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Abstract

Farmers in developing countries often lack access to timely and reliable information about modern technologies that are essential to improve agricultural productivity. The recent diffusion of mobile phones has the potential to overcome these barriers by making information available to those previously unconnected. In this paper we study the effect of mobile phone network expansion in rural India on adoption of high yielding variety seeds and chemical fertilizers. Our empirical strategy exploits geographical variation in the construction of mobile phone towers under a large government program targeting areas without existing coverage. To explore the role of mobile phones in mitigating information frictions we analyze the content of 1.4 million phone calls made by farmers to a major call center for agricultural advice. Farmers seek advice on which seed varieties and fertilizers better meet their needs and how to use them. We find that areas receiving mobile phone coverage experience higher adoption of these technologies. We also observe that farmers are often unaware of the eligibility criteria and loan terms offered by subsidized credit programs. Consistently, we find that areas receiving mobile phone coverage experience higher take-up of agricultural credit.

JEL Classification: G21, Q16, E51

Keywords: India, agriculture, HYV Seeds, Credit Card

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Technology Adoption and Access to Credit via Mobile Phones*

Apoorv Gupta† Jacopo Ponticelli‡ Andrea Tesei§

July 26, 2019

Abstract

Farmers in developing countries often lack access to timely and reliable information about modern technologies that are essential to improve agricultural productivity. The recent diffusion of mobile phones has the potential to overcome these barriers by making information available to those previously unconnected. In this paper we study the effect of mobile phone network expansion in rural India on adoption of high yielding variety seeds and chemical fertilizers. Our empirical strategy exploits geographical variation in the construction of mobile phone towers under a large government program targeting areas without existing coverage. To explore the role of mobile phones in mitigating information frictions we analyze the content of 1.4 million phone calls made by farmers to a major call center for agricultural advice. Farmers seek advice on which seed varieties and fertilizers better meet their needs and how to use them. We find that areas receiving mobile phone coverage experience higher adoption of these technologies. We also observe that farmers are often unaware of the eligibility criteria and loan terms offered by subsidized credit programs. Consistently, we find that areas receiving mobile phone coverage experience higher take-up of agricultural credit.

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I Introduction

The past two decades have seen a rapid diffusion of mobile phones in low-income countries. This technology has the potential to overcome informational barriers and provide economic opportunities to those previously unconnected. In countries where a large share of the population still derives its livelihood from farming, understanding the impact of mobile phones in agriculture is especially relevant. For example, mobile phones can make cheaper and faster for farmers to order inputs from suppliers, find workers when needed, or transfer money to friends and relatives hit by a bad harvest. In addition, mobile phones can help diffuse information about optimal agricultural practices and inputs. Limited access to this type of information has traditionally constrained farmers' adoption of modern technologies (Foster and Rosenzweig, 1995; Conley and Udry, 2010; Jack, 2013), contributing to the large gap in agricultural productivity between high and low-income countries (Gollin et al. 2014, FAO 2017).

In this paper we provide large-scale evidence on how the diffusion of mobile phone coverage mitigates information frictions and facilitates technology adoption by farmers in India. We match detailed survey data on agricultural inputs used by Indian farmers – including seed varieties, fertilizers, irrigation and credit – with geo-located data on the diffusion of mobile phone coverage. The level of geographical disaggregation of the data allows us to conduct the empirical analysis using $10{\times}10$ km cells as unit of observation. Our identification strategy exploits variation in the construction of new mobile-phone towers under a large government program: the Shared Mobile Infrastructure Program (SMIP). This program aimed at increasing mobile phone coverage in rural India through the construction of more than seven thousand towers in previously unconnected areas. For identification, we compare cells where new towers were initially proposed and eventually realized with similar and geographically close cells where new towers were initially proposed but eventually not realized.

We start by documenting that areas with larger increase in mobile phone coverage experienced larger adoption of more advanced agricultural technologies. We focus in particular on farmers' adoption of new high-yielding variety (HYV) seeds and chemical fertilizers. HYV seeds are commercially developed to increase crop yields and are one of the most prominent innovation in modern agriculture.[1] Chemical fertilizers are a key input to maximize HYV potential. We find that cells with a one standard deviation larger increase in mobile phone coverage (38 percent of a cell area) experienced a 1.6 percentage points larger increase in area farmed with HYV seeds, which is around 10 percent of the average at baseline. These cells experienced an increase of similar magnitude in the area farmed with chemical fertilizers. The magnitude of our estimates implies that

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

the coverage provided by one additional mobile phone tower (approximately 80 km^2) in previously uncovered regions increases the area farmed with HYV seeds by around 350 hectares and the area under chemical fertilizers by around 300 hectares.

