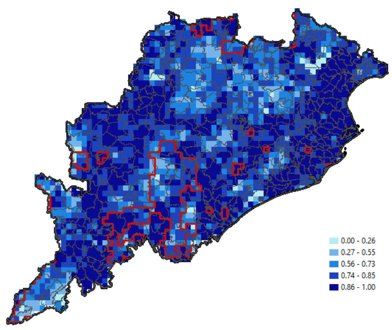
Figures and Tables

Figure 1: Coverage and Farmers Calls by Language in the State of Odisha

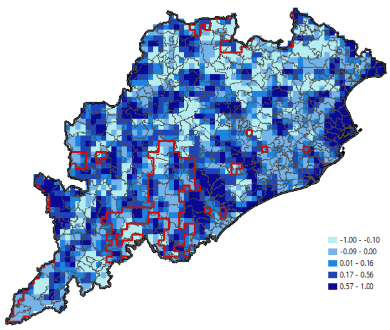
(a) Non-official language speakers



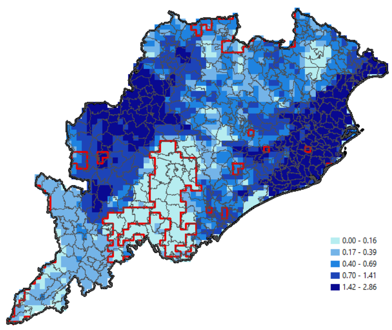
(b) Share of farmed land



(c) Change in mobile coverage

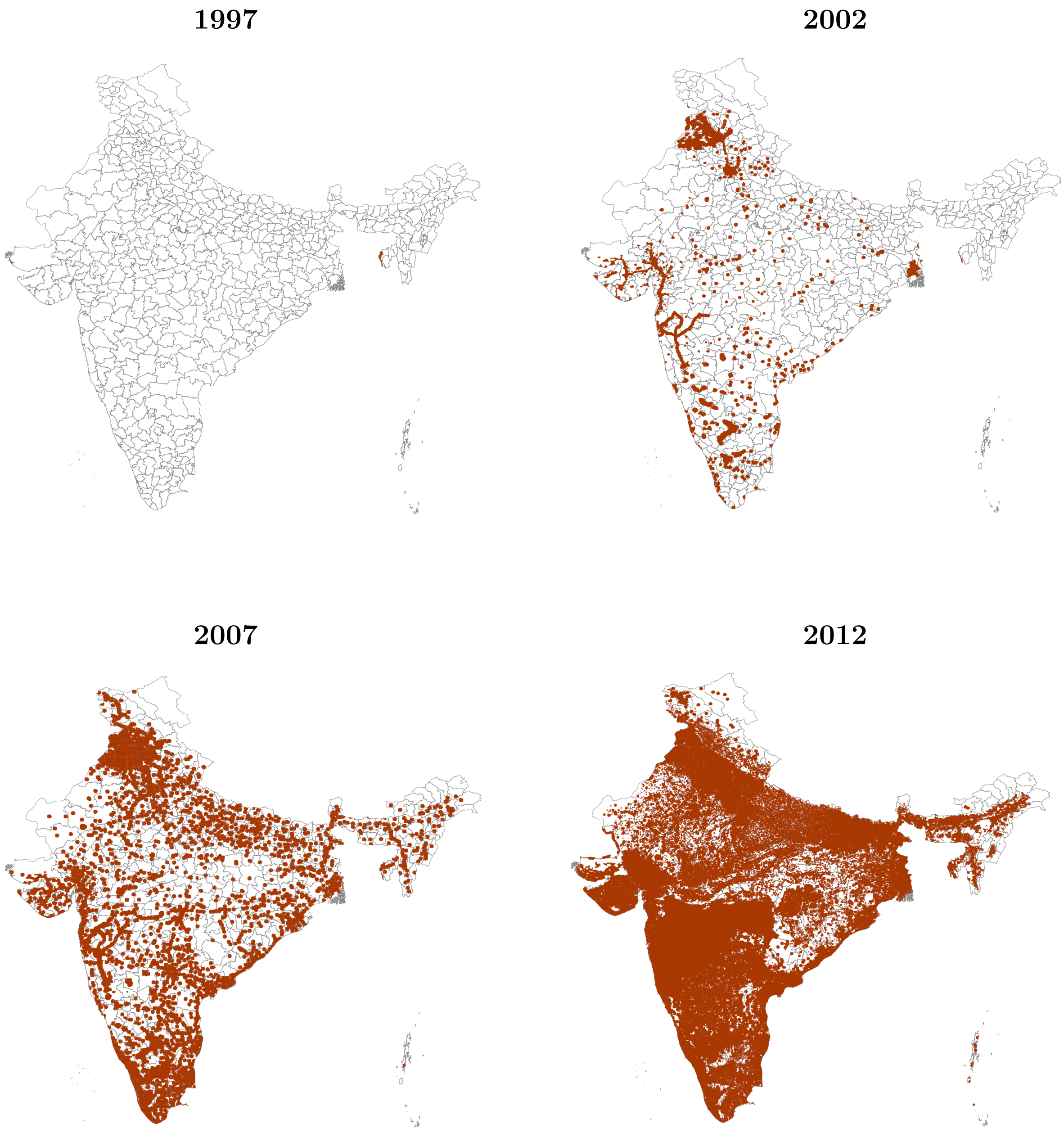


(d) Change in calls to KCC



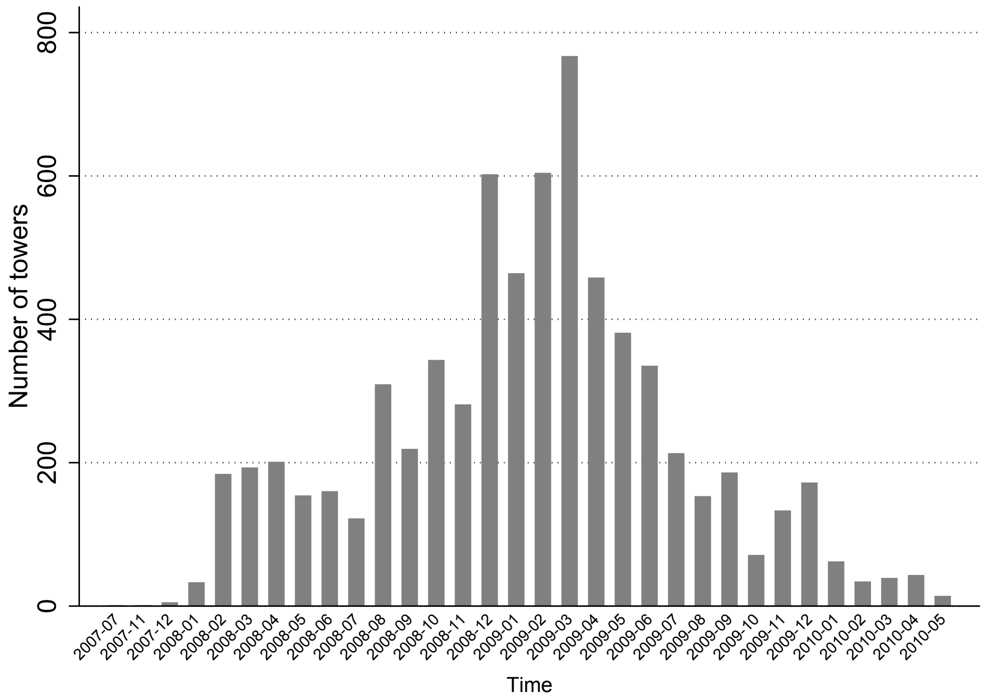
Notes: Panel (a) shows 10 × 10 km cells for the state of Odisha. Sub-district boundaries are labeled in gray. Red contours denote areas for which more than half of the population speaks one of 99 non-official languages. Source: Population Census of India (2011).
Panel (b) shows share of cell area under agricultural farming. Source: Village Census of India 2001.
Panel (c) shows the change in share of cell area under GSM mobile phone coverage between 2007-2012. Source: GSMA.
Panel (d) shows change in (log) calls received by Kisan Call Center between 2007-2012. Source: Kisan Call Center, Ministry of Agriculture

Figure 2: Mobile Phone Coverage Evolution, India 1997-2012



Notes: The figure reports geo-referenced data on mobile phone coverage for all of India at five-year intervals between 1997 and 2012. Source: GSMA.

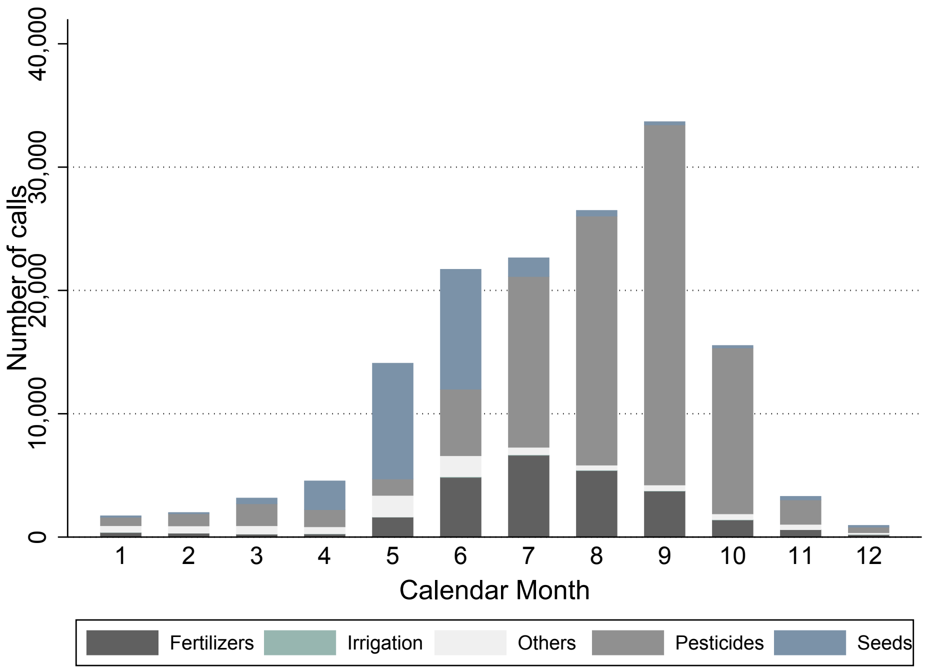
Figure 3: Timeline of tower construction under SMIS Phase I



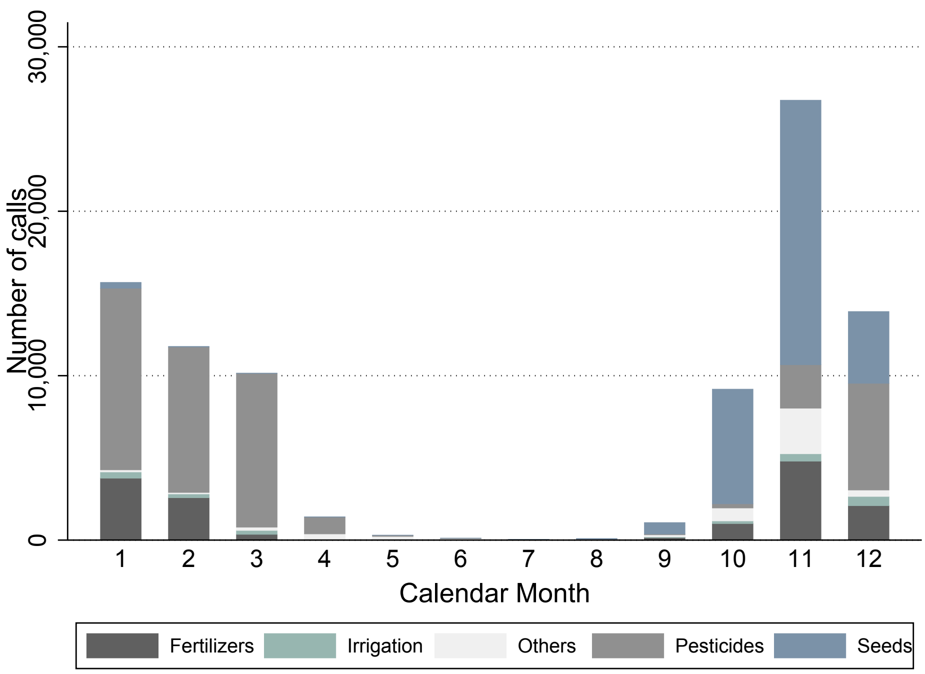
Notes: Source: Department of Telecommunications, India. Month captures the time at which the construction of the tower is completed and the tower becomes operational.