Next, we investigate the mechanisms through which mobile phone coverage affects agricultural technology adoption. Mobile phones can favor technology adoption via several channels.[2] In this paper we focus on the potential of mobile phones to mitigate information frictions. Our data is well suited to test this mechanism, as we observe the content and location of about 1.4 million calls made by Indian farmers to Kisan Call Centers (KCC) between 2006 and 2011. These centers are the largest government-sponsored and free-of-charge service for agricultural advice available in India. Crucially for our purposes, the data report both the question asked by the farmer and the answer provided by the agronomist.

Notice that information frictions can affect agricultural technology adoption in two ways. First, farmers might lack information about the very existence or the use of new technologies. For example, they might not know which new seed varieties, pesticides or fertilizers that better meet their specific needs are available, or might not know how to use them. Second, limited access to information can amplify other frictions to technology adoption. For example, farmers might not be aware of credit programs or insurance products that could help them overcome financial constraints or smooth consumption. Similarly, limited information on market prices or weather forecasts can limit risk-taking and thus agricultural innovation.[3] The stylized facts emerging from our call-level data are consistent with both these direct and indirect channels being at play. For example, we observe a substantial demand for information about agricultural technologies, with advice on seed varieties and fertilizers sought in 13 and 10.5 percent of the calls respectively. We also observe that farmers are often unaware of existing programs offering subsidized credit, or how to participate in them.[4]

Exploiting variation in tower construction under the SMIP program we show evidence consistent with mobile phone coverage relaxing information frictions for farmers. We find

[2]For example, by reducing transaction costs on money transfers, they can facilitate risk sharing and thus incentivize farmers to experiment with newer technologies. See Feder et al. (1985) for a discussion of the role of farmers' risk-aversion in adoption models. On the effect of mobile phones-based technologies on risk sharing see Jack and Suri (2014) and Blumenstock et al. (2016).

[3]A large literature has studied the determinants and obstacles to the adoption of modern agricultural technologies in developing countries. See Feder et al. (1985) and, more recently, Foster and Rosenzweig (2010) for two reviews of the theoretical and empirical literature on the topic; Conning and Udry (2007) for a review of the literature on the frictions undermining rural financial markets. Several recent papers have provided evidence on potential explanations for low technology adoption rate in developing countries including missing insurance markets (Karlan et al. 2014), inability to save enough to pay the fixed cost of adoption (Duflo et al. 2004), lack of access to high-quality inputs (Bold et al. 2017), lack of transportation infrastructure (Asher and Novosad 2018). Suri (2011) emphasizes how low adoption rates in developing countries mask large disparities in returns from adoption across farmers.

[4]We focus in particular on calls regarding credit products available to farmers because limited access to credit has been shown to limit adoption of HYV technology (Bhalla, 1979; Frankel, 2015) and because the agricultural input survey reports detailed data about credit take up.

that cells with a one standard deviation larger increase in mobile coverage experienced a 12 percent larger increase in farmers' calls about new seeds. Taken together, our estimates suggest that a 1 percent increase in mobile phone calls about seeds translates into a 0.82 percent increase in actual adoption of HYV seeds. We also find that cells with a one standard deviation larger increase in coverage experienced a 15 percent faster increase in mobile phone calls in which farmers ask questions about credit. In a large share of these calls farmers ask how to obtain a specific type of credit card offering short-term credit to small farmers at subsidized rates (Kisan Credit Cards). Consistently, we find that cells with larger increase in mobile phone coverage also experienced larger increase in short-term credit to small agricultural establishments. We think of this as suggestive evidence of an additional channel through which mobile phones can facilitate technology adoption. Constrained access to credit can limit farmers' ability to invest in activities with high expected returns, such as the adoption of more modern seeds (Karlan et al. 2014). In some instances, farmers might have the possibility to access credit at favorable terms via subsidized credit programs, but are unaware of this possibility. Mobile phones can mitigate this friction by allowing farmers to ask questions and receive information on subsidized credit programs.