Figure 4: Distribution of calls on rice and wheat across agricultural cycle

(a) Rice



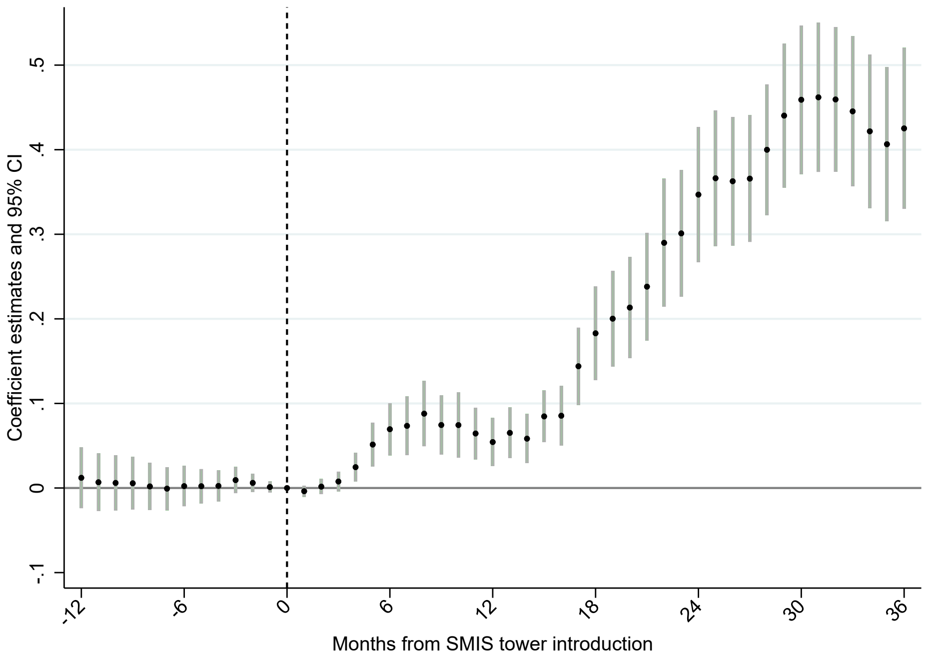
(b) Wheat



Notes: Source: Kisan Call Center, Ministry of Agriculture

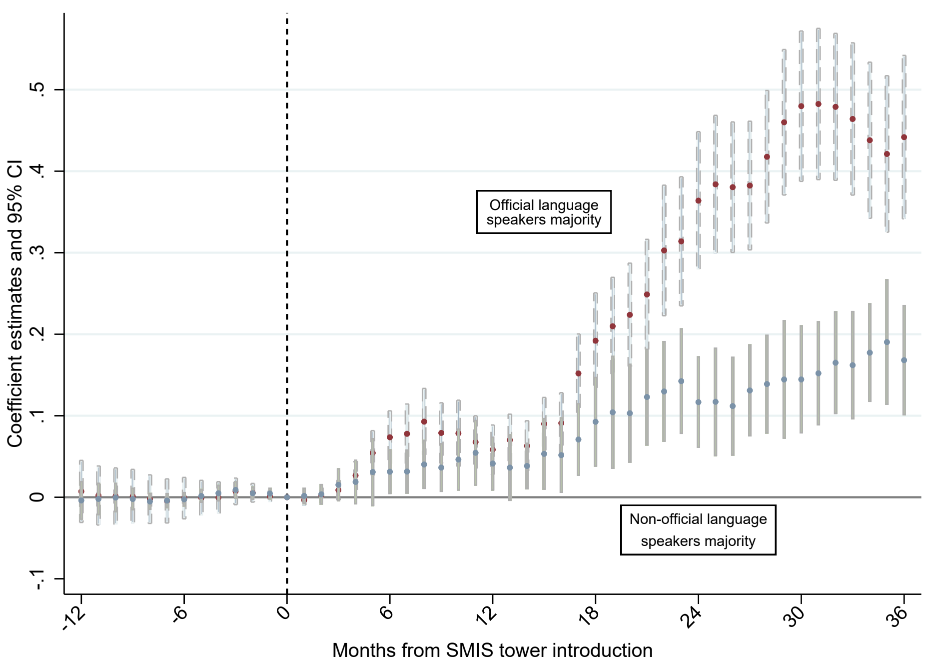
Figure 5: Farmers' Calls to KCC relative to Tower Construction - Event Study

(a) Average effects



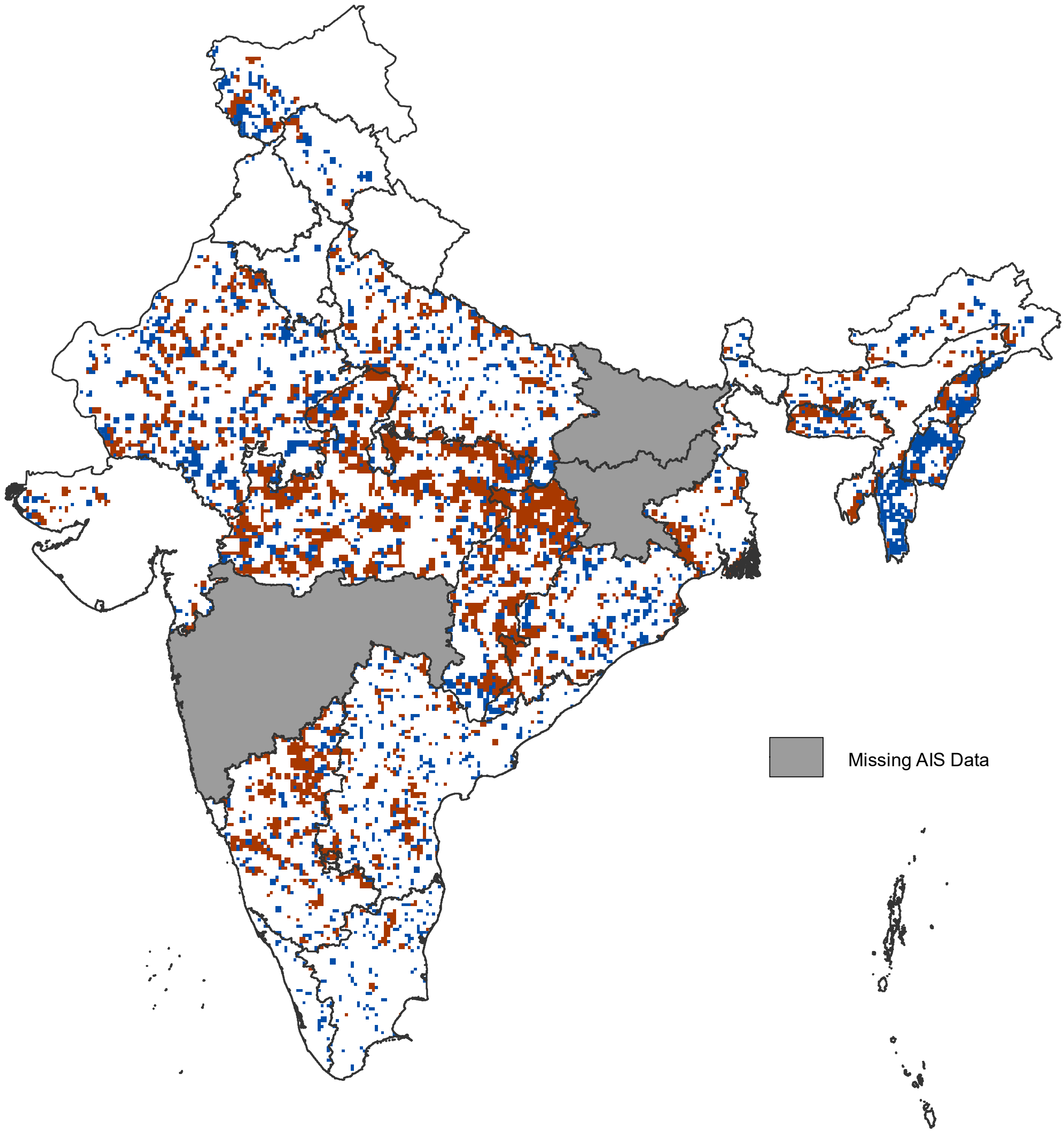
Notes: The figure plots the coefficients β_k obtained with the following specification $Ln\,(1 + \text{calls})_{it} = \alpha_i + \alpha_t + \sum_{k=-12}^{+36} \beta_k D_{it}^k + \varepsilon_{it}$. Where i cell, t month, D_{it}^k dummy equal to 1 if month $t = k$ for cell i

(b) Heterogeneous Effects by Language



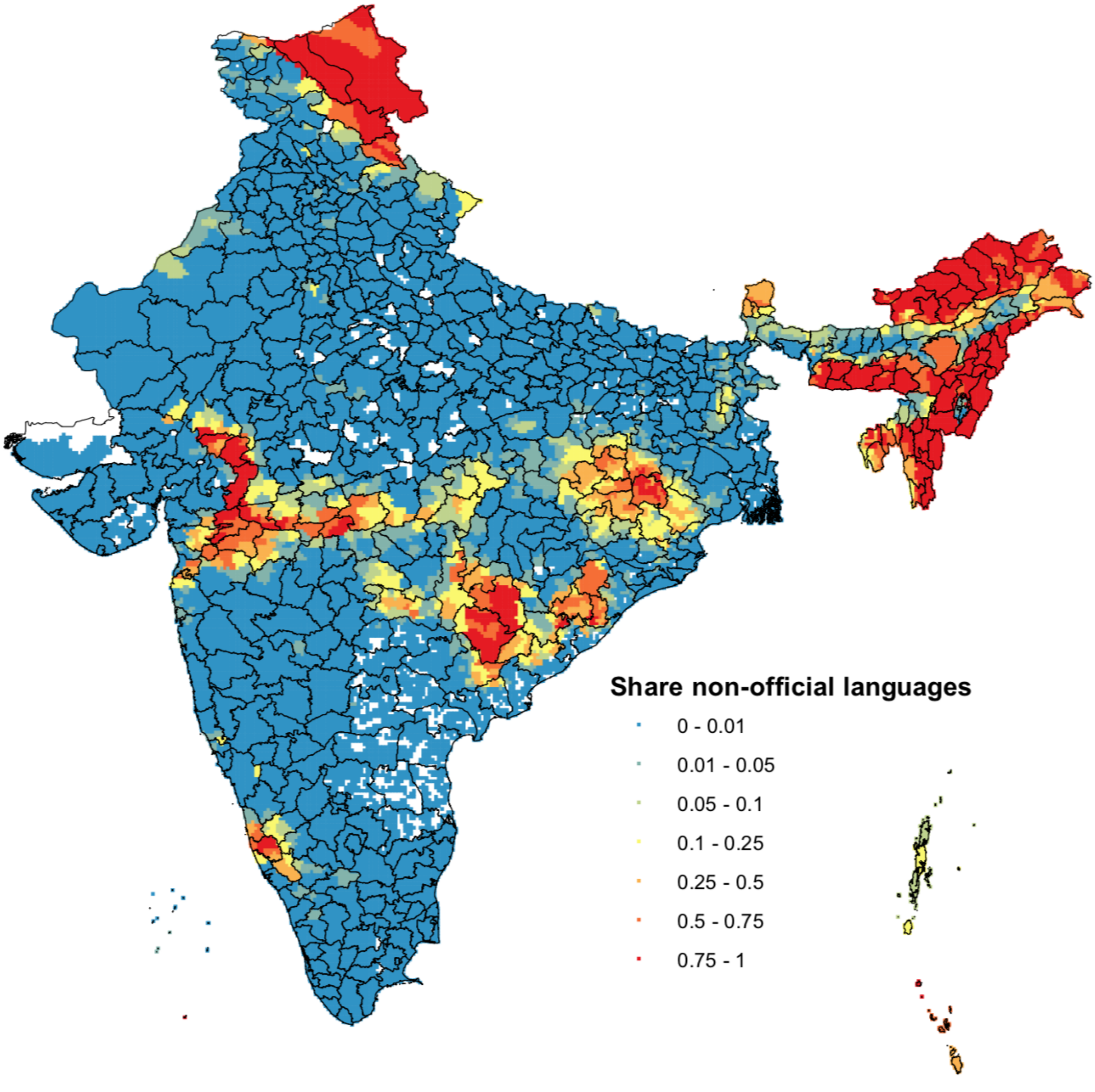
Notes: The figure plots the coefficients β_k obtained with the following specification $Ln\,(1 + \text{calls})_{it} = \alpha_i + \alpha_t + \sum_{k=-12}^{+36} \beta_k D_{it}^k + \varepsilon_{it}$. Where i cell, t month, D_{it}^k dummy equal to 1 if month $t = k$ for cell i. We estimate this specification separately for two groups of cells based on the share of population speaking non-official languages.

Figure 6: Treatment and Control cells under SMIS



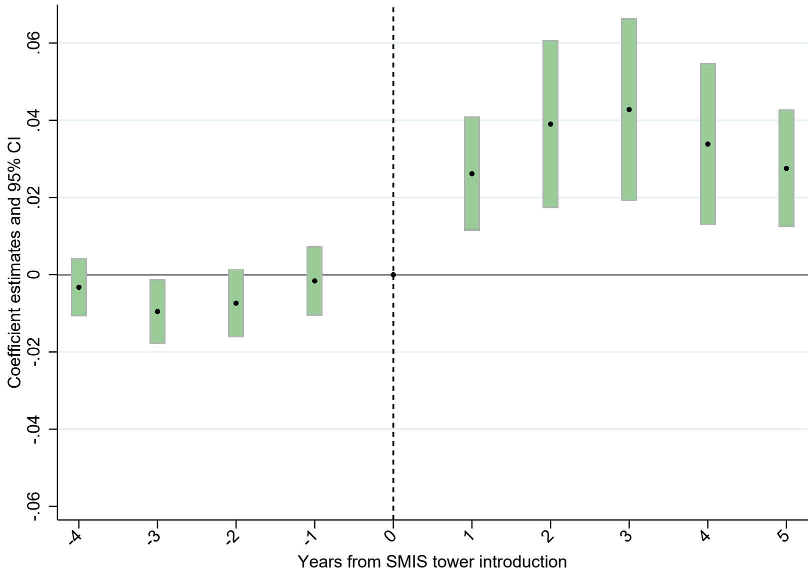
Notes: The figure shows the 6,320 10×10 km identification cells distributed across treatment (red) and control (blue) cells for all of India. State borders are marked in black. Treatment cells are those that are both proposed *and* covered by mobile tower under SMIS Phase I. Control cells are those that are proposed *and not* covered by mobile towers under SMIS Phase I. Grey areas represent states with missing AIS information.

Figure 7: Share of non-official languages in India



Notes: Share of non-official languages is the share of population speaking non-official languages in a given sub-district. Source: Population Census of India (2011).

Figure 8: Agricultural productivity relative to Tower Construction: Event Study



Notes: The figure plots the coefficients β_k obtained with the following specification $\log(yield)_{it} = \alpha_i + \alpha_t + \sum_{k=-4}^{+5} \beta_k D_{it}^k + \varepsilon_{it}$. Where i denotes cell, t denotes year, D_{it}^k dummy equal to 1 if year t is k years after (or before) the construction of first SMIS tower in cell i.

Table 1: Summary Statistics

	Mean	**Median**	**Std. Deviation**	**N**
Δ Coverage	0.756	0.926	0.321	6320
Non-official Languages (%)	0.075	0.000	0.212	6320
Δ HYV Share	0.034	0.018	0.068	6320
Δ Fertilizer Share	0.022	0.023	0.081	6310
Δ Irrigation Share	0.017	0.013	0.043	6320
Δ Pesticides Share	0.025	0.018	0.108	6142
Δ log(yield)	0.058	0.055	0.069	5033
Δ log $(1+\text{calls}_{\text{All}})$	1.294	1.167	0.918	6320
Δ log $(1+\text{calls}_{\text{Yield}})$	0.461	0.222	0.517	6320
Δ log $(1+\text{calls}_{\text{Fertilizers}})$	0.374	0.193	0.436	6320
Δ log $(1+\text{calls}_{\text{Irrigation}})$	0.093	0.034	0.13	6320
Δ log $(1+\text{calls}_{\text{Pesticides}})$	0.948	0.763	0.777	6320

Notes: Changes in variables are calculated over the 5-year interval 2007-2012. The unit of observation is a 10×10 km cell and the sample includes all cells used for identification. Only cells with non-missing Δ HYV values are considered.

Table 2: SMIS coverage ($\mathbb{1}$(Tower)) and cell characteristics (Balance Test)

Dependent variable:	1(**Tower**)				1(non-off. lang.| **Tower**)
	(1)	(2)	(3)	(4)	(5)
Determinants of Tower Relocation					
log(Population)	0.097***			0.097***	0.014
	(0.021)			(0.026)	(0.024)
Power Supply	0.019			0.010	-0.059
	(0.038)			(0.049)	(0.052)
Ruggedness	-0.080***			-0.093***	0.030
	(0.018)			(0.023)	(0.024)
Pre-trends technology/productivity					
Δ log(yield) (2002-2007)		-0.034		0.090	0.199
		(0.456)		(0.435)	(0.200)
Δ HYV Share (2002-2007)		0.091		-0.143	-0.355
		(0.455)		(0.438)	(0.300)
Socio-economic characteristics					
Agri. Workers/Working Pop.			0.078	0.109	-0.034
			(0.076)	(0.087)	(0.040)
Percent Irrigated			0.060	0.047	-0.031*
			(0.043)	(0.046)	(0.018)
Education Facility			0.071	-0.053	0.020
			(0.057)	(0.059)	(0.022)
Medical Facility			0.026	0.025	-0.003
			(0.032)	(0.038)	(0.016)
Banking Facility			-0.032	-0.068	-0.013
			(0.061)	(0.062)	(0.016)
# Phone conn. per 1000 people			0.002	0.003*	-0.001
			(0.001)	(0.002)	(0.001)
Dist. to nearest town(kms)			-0.001***	-0.001	0.000
			(0.000)	(0.001)	(0.000)
Night Lights (2006)			-0.003	-0.012	-0.000
			(0.006)	(0.007)	(0.002)
Income per capita			0.000	0.000	0.000
			(0.000)	(0.000)	(0.000)
Expense per capita			-0.000	-0.000	-0.000
			(0.000)	(0.000)	(0.000)
District f.e.	✓	✓	✓	✓	✓
Observations	6,320	5,019	6,320	5,019	3,570
R-squared	0.193	0.174	0.182	0.192	0.706

Notes: The table reports the correlation of cell-characteristics across treatment and control cells (columns 1-4) and across cells with and without a majority of non-official language speakers, conditional on treatment (column 5). The treatment variable $\mathbb{1}$(Tower) in columns (1)-(4) is a dummy variable that takes the value of 1 if a cell is both proposed *and* covered by a tower (Treatment) under SMIS Phase I and takes the value of 0 if a cell is proposed *and not* covered (Control). The dependent variable in column (5) that takes the value of 1 if the share of non-official language speakers is greater than 50% of the total population in the cell, and 0 otherwise. Column (1) focuses on the main determinants of tower relocation, *i.e.* cell's population, the availability of power supply and average ruggedness; column (2) on pre-trends in technology/productivity; column (3) on socio-economic characteristics; columns (4) and (5) consider simultaneously all observable cell characteristics. All specifications include district fixed effects. The sample includes all cells with zero cell phone coverage in 2006. Standard errors clustered at district level are reported in brackets (number of clusters = 285). Significance level: *** p<0.01, ** p<0.05, * p<0.1.

Table 3: First Stage

Outcome:	Δ Coverage		
	(1)	(2)	(3)
$\mathbb{1}$ (Tower)	0.110***	0.073***	0.074***
	[0.015]	[0.012]	[0.012]
log(Population)		0.118***	0.074***
		[0.014]	[0.013]
Power Supply		0.254***	0.164***
		[0.028]	[0.029]
Ruggedness		-0.168***	-0.139***
		[0.019]	[0.018]
Observations	6,320	6,320	6,320
F-stat	56.54	34.24	36.72
District f.e.	✓	✓	✓
Other Controls			✓

Notes: The table reports first-stage regression of Δ Coverage on treatment variable $\mathbb{1}$ (Tower). The unit of observation is a 10×10 *km* cell. Δ Coverage is the change in the share of cell area under mobile coverage from 2007 to 2012, based on the data provided by telecom companies to GSMA. $\mathbb{1}$ (Tower) is a dummy variable that takes the value of 1 if a cell is both proposed *and* covered by a tower under SMIS Phase I and takes the value of 0 if a cell is proposed *and not* covered. All specifications control for district fixed effect. Column (1) reports estimates of regression of Δ Coverage on treatment variable. Column (2) includes baseline controls of cell's (log) population, the availability of power supply and average ruggedness. Column (3) includes other controls for the cell including share of labor force employed in agricultural sector, share of agricultural land that is irrigated, access to an educational facility, access to a medical facility, access to a banking facility, number of landline phone connections per 1000 people, distance to nearest town (in *kms.*), night lights intensity, income per capita (in rupees), and expense per capita (in rupees). The sample includes all cells with zero cell phone coverage in 2006. All regressions are weighted by the cell's population. The value of the first stage Kleibergen-Paap Wald F-statistics for the validity of the instruments is also reported in all columns. Standard errors clustered at district level are reported in brackets (number of clusters = 285). Significance level: *** p<0.01, ** p<0.05, * p<0.1.

Table 4: Mobile Coverage and Farmers' Calls

Outcome:	Δ log (1+ number of calls)									
Topic of the calls:	All		Seeds		Fertilizer		Irrigation		Pesticides	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Δ Coverage	0.742***	0.828***	0.322***	0.357***	0.269***	0.304***	0.059**	0.071**	0.656***	0.731***
	[0.199]	[0.206]	[0.113]	[0.119]	[0.099]	[0.104]	[0.028]	[0.030]	[0.170]	[0.175]
Δ Coverage $\times$ Non-official Languages (%)		-0.716**		-0.300***		-0.296***		-0.099***		-0.619**
		[0.316]		[0.107]		[0.103]		[0.032]		[0.261]
Non-official Languages (%)		-0.185*		-0.061**		-0.047		-0.025*		-0.169**
		[0.096]		[0.030]		[0.030]		[0.013]		[0.084]
Observations	6,320	6,320	6,320	6,320	6,320	6,320	6,320	6,320	6,320	6,320
District f.e.	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Baseline Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Other Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

Notes: The table reports IV-2SLS estimates of the effect of mobile phone coverage on change in (log) calls received at Kisan Call Centers (KCC). The dependent variable in Columns (1)-(2) is change in all calls received at KCC; Columns (3)-(4) is change in calls about seeds; Columns (5)-(6) is change in calls about fertilizers; Columns (7)-(8) is change in calls about irrigation; Columns (9)-(10) is change in calls about pesticides. All changes are calculated between 2007-2012. The unit of observation is a 10×10 *km* cell. Δ Coverage is the change in the share of cell area covered under GSM mobile coverage between 2007-2012 instrumented using $\mathbb{1}$(Tower). $\mathbb{1}$(Tower) is a dummy variable that takes the value of 1 if a cell is both proposed *and* covered by a tower under SMIS Phase I and takes the value of 0 if a cell is proposed *and not* covered. Odd columns reports the average effect, even columns report the heterogeneous effects depending on share of cell's population speaking non-official languages. All columns include district-fixed effects, baseline controls as well as other controls. Baseline controls include cell's (log) population, the availability of power supply and average ruggedness. Other controls for the cell include share of labor force employed in agricultural sector, share of agricultural land that is irrigated, access to an educational facility, access to a medical facility, access to a banking facility, number of landline phone connections per 1000 people, distance to nearest town (in *kms.*), night lights intensity, income per capita (in rupees), and expense per capita (in rupees). The sample includes all cells with zero cell phone coverage in 2006. All regressions are weighted by the cell's population. Standard errors clustered at district level are reported in brackets (number of clusters = 285). Significance level: *** p<0.01, ** p<0.05, * p<0.1.