Overall, our results imply that the diffusion of mobile phone coverage in rural areas – coupled with the availability of call-centers for agricultural advice – has a large and positive effect on the adoption of modern agricultural technologies. We also show that our results are robust to a set of standard robustness tests and alternative specifications. In particular, we show that there are no pre-existing trends in technology adoption between cells that received coverage from new towers and cells that did not. In addition, we show that we obtain similar results when using a propensity score matching methodology in which we match each cell receiving a new tower under the program with a similar cell located in the same district but not selected for the program.

Finally, we focus on the aggregate implications of our results. To this end, we use the estimated elasticities obtained from our empirical analysis to compute the aggregate effects of mobile phone coverage on HYV adoption in rural India. Our estimates suggest that the expansion of the mobile phone network in India between 2007 and 2012 can explain around 11 percent of the observed increase in land farmed with HYV seeds during the same period.[5]

[5] To obtain this number we proceeds in two steps. First, we multiply the estimated elasticity of HYV seeds adoption to mobile coverage diffusion obtained with our IV strategy by the aggregate increase in land covered by the mobile phone network in India between 2007 and 2012. This gives us an estimate of the additional land farmed with HYV seeds in response to the aggregate increase in mobile coverage. Next, we divide the number obtained by the total increase in agricultural land farmed with HYV observed in India between 2007 and 2012. According to the Agricultural Input Survey, during this period, land farmed with HYV seeds increased by 32 percent: from approximately 81.8 million ha to 108.3 million ha. Our back of the envelope calculation suggests that around 3 million ha out of the 26.5 million ha increase can be attributed to the diffusion of mobile phone network in rural areas.

Related Literature

There is a large literature studying the determinants of technology adoption by farmers in less developed countries. This literature has pointed to several frictions that can explain observed productivity gaps across farmers operating in different countries – or in different regions within the same country. Such frictions include credit constraints, missing insurance markets, lack of infrastructure, but also gaps in access to information. De Janvry et al. (2016) argue that one of the determinants of the lag in technology adoption in regions such as Sub-saharan Africa or Eastern India is that farmers lack information about technologies such as HYV seeds. Recent research has shown that social networks are a powerful tool for information diffusion across farmers (Beaman et al. 2018). Some of this work has focused specifically on the diffusion of HYV seeds during the Green Revolution in India (Foster and Rosenzweig, 1995; Munshi, 2004). However, 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). Relative to this literature, we provide evidence consistent with mobile phone diffusion enabling access to reliable information on agricultural practices to farmers.

A recent and growing experimental literature has studied the impact of mobile phone based technologies on information diffusion about agricultural practices and farmers' behavior. For example, Casaburi et al. (2014) shows that sending SMS messages containing agricultural advice had significant positive effect on yields of small sugarcane farmers in Kenya. Cole and Fernando (2016) randomize access to a hotline for agricultural advice to households in Gujarat, India. They find evidence that the use of this phone service had a significant impact on agricultural practices, although relatively weak effect on yields. They also find that information provided through mobile phones spread within farmers' network, amplifying the effect of the agricultural extension program.[6]

Finally, there is scarce existing evidence on the effect of mobile phones on access to credit. Jack and Suri (2014) study the impact of lowering transaction costs to transfer money among individuals on risk sharing. They find that households using a mobile phone system that reduces transaction costs are better able to smooth consumption when facing negative income shocks. Karlan et al. (2016) show that reminders from banks sent via SMS help clients achieve their saving goals, which in turn can have positive effects on their income growth (Dupas and Robinson, 2013; Karlan et al., 2014). Text messages are

[6] Several other papers have studied other aspects of the impact of mobile phones on agriculture in less-developed countries: see Aker et al. (2016) and Nakasone et al. (2014) for a review. In particular, Jensen (2007) and Aker (2010) show that mobile phone coverage can reduce price dispersion in, respectively, fisheries in Southern India and agricultural goods markets in Niger. On the other hand, Fafchamps and Minten (2012) study the impact of a SMS-based agricultural information system providing market and weather information to Indian farmers and find non significant effects on cultivation practices or productivity.

also shown to improve loan repayment, although the effects are limited to non first-time borrowers and when the message includes the loan officer's name (Karlan et al., 2012). Our paper contributes to this literature by providing evidence on how the diffusion of mobile phones in conjunction with services for agricultural advice can promote access to credit by farmers. In particular, we can observe both farmers' questions about credit programs available to meet their needs and actual take-up of agricultural credit in the area where they live.

II Institutional Background

This section provides institutional details about the diffusion of mobile phones in India and the government programs used in our empirical analysis – namely, the Shared Mobile Infrastructure Program and the Kisan Call Centers for agricultural advice. The corresponding data are described in detail in Section III.