Table 5: Mobile Coverage and technology adoption

Outcome:	Δ Technology Adoption							
Technology:	HYV Seeds		Fertilizers		Irrigation		Pesticides	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δ Coverage	0.043**	0.047**	0.037	0.040*	0.023*	0.027*	0.062**	0.068**
	[0.018]	[0.019]	[0.023]	[0.023]	[0.014]	[0.015]	[0.029]	[0.029]
Δ Coverage × Non-official Languages (%)		-0.041**		-0.022		-0.027		-0.048
		[0.019]		[0.031]		[0.017]		[0.037]
Non-official Languages (%)		-0.002		-0.013		-0.006		-0.013
		[0.009]		[0.017]		[0.007]		[0.013]
Observations	6,320	6,320	6,310	6,310	6,320	6,320	6,142	6,142
District f.e.	✓	✓	✓	✓	✓	✓	✓	✓
Baseline Controls	✓	✓	✓	✓	✓	✓	✓	✓
Other Controls	✓	✓	✓	✓	✓	✓	✓	✓

Notes: The table reports IV-2SLS estimates of the effect of mobile phone coverage on changes in technology adoption between 2007-2012. The dependent variable in Columns (1)-(2) is change in share of area cultivated under HYV; Columns (3)-(4) is change in share of area cultivated under fertilizers; Columns (5)-(6) is change in share of area cultivated under irrigation; Columns (7)-(8) is change in share of area cultivated under pesticides. All changes are calculated between 2007-2012. The unit of observation is a 10×10 *km* cell. Δ Coverage is the change in the share of cell area covered under GSM mobile coverage between 2007-2012 instrumented using $\mathbb{1}$ (Tower). $\mathbb{1}$ (Tower) is a dummy variable that takes the value of 1 if a cell is both proposed *and* covered by a tower under SMIS Phase I and takes the value of 0 if a cell is proposed *and not* covered. Odd columns reports the average effect, even columns report the heterogeneous effects depending on share of cell's population speaking non-official languages. All columns include district-fixed effects, baseline controls as well as other controls. Baseline controls include cell's (log) population, the availability of power supply and average ruggedness. Other controls for the cell include share of labor force employed in agricultural sector, share of agricultural land that is irrigated, access to an educational facility, access to a medical facility, access to a banking facility, number of landline phone connections per 1000 people, distance to nearest town (in *kms.*), night lights intensity, income per capita (in rupees), and expense per capita (in rupees). The sample includes all cells with zero cell phone coverage in 2006. All regressions are weighted by the cell's population. Standard errors clustered at district level are reported in brackets (number of clusters = 285). Significance level: *** p<0.01, ** p<0.05, * p<0.1.

Table 6: MOBILE COVERAGE AND AGRICULTURAL PRODUCTIVITY

Outcome:	Δ log(yield) (2007-2012)					
			by baseline productivity (2007):			
			First Quartile	Second Quartile	Third Quartile	Fourth Quartile
	(1)	(2)	(3)	(4)	(5)	(6)
Δ Coverage	0.029	0.041**	0.052*	0.012	-0.004	0.052
	[0.020]	[0.020]	[0.030]	[0.029]	[0.030]	[0.603]
Δ Coverage × Non-official Languages (%)		-0.093***	-0.046*	-0.024	-0.025	-1.028
		[0.033]	[0.026]	[0.021]	[0.177]	[8.199]
Non-official Languages (%)		-0.014	-0.010	-0.000	-0.001	-0.235
		[0.012]	[0.010]	[0.009]	[0.065]	[1.913]
Observations	5,033	5,033	1,254	1,174	1,181	1,254
District f.e.	✓	✓	✓	✓	✓	✓
Baseline Controls	✓	✓	✓	✓	✓	✓
Other Controls	✓	✓	✓	✓	✓	✓

Notes: The table reports IV-2SLS estimates of the effect of mobile phone coverage on changes in (log) agricultural productivity between 2007-2012. Column (1) reports average effects. Column (2) reports heterogeneous effects depending on share of cell's population speaking non-official languages. Columns (3)-(6) report heterogeneous effects depending on the baseline productivity levels in 2007. Column (3) considers cells in the lowest quartile of baseline productivity and Column (6) cells in the highest quartile. The unit of observation is a 10×10 *km* cell. Δ Coverage is the change in the share of cell area covered under GSM mobile coverage between 2007-2012 instrumented using $\mathbb{1}$ (Tower). $\mathbb{1}$ (Tower) is a dummy variable that takes the value of 1 if a cell is both proposed *and* covered by a tower under SMIS Phase I and takes the value of 0 if a cell is proposed *and not* covered. All columns include district-fixed effects, baseline controls as well as other controls. Baseline controls include cell's (log) population, the availability of power supply and average ruggedness. Other controls for the cell include share of labor force employed in agricultural sector, share of agricultural land that is irrigated, access to an educational facility, access to a medical facility, access to a banking facility, number of landline phone connections per 1000 people, distance to nearest town (in *kms.*), night lights intensity, income per capita (in rupees), and expense per capita (in rupees). The sample includes all cells with zero cell phone coverage in 2006. All regressions are weighted by the cell's population. Standard errors clustered at district level are reported in brackets (number of clusters = 285). Significance level: *** p<0.01, ** p<0.05, * p<0.1.

Table 7: MOBILE COVERAGE AND LONG-RUN AGRICULTURAL PRODUCTIVITY

Outcome:	Δ log(yield) (2007-2017)					
			by baseline productivity (2007):			
			First Quartile	Second Quartile	Third Quartile	Fourth Quartile
	(1)	(2)	(3)	(4)	(5)	(6)
Δ Coverage	0.053**	0.068***	0.055*	0.004	-0.064	-0.059
	[0.024]	[0.025]	[0.029]	[0.048]	[0.060]	[0.454]
Δ Coverage $\times$ Non-official Languages (%)		-0.117***	-0.030	-0.028	-0.199	0.769
		[0.043]	[0.033]	[0.028]	[0.594]	[6.127]
Non-official Languages (%)		-0.039**	-0.007	-0.014	-0.077	0.180
		[0.017]	[0.009]	[0.012]	[0.213]	[1.426]
Observations	5,023	5,023	1,254	1,170	1,181	1,254
District f.e.	✓	✓	✓	✓	✓	✓
Baseline Controls	✓	✓	✓	✓	✓	✓
Other Controls	✓	✓	✓	✓	✓	✓

Notes: The table reports IV-2SLS estimates of the effect of mobile phone coverage on changes in long-run agricultural productivity between 2007-2017. Column (1) reports average effects. Column (2) reports heterogeneous effects depending on share of cell's population speaking non-official languages. Columns (3)-(6) report heterogeneous effects depending on the baseline productivity levels in 2007. Column (3) considers cells in the lowest quartile of baseline productivity and Column (6) cells in the highest quartile. The unit of observation is a 10×10 *km* cell. Δ Coverage is the change in the share of cell area covered under GSM mobile coverage between 2007-2012 instrumented using $\mathbb{1}$ (Tower). $\mathbb{1}$ (Tower) is a dummy variable that takes the value of 1 if a cell is both proposed *and* covered by a tower under SMIS Phase I and takes the value of 0 if a cell is proposed *and not* covered. All columns include district-fixed effects, baseline controls as well as other controls. Baseline controls include cell's (log) population, the availability of power supply and average ruggedness. Other controls for the cell include share of labor force employed in agricultural sector, share of agricultural land that is irrigated, access to an educational facility, access to a medical facility, access to a banking facility, number of landline phone connections per 1000 people, distance to nearest town (in *kms.*), night lights intensity, income per capita (in rupees), and expense per capita (in rupees). The sample includes all cells with zero cell phone coverage in 2006. All regressions are weighted by the cell's population. Standard errors clustered at district level are reported in brackets (number of clusters = 285). Significance level: *** p<0.01, ** p<0.05, * p<0.1.

Appendix for:

Access to Information, Technology Adoption and Productivity: Large-Scale Evidence from Agriculture in India

For Online Publication

A Calls to Kisan Call Center

In this section we describe the methodology followed to extract crop information and type of query made by farmers in all calls to Kisan Call Centers (KCC). KCC agronomists record the correct information on crop and the category of the query in less than 10% of the calls. In the remaining cases, we use the details contained in two text fields available in the KCC data, i.e. farmer's query and agronomist's answer, to obtain the information. To illustrate the procedure, consider the following calls received by the KCC:

Sno	Date	State	District	Crop	QueryType	QueryText	Answer
1	07/22/2009	Uttar Pradesh	Ambedkar Nagar	-	-	Fertilizer Dose in Paddy	Give NPK 120kg 60kg 60kg/hac
2	09/07/2009	Madhya Pradesh	Sagar	-	-	How to control temite in soyabean?	Spray Chlorpyrifos @ 30ml/pump

In Call 1, the farmer calls KCC to get information on the fertilizer dose in Paddy (Rice). The information on crop in the KCC data is missing under the "Crop" field but it is clearly available in the text of the query (variable "QueryText"). Similarly in Call 2, the farmer inquires how to control termites (which is incorrectly recorded as "temites" in QueryText) for Soyabean crop. Similar to the previous call, both the crop information and category of call are missing in the recorded data. We use the information in "QueryText" to deduce what is the crop the farmer is enquiring about (*Soyabean*). We also use the information in the "Answer" field which recommends using Chlorpyrifos to assign the "QueryType" of the call as *Pesticides*.

A.1. Categorizing Crops

We extract crop information based on methodology described above – using information within the text of the query or the answer of the KCC agronomist to the query. In many cases, crops names are recorded in Hindi. For example, Rice is commonly known as *Dhan* in Hindi. Similarly, Wheat is recorded as *Gehun*; Maize is recorded as *Makka*. We detect all these instances and convert the corresponding crop names to English.

A.2. Categorizing Query Categories

We classify calls into 17 broad categories.[1] Here we describe in detail the assignment of the main query categories used in the paper – calls on seeds, fertilizers, irrigation and pesticides.

Calls on Seeds: We classify as farmers' calls on seeds those calls made to obtain information on hybrid seed varieties or calls made to inquire about seed varieties. We use information in either the text of the query or in the answer of the KCC agronomist.

[1] These categories include Pesticides, Yields, Fertilizers, Weather, Field Preparation, Market Information, Credit, Cultivation, Irrigation, Contact Information, Soil Testing, Mechanization, Government Schemes, Seed Availability, Crop Insurance, General Information and Others. The first seven categories are associated with 90% of the calls. We collapse all categories with less than 1% of calls into a combined category of "Others" which in total makes up about 10% of the calls.

In particular, we classify as calls on seeds: (i) calls directly asking about the hybrid varieties related to a crop (ii) inquires or answers about specific high-yielding varieties seeds. For example, farmers ask about the following high-yielding varieties of wheat: DHM-1, WH-542, UP-2338, HUW-468, PVM-502 or about the following high-yielding varieties of cotton: RCH-134, RCH-208, RCH-317, MRC-6301, MRC-6304. Table A.1 below provides an illustrative example for this:

Table A.1: Sample calls on Seeds

Sno	Date	State	District	Crop	QueryType	QueryText	Answer
1	10/17/2010	Haryana	Mahendra- -garh	Wheat	Seeds	Improved varieties of wheat	PBW-343,WH-711, WH-542,DBW-1
2	03/28/2009	Andhra Pradesh	East Godavari	Maize	Seeds	Asked about Varieties	Recommended DHM-107 or 109

Calls on Fertilizers: We classify as farmers' calls on fertilizers: (i) calls seeking general information on fertilizer dosage (ii) calls directly asking remedies for nutrient deficiencies in crops (iii) queries or replies based on required dosage of specific fertilizers, *e.g.* N-P-K or Urea (iv) calls seeking information on plant growth regulators, seed treatment or solution to leaf drop. For example, in many calls farmers asks about the dosage of specific fertilizers, *e.g.* D.A.P. (Diammonium phosphate). In few other calls, the agronomist prescribes specific amounts to be used for different chemicals of the fertilizer N-P-K. Table A.2 below provides an illustrative example from our exercise.

Table A.2: Sample calls on Fertilizers

Sno	Date	State	District	Crop	QueryType	QueryText	Answer
1	02/17/2011	Punjab	Amritsar	Wheat	Fertilizers	Sulphur deficiency in wheat	Apply 100 kg gympsum per acre before sowing
2	07/03/2009	Uttar Pradesh	Firozabad	Rice	Fertilizers	Fertilizer dosage in rice	N-120kg, P-60kg K-120kg, ZN-20kg/hec.
3	07/20/2011	Punjab	F.G.Sahib	Rice	Fertilizers	D.A.P dose in paddy	27 kg per acre
4	12/06/2010	West Bengal	Midnapore (East)	Rape	Fertilizers	Flower dropping in mustard	Apply Zinc Sulfate 2 gram/liter water
5	08/09/2011	Mahara- -shtra	Parbhani	Cotton	Fertilizers	Stunted growth of cotton	Spray Urea 100 grams in 10 litre water

Calls on Irrigation: In order to classify calls on irrigation, we use farmers' queries seeking information: (i) directly about irrigation practices (ii) or about water management in the field. Table A.3 below provides an illustrative example: in the first two calls farmers ask about the suitable time for particular stages of irrigation. In the last case, a farmer is seeking information on the quantity of water for irrigating the field.

Table A.3: Sample calls on Irrigation

Sno	Date	State	District	Crop	QueryType	QueryText	Answer
1	01/15/2011	Madhya Pradesh	Sehore	Wheat	Irrigation	Suitable time for 2^{nd} irrigation in wheat	At tillering stage *i.e.* 40-45 days
2	03/11/2010	Bihar	Palamu	Wheat	Irrigation	Minimum irrigation schedule for wheat	20-25,40-45,70-75,90 -95,105 days after sowing
3	06/10/2011	Bihar	Rohtas	Rice	Irrigation	Water management in rice	5-6 *cm* water given in rice field

Calls on pesticides: We classify as farmers' calls on pesticides: (i) calls seeking information specifically about pesticides (ii) agronomist suggesting the use of certain pesticides like Quinalphos, Carbofuran and Chlorpyrifos [2] (ii) calls asking about solutions for pest infection (iii) calls related to plant protection (iv) inquiries about weed control. Table A.4 below provides few examples of calls on pesticides after applying our methodology described above.

Table A.4: Sample calls on Pesticides

Sno	Date	State	District	Crop	QueryType	QueryText	Answer
1	08/29/2010	Andhra Pradesh	Anant- -hapur	Groundnut	Pesticides	Asked about spodoptera damage in groundnut	Spray Quinalphos 2ml/1 liter water
2	07/26/2011	Punjab	Mansa	Rice	Pesticides	Info. regarding control of termite in rice	Apply dilute 1 litre Chlorpyrifos 20ec in 2 litres
3	11/29/2009	Rajasthan	Alwar	Wheat	Pesticides	Prevention of Nematod problem in Wheat	Use Carbofuran 3G 20KG. per hectare soil treatment
4	09/04/2010	Uttar Pradesh	Bareilly	Rice	Pesticides	Insect Control in rice	Apply Endosulphon 35EC at 1.5 ml/lit of water
5	03/09/2011	Gujarat	Surat	Sugarcane	Pesticides	Ask for weed control	Suggested hand weeding
6	08/09/2011	Bihar	Deoghar	Rice	Pesticides	Plant protection in paddy	Given details about plant protection

[2] Quinalphos is an pesticide widely used in India for wheat, rice, coffee, sugarcane, and cotton. Carbofuran is a pesticide used to control insects in a wide variety of field crops, including potatoes, corn and soybeans. Chlorpyrifos is a pesticide used to kill a number of pests, including insects and worms.

B Data Validation

In this section, we validate our two measures of technology adoption — i.e. share of cell area farmed under HYV seeds and share of cell area that is irrigated (described in Section 3.4) — using alternative datasets that are publicly available to researchers.

1. HYV Adoption. Information on the use of HYV seeds at village level is seldom available. Two publicly available survey data sets that report such information are the ICRISAT Village Dynamics in South Asia (VDSA) and the Tamil Nadu Socioeconomic Mobility Survey (TNSMS) conducted by the Economic Growth Center at Yale University. Both data sets are based on household surveys that collect information on cultivation practices. Both data sets record the crops farmed by each household, the total area farmed under each crop and how much of the farmed area is cultivated with improved or HYV seed variety.

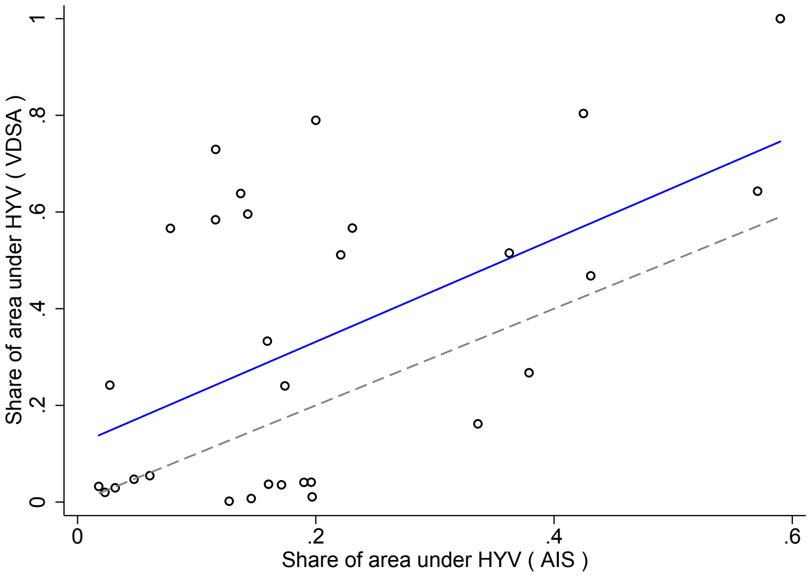
The two data sets differ in their finest identifiable geographic unit of observation. The finest geographical unit of observation in the VDSA data is a village. The survey covers 17 villages in 2012 with non-missing information on HYV seeds.[3] While the TNSMS covers more villages than VDSA, it does not provide village identifiers like VDSA. The finest geographical unit of observation available in TNSMS is much larger than our 10×10 *km* cell and therefore it is not well suited to validate our measure. Moreover, while TNSMS only covers villages within the state of Tamil Nadu, VDSA spans the five states of Andhra Pradesh, Gujarat, Karnataka, Madhya Pradesh and Maharashtra. Therefore, we use information available in the VDSA data to cross-validate our measure of HYV adoption, as described next.

We compare our measure of share of area farmed with HYV seeds against the one reported in the VDSA data. To do so, we use information in the VDSA data to calculate the total area farmed in each village under a given crop as well as how much of that area is cultivated using HYV seeds. Similarly, we use the share of area farmed with a given crop in a given cell using the data from the Agricultural Input Survey and the methodology described in section 3.4. We then map each 10×10 *km* cell to VDSA villages based on village centroids. This provides us with 30 observations at the cell-crop level for which we observe HYV adoption in both the VDSA and with our measure. Appendix Figure B.1 shows that our measure is positively correlated with the VDSA measure: the slope of the line is 1.06 and statistically significant ($t = 4.33$).

2. Share of irrigated land. Next, we compare our measure of share of cell area that is irrigated against the same measure constructed using information available in Village Census of India 2001. The village census reports information on area of land irrigated for all Indian villages for the year 2001. We construct a measure of share of irrigated land area for each of our 10×10 *km* cell by assigning villages to cells based on the geographical coordinates for the centroid of the village. We compare our measure of share of cell area irrigated in the year 2001 against the one reported in the village census data. This provides us with 25,017 observations at the cell level for which we observe share of irrigated land in both the Village Census and with our measure. Appendix Figure B.2

[3] VDSA only covers six villages consistently between 2002-2012. Four of these villages are in the state of Maharashtra. This limits our ability to compare our measure of *changes* in share of area under HYV seeds as AIS does not cover Maharashtra until 2012. We therefore only compare the *levels* of share of area under HYV seeds in 2012.

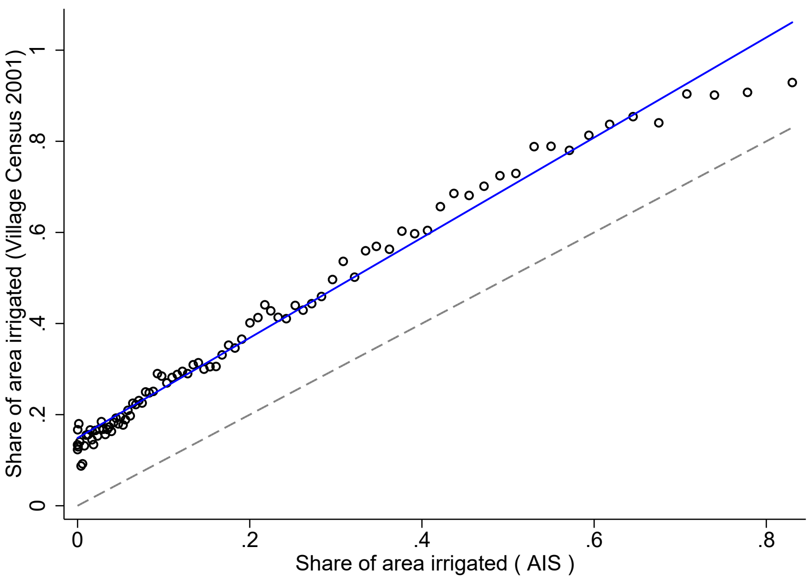
Figure B.1: Data Validation: HYV Adoption



Notes: The graph reports the share of crop area under HYV as calculated from ICRISAT VDSA (Village Dynamics in South Asia) micro data against the share of crop area under HYV seeds as calculated from AIS (Agricultural Input Survey). Each dot represents a cell-crop observation for the two measures of share of area under HYV seeds in 2012. The figure has 30 observations and the slope of the line is 1.06 (t = 4.33). The dashed gray line is the 45 degree line.

shows that our measure is positively correlated with the Village Census measure: the slope of the line is 1.1 and statistically significant (t = 43.75).

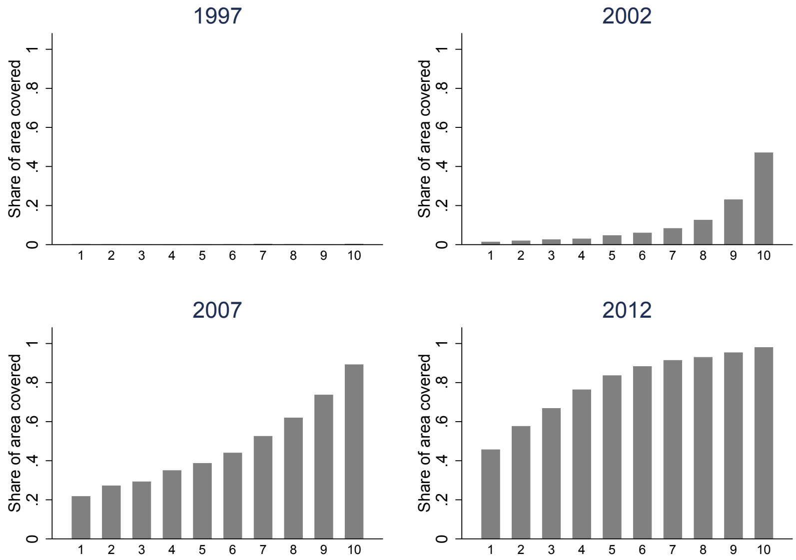
Figure B.2: Data Validation: Share of irrigated area



Notes: The graph reports the share of cell area under irrigation as calculated from Villages Census of India 2001 against the share of cell area under irrigation as calculated from AIS (Agricultural Input Survey) 2001. Each dot has 1 percent of observation based on the share of irrigated area measured through AIS and represents the average of the two measures of share of area under irrigation in 2001. The slope of the line is 1.1 (t = 43.75). The dashed gray line is the 45 degree line.