According to data from the Global System for Mobile Communication Association (GSMA), reported in Figure I, India had virtually no mobile phone coverage until the end of the 1990s. From then on, the mobile phone network increased exponentially, covering 22 percent of the population in 2002, 61 percent in 2007 and 89 percent in 2012.[7] Accordingly, 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 traditional pattern of diffusion (Buys et al., 2009; Aker and Mbiti, 2010), the spatial roll-out of mobile phone coverage in India started in urban areas and only later reached the rural areas. This is shown in Figure II, which reports - at 5-year intervals - the average share of land covered by mobile phones across cells by initial level of urbanization. As a proxy for urbanization we use night light intensity (fixed at 1996 levels), which is available at cell level from satellite data. In 1997, our baseline year, there was virtually no mobile phone coverage in India. After 1997, the speed of diffusion differed in urban areas relative to rural ones. Cells in the highest decile of night light intensity had, on average, 40 percent of their area covered by the mobile phone network by 2002, more than 80 percent in 2007, and close to full coverage by 2012.[8] 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.

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

[7] 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.

[8] We focus on these 4 years as they correspond to the Agricultural Input Survey data used in the empirical analysis.

private telecommunication companies. In 2007, the government implemented the Shared Mobile Infrastructure Program (SMIP), aimed at providing subsidies to telecom operators for the construction and maintenance of mobile towers in identified rural areas without existing mobile coverage. Each tower was shared by three telecom providers in order to reduce the per-provider cost associated with tower setup and management. Under Phase-I of the program, a total of 7,871 sites across 500 districts were initially identified as potential location for new towers. Villages or cluster of villages not covered by mobile phone network and with a population of at least 2,000 were prioritized. Telecom operators were responsible for installing and maintaining the towers between 2007 and 2013.[9] Of the 7,871 proposed towers under Phase-I, 7,003 were eventually constructed and became operational.

Alongside the rapid spread of mobile phone coverage and subscriptions, a number of SMS- and call-based services were created with the aim of providing the predominantly agricultural population of India with information about available agricultural technologies and their use, advice on land allocation, information on crop prices, weather reports, information on pests and how to deal with them, and information on credit. Figure III shows the timing of introduction of the largest Indian providers of agricultural advice. The Kisan Call Centers were introduced in January 2004 by the Indian Ministry of Agriculture and were the first providers of general agricultural advice via mobile phone calls. Compared to other early agricultural services, mostly focused on providing market price information, KCC provides a broader range of services, from advice on which pesticides and varieties of seeds to use to obtain higher yields, to information about weather conditions, advice on field preparation, on market prices, and credit information.[10] KCC are spread across all Indian states and allow farmers to call a toll-free number to get answers to their queries. The calls are answered in the local language by trained KCC agricultural graduates, who address the query based on their knowledge and on a database of previous answers to similar queries. Ninety eight percent of the calls are answered using the software management system. In case the representative is not able to answer the question, the query is forwarded to a senior expert.

[9] 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.

[10] 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. Mobile phones and Internet based services though are not the only tools available to farmers to access information on agricultural practices. As of 2005, radio and TV programs still accounted for 13 and 9.3 percent, respectively, of sources of information accessed by farmers (Glendenning et al., 2010).

III Data description

We use four main data sources in our empirical analysis: (i) the geo-located data on mobile phone coverage from GSMA, (ii) the data on input use by Indian farmers from the Agricultural Input Survey (AIS), (iii) the location of mobile phone towers under the SMIP program from the Department of Telecommunications, and (iv) the proprietary data on farmers' calls from the Kisan Call Centers. Finally, we describe the sources of the large set of additional socio-economic and geographic variables used in the empirical analysis.

Our primary geographical units of observation in the analysis are cells of 0.083×0.083 degree resolution, approximately corresponding to areas of 10×10 km at the equator. We use data at this level to match the information from multiple datasets, which come at different levels of geographical aggregation. Overall, India is split into 41,495 cells, about two-thirds of which report consistent information from the Agricultural Input Survey between 1997 and 2012. Since cells' 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. In total, cells are distributed over 524 districts.[11]

In what follows we describe each of the main datasets used in the empirical analysis.

III.A GSMA Mobile Phone Coverage

Data on mobile phone coverage are collected by the GSMA, the association representing the interests of the mobile phone industry worldwide, in partnership with Collins Bartholomew, a digital mapping provider. The data come from submissions made directly from mobile operators for the purpose of constructing a roaming coverage map service used by network operators and users.

The coverage 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 that have been licensed to us provide, for all years between 1998 and 2012, yearly geo-located information on mobile phone coverage aggregated across all operators. The data report separate information on the availability of 2G, 3G and 4G technology. Our results, however, refer to a period when the only technology available was effectively 2G. 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).

[11] 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 Census Map (Population Census), which contains a short history for each district including how the district was created. The most common case is that new districts are created by carving out a part of a pre-existing district.

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 (GSMA, 2012; Sauter, 2006). Manacorda and Tesei (2016) use the GSMA data to study the effects of mobile coverage expansion on political mobilization in Africa.

III.B Agricultural Input Survey of India

The Agricultural Input Survey is conducted by the Ministry of Agriculture to collect information on input use by Indian farmers. It is conducted, along with the Agricultural Census of India, at 5-year intervals. Under 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.[12] The main objective of the survey is to collect information on agricultural inputs. In particular, the survey covers the following inputs: seeds, chemical fertilizers, organic manures and pesticides, agricultural machinery and agricultural credit. As for seeds, the survey records separately the use of traditional seeds versus high-yielding variety seeds. HYV are hybrid seeds with desirable characteristics such as improved responsiveness to fertilizers, dwarfness, and early maturation in the growing season. HYV seeds are developed in order to increase crop yields.[13]

Data from the AIS is aggregated and made available by the Ministry of Agriculture at the district-crop-farm size level.[14] For our main analysis, we aggregate across farm sizes and exploit information on input use at the district-crop level. We use the last 4 waves of the AIS covering the period from 1997 to 2012.[15]

AIS data cover 26,537 cells (or 64 percent of total grid-cells of India) in a consistent way between 1997 and 2012. The remaining 36 percent of cells are either located in areas with no agricultural production or are part of those states that do not consistently participate in the survey.

III.C Tower Location under SMIP

Our data on proposed locations of mobile phone towers under the Phase I of the SMIP program comes from the Center for Department of Telematics (C-DoT) - the consulting

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

[13] New varieties are constantly developed and introduced in the Indian market since the mid 1960s (the IR8 rice, flagship of the Green Revolution, was introduced in 1966). In the period between 2002 and 2013, 47 new varieties have been introduced covering different oilseeds, cereals and vegetables including rice, groundnut, wheat, millet, soy and cotton.

[14] Information on agricultural credit, which is not associated with a specific crop, is available at the district-farm size level, rather than district-crop-farm size level.

[15] The survey year for the four waves are 1996/97, 2001/02, 2006/07 and 2011/12. In the paper, we use the terminology 1997 when referring to the survey year 1996/97 of the Agricultural Input Survey which runs from 1^{st} July, 1996 to 30^{th} June, 1997. This terminology applies to all four waves.

arm of the Department of Telecommunications of India. The C-DoT provided us with the geographical coordinates of the 7,871 proposed towers, the geographical coordinates of the 7,353 constructed towers, and the exact dates on which these towers became operational. To estimate tower's coverage, 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).

We use information on towers' operational dates and inspection reports to remove an additional 350 towers with either missing date of initial operation or that were reported as not operated by telecommunication company. This provides us with 7,003 mobile towers that were constructed and became operational under Phase I of the SMIP program. Figure IV provides a time line 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 constructed between the second half of 2008 and the first half of 2009.

III.D Farmers' Calls to Kisan Call Centers

Data on farmers' calls are from the Department of Agriculture, Cooperation and Farmers Welfare. For every call received in one of the 25 call centers, the KCC representative 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 by the agronomist.[16] The department maintains record of these calls starting from 2006. Figure V shows the total number of calls to Kisan Call Centers in the period 2006 to 2011. As shown, the number of calls increases substantially starting in 2009, going from a few hundreds in 2008 to around four hundred thousands per year in 2009 and 2010, and reaching over half a million in 2011. This increase has been the result of a large advertising campaign as well as a change in the toll-free number used to call the KCC that made it accessible to mobile phones of all service providers.[17]

Figure VI (a) shows the distribution of calls to Kisan Call Centers by month. Summer months – which correspond to the $kharif$ growing season – are those were most calls are received. Panel (b) shows the distribution of calls by time of the day. As shown, calls happen between 6AM and 9PM, with a peak around later morning hours. Finally, panel (c) shows the distribution of calls by crop. The two crops farmers call more about are rice and wheat, which are also the two largest crops by area farmed in India – 44.7 and 27.5 million hectares in 2000 according to FAO data.