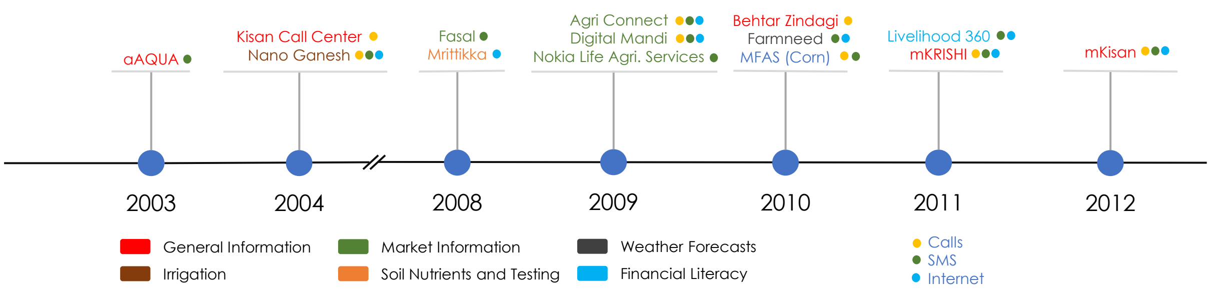
C Empirics: Additional Results

Figure C.1: Mobile Phone Coverage by night lights intensity



Notes: The average share of land with mobile phone coverage in each decile is calculated for the 4 years in which the Agricultural Input Survey was conducted: 1997, 2002, 2007 and 2012. night lights intensity data refers to 1996.

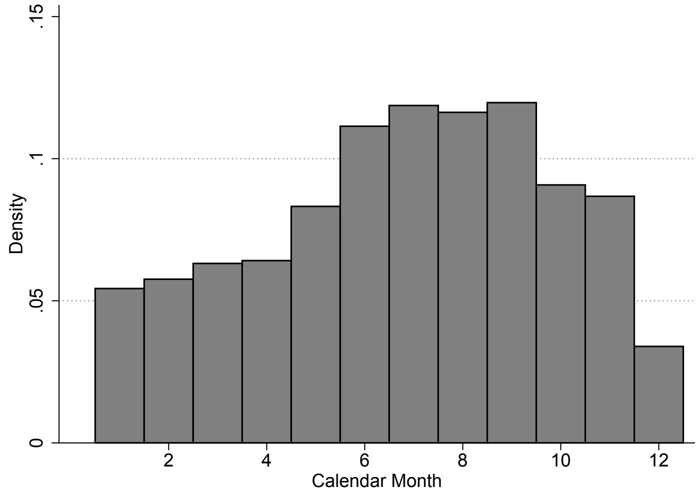
Figure C.2: Indian Providers of Agricultural Advice Services: A Timeline



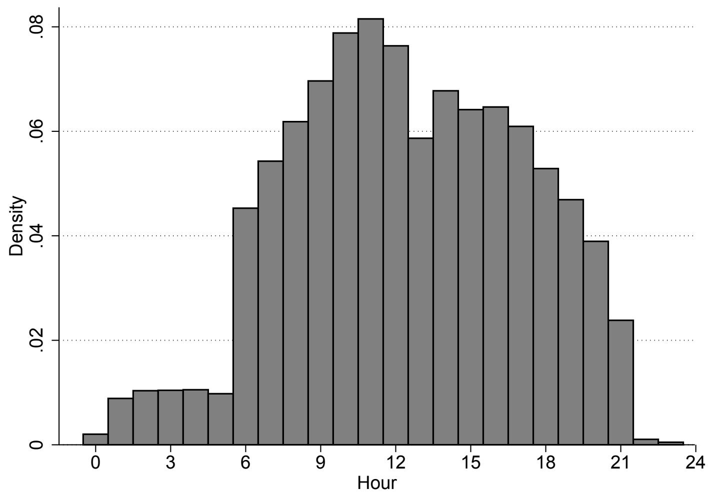
Notes: Source: GSMA mAgri Deployment Tracker

Figure C.3: Distribution of calls made to kisan call center

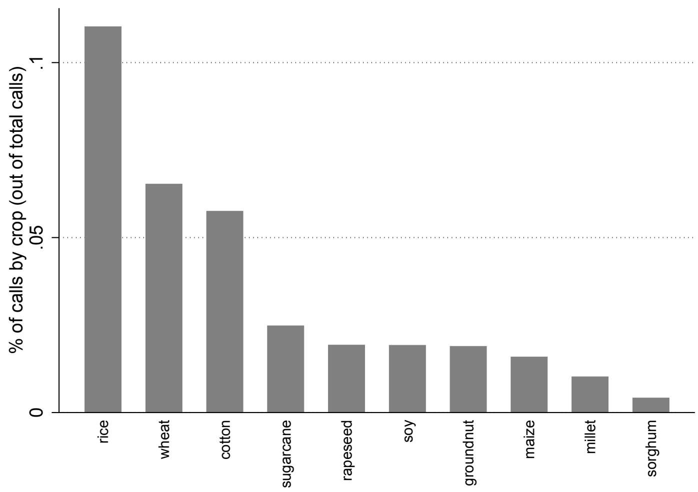
(a) Calls by Calendar Month



(b) Calls by Time of Day

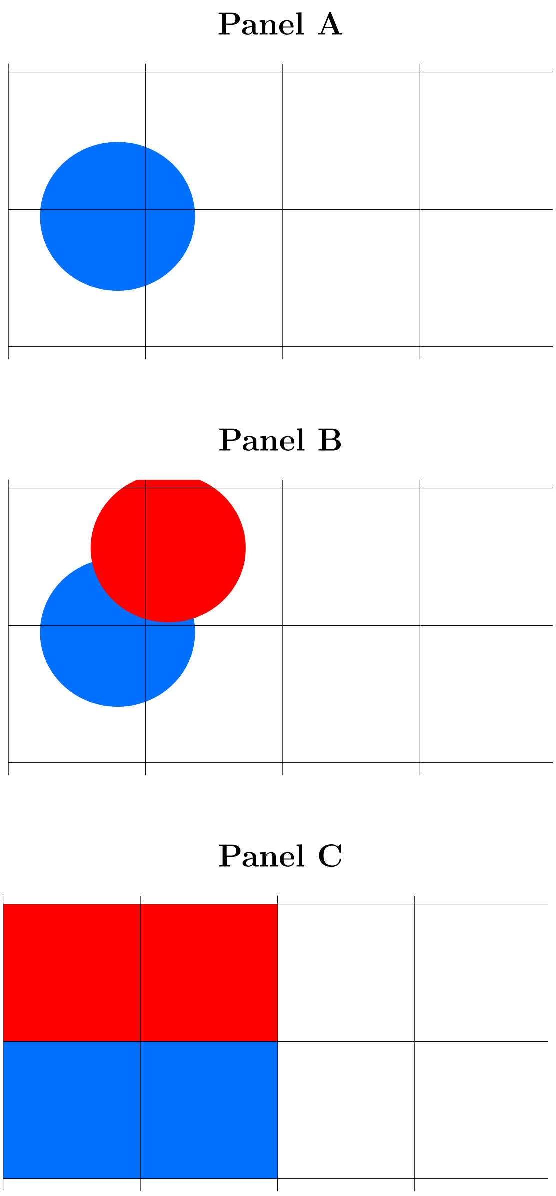


(c) Calls by Crop



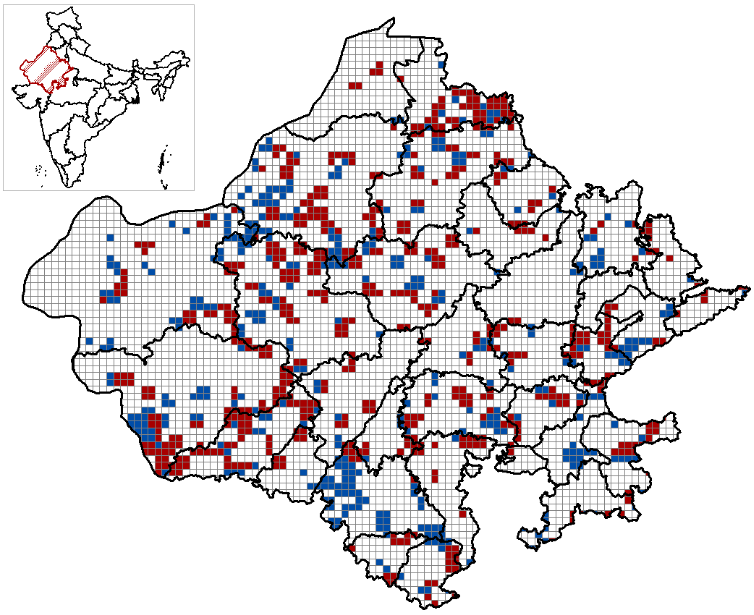
Notes: Source: Kisan Call Center, Ministry of Agriculture

Figure C.4: An example of classification of cells into treatment and control groups



Notes: The figure provides an illustration of classification of cells into treatment (red) and control (blue) group. Panel A shows area covered by a *proposed* tower under SMIS. Panel B shows the area covered by an *actual* tower eventually constructed. Panel C shows the assignment of cells into treatment and control groups.

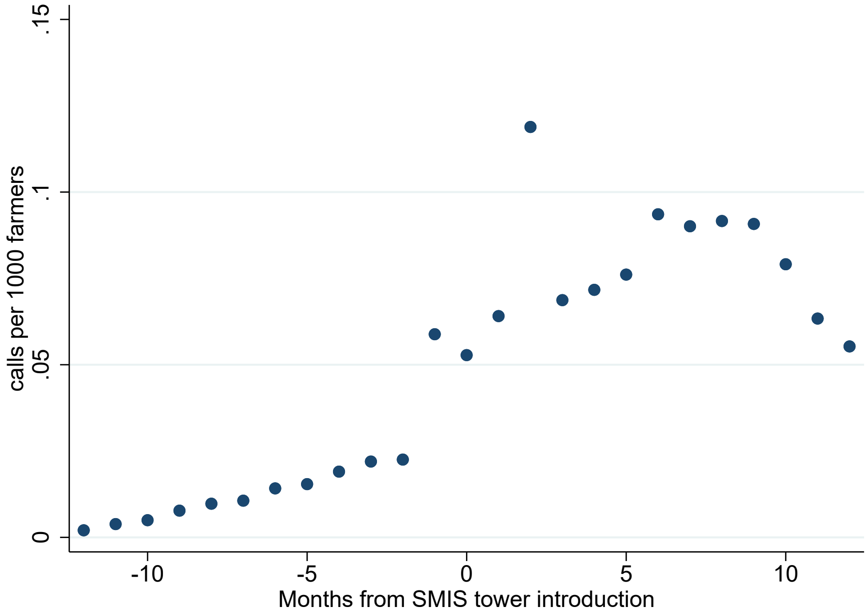
Figure C.5: Treatment and Control Cells
(Rajasthan State)



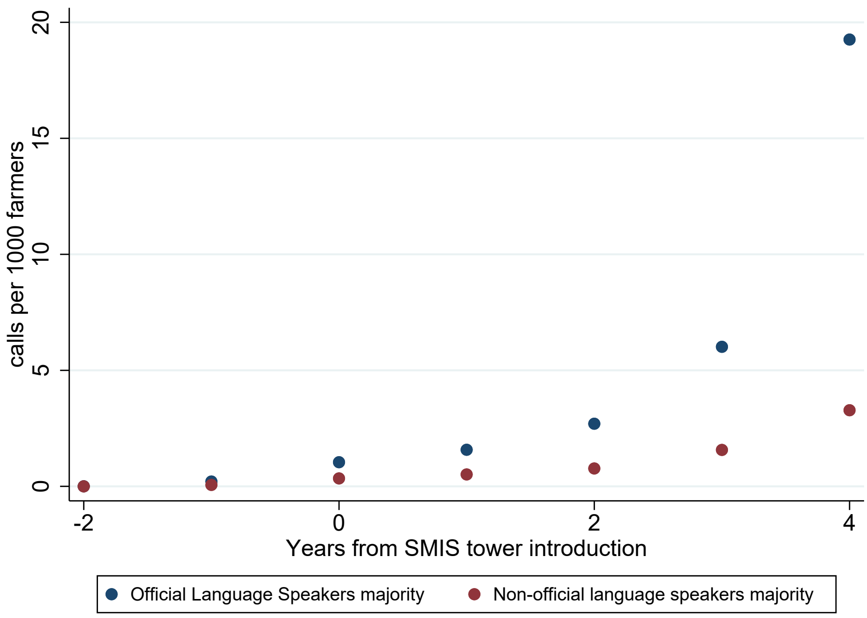
Notes: 10×10 Km treatment (red) and control (blue) cells for the state of Rajasthan. District boundaries are labeled in black. Treatment cells are those that are both proposed *and* covered by mobile tower under SMIS Phase I. Control cells are those that are proposed *and not* covered by mobile tower under SMIS Phase I.