[16] The version of the data provided to us by the Department of Agriculture does not contain farmers' name or contact information. Thus, we cannot identify farmers that call multiple times.

[17] This advertising campaign mostly took the form of TV ads. Ads were in all major languages, broadcasted in both public and private TV channels, and at times matching farmer's preferences in different states.

In Appendix A we provide a detailed description of the keywords that we use to categorize calls to Kisan Call Centers by topic. Around fifty percent of calls are about pests and how to deal with them. Farmers receive detailed advice on which pesticide (if any) they should use, as well as information on dosage (grams per liter) and number of applications. The second most represented category is calls about on to improve yields or – more specifically – which varieties of seeds to use in order 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).[18] Figure VII shows the number of calls about rice – panel (a) – and wheat – panel (b) – by month as well as by type of question asked by the farmer. First, notice that rice and wheat are farmed during different seasons, a pattern that is reflected in the distribution of calls. Rice is primarily 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 primarily 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 calls is consistent with the agricultural calendar described above. For example, rice farmers mostly ask questions on which seeds to use in the months of 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 plants from pests. Similar patterns can be observed for wheat.

Finally, we briefly describe calls in which farmers ask information about credit. In most of these calls farmers ask questions regarding a specific program of subsidized credit available to Indian farmers. This program is distributed via Kisan credit cards. Kisan credit cards were introduced in 1998 by the Reserve Bank of India as a mechanism to provide access to small loans to farmers, and it is the main channel through which commercial banks provide credit to the agricultural sector. Bista et al. (2012) report that between 15 and 40 percent (depending on the year) of credit to farmers coming from cooperative banks, regional rural banks or commercial bank is issued through Kisan credit cards. Thus, knowledge about how these cards work, how to obtain them and what interest rate they charge is crucial for farmers' access to credit, especially in rural areas with limited presence of bank branches.

III.E Other Observable Characteristics at Cell-Level

We use data on land use at cell-level from the GAEZ dataset of the Food and Agricultural Organization (FAO). The GAEZ dataset reports information on the amount of land

[18] 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 Kisan Call Centers between 2006 and 2011.

– expressed in hectares – farmed with a specific crop in a given cell. The data refers to the baseline year 2000. In the empirical analysis 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 data aggregated at the country level, 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. We use information on baseline crop composition for each cell in order to construct our cell-level measure of time-varying adoption of HYV seeds, fertilizers and access to credit. In particular, we assume that crop-composition is fixed over time and we exploit variation in the adoption of modern agricultural technologies at the district-crop level, available from the Agricultural Input Survey.

We use data from the Village Survey of the Indian Population Census of 2001 to calculate a large array of cell characteristics at baseline. We assign villages to 10×10 km cells based on the geographical coordinates for the centroid of the village.[19] Village-level information is then aggregated to obtain cell-level characteristics. These characteristics include: population, quality of infrastructure (fraction of villages in the cell with access to power supply, education facility, medical facility, banking facility, number of telephone connections), measures of socio-economic development (night lights, literacy rate, income per capita), administrative features (level-2 administrative unit – districts – the majority of the cell belongs to, distance to nearest town). Importantly, we also include agricultural characteristics of the cell (share of agricultural workers, percentage of irrigated land) as well as cell-specific measures of changes in agricultural technology adoption over time. Finally, we construct a measure of cell-level terrain ruggedness using the Terrain Ruggedness Index obtained from Nunn and Puga (2012). Table C.5 reports summary statistics for these variables.

IV Empirics

In this section we describe our empirical strategy. We start in section IV.A by presenting a set of baseline correlations in the data for India as a whole. The objective of this section is to provide a set of baseline stylized facts on the relationship between the diffusion of mobile coverage across India and adoption of new agricultural technologies by farmers. Next, in section IV.B we describe our identification strategy based on variation in coverage by mobile phone towers constructed under the SMIP program.

IV.A Baseline Correlations for India

We start by documenting a set of baseline correlations between the expansion of mobile phone coverage and the adoption of modern agricultural technologies in India as a whole.

[19] Obtained from `http://india.csis.u-tokyo.ac.jp`.