Figure C.6: Evolution of calls to KCC per farmer around tower construction

(a) One year before and after tower construction, by month



(b) Two years before and four years after tower construction, by year



Notes: The figure plots the number of monthly calls per 1000 farmers in a cell in the one year before and one year after the cell received its first tower under SMIS Phase I (Panel (a)), and the number of yearly calls per 1000 farmers in a cell in the two years before and four years after the cell received its first tower under SMIS Phase I (Panel (b)).

Table C.5: Summary Statistics for Cell Characteristics

	Mean	**Median**	**Standard Deviation**	**N**
log (Population)	10.06	9.99	0.76	6320
Power Supply	0.78	0.92	0.29	6320
Ruggedness	0.47	0.20	0.89	6320
Agri. Workers/Working Pop.	0.57	0.57	0.14	6320
Agri. Land/Cultivable Area	0.45	0.47	0.22	6320
Percent Irrigated	0.36	0.27	0.32	6320
Δ HYV Share (2002-2007)	0.01	0.01	0.06	5019
Δ HYV Share (1997-2002)	0.05	0.04	0.11	4986
Literacy Rate	0.43	0.44	0.12	6320
Education Facility	0.85	0.91	0.17	6320
Medical Facility	0.35	0.29	0.26	6320
Banking Facility	0.06	0.03	0.10	6320
# Phone conn. per 1000 people	1.22	0.30	3.33	6320
Dist. to nearest town(kms)	26.40	20.00	22.31	6320
Night Lights (2006)	1.43	0.72	1.84	6320
Income per capita	75.46	16.76	351.36	6320
Expense per capita	66.44	16.15	268.09	6320

Notes: The unit of observation is a 10×10 *km* cell. The variables reported are (log) population, fraction of villages in the cell with access to power supply, ruggedness of the cell, share of agricultural workers, share of cultivable land under agriculture, percentage of irrigated land, changes in share of land under HYV, literacy rate, education facility, medical facility, banking facility, number of telephone connections per 1000 people, night lights, distance to nearest town, (monthly) income per capita, and (monthly) expense per capita.

Table C.6: Robustness: Mobile Coverage and Technology Adoption

Outcome:	Δ Technology Adoption							
Technology:	Fertilizers in areas under HYV		Fertilizers in areas not under HYV		Irrigation in areas under HYV		Irrigation in areas not under HYV	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δ Coverage	0.047**	0.051**	-0.005	-0.005	0.035**	0.042**	-0.012	-0.015*
	[0.022]	[0.023]	[0.013]	[0.014]	[0.018]	[0.019]	[0.008]	[0.009]
Δ Coverage × Non-official Languages (%)		-0.030		0.007		-0.054***		0.027
		[0.024]		[0.017]		[0.020]		[0.017]
Non-official Languages (%)		0.001		-0.013**		-0.019*		0.013*
		[0.015]		[0.005]		[0.010]		[0.007]
Observations	6,310	6,310	6,310	6,310	6,320	6,320	6,320	6,320
District f.e.	✓	✓	✓	✓	✓	✓	✓	✓
Baseline Controls	✓	✓	✓	✓	✓	✓	✓	✓
Other Controls	✓	✓	✓	✓	✓	✓	✓	✓

Notes: The table reports IV-2SLS estimates of the effect of mobile coverage on the share of area under fertilizers (Columns 1-4) and the share of area irrigated (Columns 5-8) between 2007-2012. The unit of observation is a 10×10 km cell. Δ Coverage is the change in the share of cell area covered under GSM mobile coverage between 2007-2012 instrumented using $\mathbb{1}$ (Tower). $\mathbb{1}$ (Tower) is a dummy variable that takes the value of 1 if a cell is both proposed *and* covered by a tower under SMIS Phase I and takes the value of 0 if a cell is proposed *and not* covered. Odd columns reports the average effect, even columns report the heterogeneous effects depending on share of cell's population speaking non-official languages. Columns (1)-(2) and (5)-(6) report the estimates for area cultivated with HYV seeds and Columns (3)-(4) and (7)-(8) report the estimates for area not cultivated with HYV seeds. All columns include district-fixed effects, baseline controls as well as other controls. Baseline controls include cell's (log) population, the availability of power supply and average ruggedness. Other controls for the cell include share of labor force employed in agricultural sector, share of agricultural land that is irrigated, access to an educational facility, access to a medical facility, access to a banking facility, number of landline phone connections per 1000 people, distance to nearest town (in $kms.$), night lights intensity, income per capita (in rupees), and expense per capita (in rupees). The sample includes all cells with zero cell phone coverage in 2006. All regressions are weighted by the cell's population. Standard errors clustered at district level are reported in brackets (number of clusters = 285). Significance level: *** p<0.01, ** p<0.05, * p<0.1.

Table C.7: Robustness: additional interaction terms

	Baseline (1)	+ Δ Coverage × Agriculture (2)	+ Δ Coverage × Isolation (3)	+ Δ Coverage × Income (4)	+ Δ Coverage × ((2)+(3)+(4)) (5)
			Panel A: Δ log(1+ number of calls)		
Δ Coverage	0.828***	1.149**	0.680***	0.809***	0.965*
	[0.206]	[0.508]	[0.181]	[0.202]	[0.578]
Δ Coverage × Non-official Languages (%)	-0.716**	-0.690**	-0.878*	-0.713**	-0.916
	[0.316]	[0.331]	[0.481]	[0.307]	[0.729]
Non-official Languages (%)	-0.185*	-0.203*	-0.234**	-0.188*	-0.273
	[0.096]	[0.108]	[0.117]	[0.098]	[0.202]
Observations	6,320	6,320	6,320	6,320	6,320
			Panel B: Δ Technology Adoption (HYV seeds)		
Δ Coverage	0.047**	0.095**	0.044**	0.049***	0.093*
	[0.019]	[0.044]	[0.018]	[0.018]	[0.049]
Δ Coverage × Non-official Languages (%)	-0.041**	-0.050***	-0.049	-0.041**	-0.059
	[0.019]	[0.019]	[0.046]	[0.019]	[0.056]
Non-official Languages (%)	-0.002	-0.006	-0.004	-0.002	-0.008
	[0.009]	[0.010]	[0.016]	[0.009]	[0.019]
Observations	6,320	6,320	6,320	6,320	6,320
			Panel C: Δ log(yield)		
Δ Coverage	0.041**	0.091*	0.037*	0.046**	0.091**
	[0.020]	[0.051]	[0.021]	[0.020]	[0.045]
Δ Coverage × Non-official Languages (%)	-0.093***	-0.095***	-0.101**	-0.095***	-0.107**
	[0.033]	[0.034]	[0.039]	[0.032]	[0.042]
Non-official Languages (%)	-0.014	-0.016	-0.016	-0.014	-0.018
	[0.012]	[0.011]	[0.013]	[0.011]	[0.013]
Observations	5,033	5,033	5,033	5,033	5,033
District f.e.	✓	✓	✓	✓	✓
Baseline Controls	✓	✓	✓	✓	✓
Other Controls	✓	✓	✓	✓	✓

Notes: The table tests the robustness of our baseline IV-2SLS estimates to the inclusion on an additional set of interaction terms. The dependent variable in Panel A is the change in (log) calls received at KCC; in Panel B is the change in share of area cultivated under HYV; in Panel C is the change in (log) agricultural productivity between 2007-2012. Column (1) reports baseline estimates of equation (4). Column (2) includes additionally the interactions of share of labor force employed in agricultural sector and share of agricultural land that is irrigated × Δ Coverage. Column (3) includes the interactions of distance to nearest town and average ruggedness × Δ Coverage. Column (4) includes the interactions of night lights intensity and income per capita × Δ Coverage. Column (5) includes simultaneously all the interactions in the previous columns. The unit of observation is a 10×10 *km* cell. Δ Coverage is the change in the share of cell area covered under GSM mobile coverage between 2007-2012 instrumented using $\mathbb{1}$ (Tower). $\mathbb{1}$ (Tower) is a dummy variable that takes the value of 1 if a cell is both proposed *and* covered by a tower under SMIS Phase I and takes the value of 0 if a cell is proposed *and not* covered. All columns include district-fixed effects, baseline controls as well as other controls. Baseline controls include cell's (log) population, the availability of power supply and average ruggedness. Other controls for the cell include share of labor force employed in agricultural sector, share of agricultural land that is irrigated, access to an educational facility, access to a medical facility, access to a banking facility, number of landline phone connections per 1000 people, distance to nearest town (in *kms.*), night lights intensity, income per capita (in rupees), and expense per capita (in rupees). The sample includes all cells with zero cell phone coverage in 2006. All regressions are weighted by the cell's population. Standard errors clustered at district level are reported in brackets (number of clusters = 285). Significance level: *** p<0.01, ** p<0.05, * p<0.1.

Table C.8: SMIS coverage ($\mathbb{1}$ (Tower)) and share of cell area under 3 crops with highest increase in HYV in district

Dependent variable:	$\mathbb{1}$**(Tower)**		
	(1)	(2)	(3)
% of cell area under:			
Top 1 crop	0.076		
	[0.125]		
Top 2 crops		0.051	
		[0.092]	
Top 3 crops			0.116
			[0.081]
Observations	6,320	6,320	6,320
R-squared	0.195	0.195	0.195
District f.e.	✓	✓	✓
Baseline Controls	✓	✓	✓
Other Controls	✓	✓	✓

Notes: The table reports the correlation of share of cell area under crops in our sample (used in equation 1) across treatment and control cells from a multivariate OLS regression of probability of being covered by a tower under SMIP Phase I ($\mathbb{1}$ (Tower)) on share of cell area covered by crops as reported in FAO. All specifications include district fixed effects, baseline controls and other controls. Column (1) reports the coefficient on the share of cell area farmed under the crop with highest percent increase in HYV share in cell's district between 2007 and 2012; Column (2) reports the coefficient on the share of cell area farmed under the top 2 crops with highest percent increase in HYV share in cell's district; Column (3) reports the coefficient on the share of cell area farmed under the top 3 crops with highest percent increase in HYV share in cell's district. Baseline controls include cell's (log) population, the availability of power supply and average ruggedness. Other controls for the cell include share of labor force employed in agricultural sector, share of agricultural land that is irrigated, access to an educational facility, access to a medical facility, access to a banking facility, number of landline phone connections per 1000 people, distance to nearest town (in *kms.*), night lights intensity, income per capita (in rupees), and expense per capita (in rupees). The sample includes all cells with zero cell phone coverage in 2006. All regressions are weighted by the cell's population. Standard errors clustered at district level are reported in brackets. Significance level: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table C.9: ROBUSTNESS: EFFECTS OF MOBILE PHONE COVERAGE, STANDARD ERRORS ADJUSTING FOR SPATIAL CORRELATION

	Δ log(1+ # of calls)		Δ Tech. Adoption (HYV Seeds)		Δ log(yield)	
	(1)	(2)	(3)	(4)	(5)	(6)
ΔCoverage	0.742	0.828	0.043	0.047	0.029	0.041
Spatial Correlation, threshold:50 km	[0.169]***	[0.177]***	[0.015]***	[0.016]***	[0.017]*	[0.017]**
Spatial Correlation, threshold:150 km	[0.185]***	[0.192]***	[0.016]***	[0.017]***	[0.018]	[0.018]**
Spatial Correlation, threshold:300 km	[0.193]***	[0.196]***	[0.016]***	[0.017]***	[0.020]	[0.019]**
Spatial Correlation, threshold:500 km	[0.206]***	[0.201]***	[0.016]***	[0.016]***	[0.021]	[0.020]**
Δ Coverage× Non-official Languages (%)		-0.716		-0.041		-0.093
Spatial Correlation, threshold:50 km		[0.242]***		[0.019]**		[0.020]***
Spatial Correlation, threshold:150 km		[0.308]**		[0.019]**		[0.024]***
Spatial Correlation, threshold:300 km		[0.318]**		[0.017]**		[0.025]***
Spatial Correlation, threshold:500 km		[0.302]**		[0.017]**		[0.024]***
Non-official Languages (%)		-0.185		-0.002		-0.014
Spatial Correlation, threshold:50 km		[0.077]**		[0.007]		[0.006]**
Spatial Correlation, threshold:150 km		[0.099]*		[0.008]		[0.007]**
Spatial Correlation, threshold:300 km		[0.119]		[0.007]		[0.007]**
Spatial Correlation, threshold:500 km		[0.133]		[0.006]		[0.006]**
Observations	6,320	6,320	6,320	6,320	5,033	5,033
District f.e.	✓	✓	✓	✓	✓	✓
Baseline Controls	✓	✓	✓	✓	✓	✓
Other Controls	✓	✓	✓	✓	✓	✓

Notes: The table reports results for alternate spatial clustering across cells. All definitions and specifications are the same as in Table 4, Table 5, and Table 6. Alternate standard errors adjusted for spatial correlation are provided below the estimates and are estimated using the (Conley 1999) correction for spatial correlation across cells, allowing the relationship to vary between 50 km and 500 km. Significance level: *** p<0.01, ** p<0.05, * p<0.1.