To this end, we estimate the following equation in first differences:

$$\Delta\left(\frac{Area^k}{Area}\right)_{idt} = \alpha_d + \beta\,\Delta Coverage_{idt} + u_{idt} \tag{1}$$

Where the outcome variable is the change in the share of land farmed with a given technology k in cell i located in district d, the independent variable is the change in the share of land covered by mobile phone signal in the same cell, and α_d are district fixed effects capturing common trends across cells located in the same Indian district.

The share of land farmed with a given agricultural technology in a given cell is approximated as follows:

$$\left(\frac{Area^k}{Area}\right)_{idt} \approx \sum_{c\in O_i}\left[\left(\frac{Area^k}{Area}\right)_{dct} \times \left(\frac{Area_{idc,t=2000}}{Area_{id,t=2000}}\right)\right] \tag{2}$$

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 is observed at district-crop level in the Agricultural Input Survey. It 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. It is observed at cell level in the FAO-GAEZ dataset. This variable captures the initial allocation of land across crops in a given cell in the baseline year 2000. 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. Notice that to construct this approximation we use a neutral assignment rule of agricultural technologies across cells in a district. That is, we apply the share of land farmed using technology k for a given crop and district to all land farmed with that crop in that district.[20] In Appendix B we validate this measure using a small sample of cells for which we observe adoption of high-yielding variety seeds at village level from publicly available surveys. Notice that, under this definition, the coefficient β in equation (1) captures the percentage point change of area farmed with technology k in a given cell for a one percentage point increase in area covered by mobile phone signal in the same cell.

We estimate equation (1) using as outcome variable the change in the share of land farmed with high-yielding variety seeds – as opposed to traditional seeds – in a given cell. Changes are calculated between waves of the Agricultural Input Survey, which is run at 5-year intervals between 1997 and 2012. We estimate equation (1) separately

[20] An example might help to clarify this idea. 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: $(0.2 \times 0.4) + (0.5 \times 0.6) = 0.38$.

for each pair of waves. Table II reports the main correlations in the data. The results indicate that variation in mobile phone coverage is strongly correlated with adoption of high-yielding varieties between 2007 and 2012, while the coefficients are close to zero and not statistically significant in the periods 1997 to 2002, and 2002 to 2007. In terms of magnitude, estimates in columns (1) and (2) suggest that, between 2007 and 2012, one standard deviation increase in area covered by mobile phones is associated with a 1 percentage point increase in area farmed with HYV seeds, or 0.2 percentage point when comparing cells within the same district.[21]

High-yielding variety seeds have been available in India since the Green Revolution – which started in the mid-1960s – so the timing of the effect cannot be driven by the timing of introduction of this technology. The timing of the effect is instead consistent with the pattern of mobile phone coverage diffusion in rural India documented in Figure II, and with the introduction of agricultural extension programs provided via mobile phones. As shown in Figure III, these programs have been widely available to farmers only starting from the mid-2000s.

IV.B Identification Strategy

A concern with estimating equation (1) is that the evolution of mobile phone coverage is not randomly allocated across cells. First, the direction of causality may run in the opposite direction, as farmers adopting new agricultural technologies may also demand more mobile phone services. Second, mobile phone coverage and technology adoption may be spuriously correlated due to unobserved cell characteristics, such as the rate of local economic growth. Faster development might push higher mobile phone penetration while also favoring farmers' adoption of new technologies, for example to serve an increase in local demand.

In this section, we present an identification strategy that aims at generating plausibly exogenous variation in mobile phone coverage across cells. We exploit variation in the construction of mobile phone towers under the Shared Mobile Infrastructure Program. As described in Section II, in the initial phase of this program (Phase I), the Department of Telecommunications identified 7,871 potential locations for the construction of mobile phone towers. Given that the objective of the SMIP was to promote inclusion of rural and previously unconnected areas, the proposed locations share several common characteristics. First, they are in rural areas with no (or limited) pre-existing mobile phone coverage at the time of the program. Second, in order to maximize the impact of the program, proposed tower locations were chosen to guarantee coverage to a population above a min-

[21] To avoid selection driving differences across waves,we restrict the sample to cells for which we observe both mobile phone coverage and technology adoption in *all* periods. This leaves us with a balanced panel of 26,537 cells. Point estimates are very similar in size if we remove this restriction and use the full sample of 34,155 cells covered in the AIS. In this case, the point estimate is 0.018, statistically significant at the 1 percent level.

imum threshold of 2,000 inhabitants or 400 households. Thus, areas potentially covered by new towers tend to be rural areas where the majority of the population is employed in agriculture and with no previous mobile phone coverage.