Table C.10: Robustness: continuous measure (2SLS) (2007-2012)

Outcome:	Δ Coverage	Δ log (1+ number of calls)				
Topic of the calls:		All	Seeds	Fertilizer	Irrigated	Pesticides
	(1)	(2)	(3)	(4)	(5)	(6)
% covered by SMIS	0.149***					
	[0.017]					
Δ Coverage		0.546***	0.189**	0.161***	0.042***	0.489***
		[0.132]	[0.074]	[0.062]	[0.015]	[0.121]
Δ Coverage × Non-official Languages (%)		-0.560**	-0.227***	-0.219***	-0.062**	-0.469**
		[0.221]	[0.085]	[0.075]	[0.025]	[0.200]
Non-official Languages (%)		-0.170**	-0.058**	-0.040	-0.017*	-0.152**
		[0.071]	[0.026]	[0.025]	[0.010]	[0.066]
Observations	6,320	6,320	6,320	6,320	6,320	6,320
F-stat	79.60					
Outcome:		Δ Technology Adoption				Δ log(yield)
Technology:		HYV Seeds	Fertilizers	Irrigation	Pesticides	
		(7)	(8)	(9)	(10)	(11)
Δ Coverage		0.030***	0.025*	0.017	0.037*	0.026**
		[0.011]	[0.014]	[0.011]	[0.019]	[0.011]
Δ Coverage × Non-official Languages (%)		-0.027*	-0.011	-0.020	-0.044	-0.065***
		[0.014]	[0.024]	[0.016]	[0.031]	[0.022]
Non-official Languages (%)		0.000	-0.011	-0.005	-0.015	-0.008
		[0.008]	[0.013]	[0.005]	[0.011]	[0.008]
Observations		6,320	6,310	6,320	6,142	5,033
District f.e.	✓	✓	✓	✓	✓	✓
Baseline Controls	✓	✓	✓	✓	✓	✓
Other Controls	✓	✓	✓	✓	✓	✓

Notes: The table reports the robustness of our baseline IV-2SLS estimates to using as the treatment variable the share of cell covered by SMIS towers instead of an indicator variable. The unit of observation is a 10×10 *km* cell. Column (1) reports the first-stage regression of Δ Coverage on cell area covered by a SMIS tower (% covered by SMIS tower). In Columns (2)-(11), Δ Coverage is the change in the share of cell area under GSM mobile coverage from 2007 to 2012, instrumented using % of cell covered by SMIS. Columns (2)-(6) estimate the effect of change in mobile coverage on change in number of (log) calls to the KCC. Column (2) estimates the effect on total calls, Column (3) on calls about seeds, Column (4) on calls about fertilizers, Column (5) on calls about irrigation, and Column (6) on calls about pesticides. Columns (7)-(10) estimate the effect of change in mobile coverage on change in technology adoption. Column (7) focuses on share of land under HYV seeds, Column (8) on share of land under fertilizers, Column (9) on share of irrigated land, Column (10) on share of land under pesticides. Columns (11) estimates the effect of change in mobile coverage on change in agricultural productivity. All columns include district-fixed effects, baseline controls as well as other controls. Baseline controls include cell's (log) population, the availability of power supply and average ruggedness. Other controls for the cell include share of labor force employed in agricultural sector, share of agricultural land that is irrigated, access to an educational facility, access to a medical facility, access to a banking facility, number of landline phone connections per 1000 people, distance to nearest town (in *kms.*), night lights intensity, income per capita (in rupees), and expense per capita (in rupees). The sample includes all cells with zero cell phone coverage in 2006. All regressions are weighted by the cell's population. Standard errors clustered at district level are reported in brackets (number of clusters = 285). Significance level: *** p<0.01, ** p<0.05, * p<0.1.

Table C.11: Price effects: effects of mobile coverage after market fixed effects

Outcome:	Δ Technology Adoption				Δ log(yield)
Technology:	HYV Seeds	Fertilizers	Irrigation	Pesticides	
	(1)	(2)	(3)	(4)	(5)
Δ Coverage	0.054***	0.050**	0.027	0.053**	0.038**
	[0.017]	[0.023]	[0.017]	[0.023]	[0.018]
Δ Coverage × Non-official Languages (%)	-0.033	-0.026	0.001	-0.053	-0.161
	[0.028]	[0.044]	[0.025]	[0.060]	[0.108]
Non-official Languages (%)	-0.007	-0.020*	-0.003	-0.020	-0.028
	[0.008]	[0.011]	[0.007]	[0.014]	[0.031]
Observations	6,092	6,081	6,092	5,914	4,840
District f.e.	✓	✓	✓	✓	✓
Baseline Controls	✓	✓	✓	✓	✓
Other Controls	✓	✓	✓	✓	✓
Market f.e.	✓	✓	✓	✓	✓

Notes: The table tests for alternate channel of price effects of mobile phone coverage by including agricultural market fixed-effects to our specification (6). The unit of observation is a 10×10 *km* cell. ΔCoverage is the change in the share of cell area covered under GSM mobile coverage between 2007-2012 instrumented using 𝟙 (Tower). 𝟙 (Tower) is a dummy variable that takes the value of 1 if a cell is both proposed *and* covered by a tower under SMIS Phase I and takes the value of 0 if a cell is proposed *and not* covered. The dependent variable in Column (1) is change in share of area cultivated under HYV; Column (2) is change in share of area cultivated under fertilizers; Column (3) is change in share of area cultivated under irrigation; Column (4) is change in share of area cultivated under pesticides; Column (5) is change in (log) agricultural productivity. All changes are calculated between 2007-2012. All columns include market-fixed effects in addition to district-fixed effects, baseline controls as well as other controls. Baseline controls include cell's (log) population, the availability of power supply and average ruggedness. Other controls for the cell include share of labor force employed in agricultural sector, share of agricultural land that is irrigated, access to an educational facility, access to a medical facility, access to a banking facility, number of landline phone connections per 1000 people, distance to nearest town (in *kms.*), night lights intensity, income per capita (in rupees), and expense per capita (in rupees). The sample includes all cells with zero cell phone coverage in 2006. All regressions are weighted by the cell's population. Standard errors clustered at district level are reported in brackets (number of clusters = 285). Significance level: *** p<0.01, ** p<0.05, * p<0.1.

Table C.12: Mobile coverage and language concentration

Outcome:	Δ Technology Adoption (HYV share)	Δ log(yield)
	(1)	(2)
Δ Coverage	0.043**	0.048*
	[0.021]	[0.025]
Δ Coverage × Non-official Languages (%)	-0.052***	-0.083***
	[0.019]	[0.031]
Non-official Languages (%)	-0.006	-0.017
	[0.009]	[0.012]
Δ Coverage × Language concentration	0.030	-0.044
	[0.056]	[0.052]
Language concentration	0.014	0.004
	[0.009]	[0.007]
Observations	6,319	5,032
District f.e.	✓	✓
Baseline Controls	✓	✓
Other Controls	✓	✓

Notes: The table tests for effects of language concentration for our estimates. The unit of observation is a 10×10 *km* cell. ΔCoverage is the change in the share of cell area covered under GSM mobile coverage between 2007-2012 instrumented using $\mathbb{1}$ (Tower). $\mathbb{1}$ (Tower) is a dummy variable that takes the value of 1 if a cell is both proposed *and* covered by a tower under SMIS Phase I and takes the value of 0 if a cell is proposed *and not* covered. The dependent variable in Column (1) is change in share of area cultivated under HYV, and Column (2) is change in (log) agricultural productivity. All changes are calculated between 2007-2012. All columns control for language concentration (and × Δ Coverage), where language concentration in cell i is defined as: Language Concentration$_i$ $= 1 - \sum_l(\text{share of cell } i \text{ population speaking language } l)^2$. All columns include district-fixed effects, baseline controls as well as other controls. Baseline controls include cell's (log) population, the availability of power supply and average ruggedness. Other controls for the cell include share of labor force employed in agricultural sector, share of agricultural land that is irrigated, access to an educational facility, access to a medical facility, access to a banking facility, number of landline phone connections per 1000 people, distance to nearest town (in *kms.*), night lights intensity, income per capita (in rupees), and expense per capita (in rupees). The sample includes all cells with zero cell phone coverage in 2006. All regressions are weighted by the cell's population. Standard errors clustered at district level are reported in brackets (number of clusters = 285). Significance level: *** p<0.01, ** p<0.05, * p<0.1.

Table C.13: Spillover effects of mobile coverage on nearby cells

Outcome:	Δ Technology Adoption				Δ log(yield)
Technology:	HYV Seeds	Fertilizers	Irrigation	Pesticides	
	(1)	(2)	(3)	(4)	(5)
Δ Coverage	-0.004	0.004	0.017	0.051	0.030
	[0.031]	[0.031]	[0.020]	[0.054]	[0.032]
Δ Coverage × Non-official Languages (%)	0.007	-0.002	-0.015	-0.044	-0.066
	[0.057]	[0.075]	[0.032]	[0.062]	[0.064]
Non-official Languages (%)	0.020	0.001	-0.006	0.003	0.003
	[0.019]	[0.024]	[0.010]	[0.020]	[0.023]
Observations	5,772	5,747	5,772	5,646	4,531
District f.e.	✓	✓	✓	✓	✓
Baseline Controls	✓	✓	✓	✓	✓
Other Controls	✓	✓	✓	✓	✓

Notes: The table reports IV-2SLS estimates of the effect of change in mobile phone coverage in a cell on technology adoption and agricultural productivity for nearby cells. A catchment area for a treatment cell is defined as all other cells adjacent to the treatment cell, excluding any cells that were originally either a treatment cell or control cell. Outcomes are then averaged across spillover cells. The specification is identical to the main specification 6 for estimating direct effects. The dependent variable in Column (1) is change in share of area cultivated under HYV; Column (2) is change in share of area cultivated under fertilizers; Column (3) is change in share of area cultivated under irrigation; Column (4) is change in share of area cultivated under pesticides; Column (5) is change in (log) agricultural productivity. All changes are calculated between 2007-2012. ΔCoverage is the change in the share of cell area covered under GSM mobile coverage between 2007-2012 for the treatment cell instrumented using $\mathbb{1}$ (Tower). $\mathbb{1}$ (Tower) is a dummy variable that takes the value of 1 if the treatment cell is both proposed *and* covered by a tower under SMIS Phase I and takes the value of 0 if a cell is proposed *and not* covered. All columns include district-fixed effects, baseline controls as well as other controls. Baseline controls include cell's (log) population, the availability of power supply and average ruggedness. Other controls for the cell include share of labor force employed in agricultural sector, share of agricultural land that is irrigated, access to an educational facility, access to a medical facility, access to a banking facility, number of landline phone connections per 1000 people, distance to nearest town (in *kms.*), night lights intensity, income per capita (in rupees), and expense per capita (in rupees). The sample includes all cells with zero cell phone coverage in 2006. All regressions are weighted by the cell's population. Standard errors clustered at district level are reported in brackets (number of clusters = 285). Significance level: *** p<0.01, ** p<0.05, * p<0.1.