For identification purposes, we exploit the fact that not all the locations in the initial list prepared by the Department of Telecommunications eventually received a mobile phone 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 district where towers were initially proposed but eventually not constructed.

Although all proposed locations share common characteristics, the decision to relocate or cancel a tower is not random. Three main determinants of this decision have emerged from our conversations with the public officials at the Department of Telecommunications. First, towers could be relocated to maximize the population covered. In addition, towers could be relocated due to logistical issues that were only realized when visiting the location sites. In particular, terrain ruggedness and lack of a connection to the electricity grid could determine the decision to relocate or cancel the construction of a tower.

We test for these determinants in Table III. The outcome is an indicator variable – $Tower$ – which is equal to one for cells that eventually received coverage from new towers (which we refer to as treatment cells hereafter) and zero for those that eventually did not (control cells hereafter).[22] As shown, the conditional probability of eventually receiving mobile coverage is higher for cells with higher initial population, with connection to the electricity grid and with flatter terrain. Notice that these three determinants remain statistically significant – and with coefficients of similar magnitudes – when used in the same specification as shown in column (4).

In the empirical analysis we add these three controls to our baseline specification. Ideally, controlling for these three determinants should absorb most differences between treatment and control cells. To test this assumption we explore the correlation between the indicator variable $Tower$ and a large set of cell characteristics observed in 2001 and sourced from the Village Survey of the Population Census of India. The results, reported in Table IV, show that, net of the main determinants of relocation and district fixed effects, treatment and control cells are comparable along a large set of observable characteristics. In particular, villages in treatment and control cells have similar baseline characteristics when focusing on the agricultural sector: differences in the agricultural employment share and the percentage of irrigated agricultural land are not statistically different from zero. In addition, villages in treatment and control cells are comparable in terms of baseline access

[22]We compute coverage for each new tower based on its technical specifications, which report a 5 km coverage radius around its centroid. Figure VIII provides a visual example of how we classify cells into treatment and control group based on proposed and actual tower location. Our final sample is composed of 6,562 cells, out of which 4,761 are in the treatment group and 1,801 in the control group. All our results are robust to using the share of land covered by SMIP towers instead of an indicator variable, as discussed in section V.B.

to information from the outside world as measured by number of landlines per capita and distance to the nearest urban center. Finally, notice that treatment and control cells are not statistically different in terms of proxies of economic development, such as night light intensity and average income per capita.

Figure IX reports the geographical distribution of treatment (in red) and control (in blue) cells across India. Figure X shows the grid of cells as well as the administrative boundaries for the 32 districts for the state of Rajasthan — the largest Indian state by area. Remember that our identification exploits within-district variation in treatment and control status across SMIP cells. There are on average 27 cells per district in our final sample.[23]

V Results

In this section we present the main empirical results of the paper. We start in section V.A by presenting the first stage relationship between tower construction under the SMIP program and mobile phone coverage. Next, we exploit the identification strategy presented in section IV.B to estimate the effect of mobile coverage on adoption of agricultural technologies. Finally, in section V.C, we explore the mechanisms that can rationalize our results.

V.A First Stage

In this section we report the results of estimating the following first stage regression:

$$\Delta Coverage_{idt} = \alpha_d + \gamma \mathbb{1}\left(\text{Tower}\right)_{id,t-1} + \delta X_{id,t=2001} + u_{idt} \tag{3}$$

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 SMIP tower location.[24] The coefficient of interest is γ, which captures the

[23] In our dataset, there are 15,197 cells with positive potential coverage from SMIP towers and non-missing information on technology adoption from the Agricultural Input Survey. Out of these, we focus on those cells that have zero mobile coverage at the beginning of the program (i.e., in 2006), which gives us a final sample of 6,562 cells. The rationale of the SMIP program was to provide mobile phone coverage to previously uncovered areas. However, according to our data, the median initial coverage among the 15,197 cells potentially affected by Phase I of the SMIP program was 11 percent in 2007. In the main empirical analysis presented in the paper we focus on the 6,562 cells with no initial mobile phone coverage according to our data. All our results are robust to using all 15,197 cells potentially affected by the Phase I of SMIP, as discussed in the section V.B.

[24] 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 SMIP to be the sole source of variation in change in GSMA coverage, even in rural

effect of tower construction under the SMIP program on the change in coverage in a given cell. Finally, $X_{id,t=2001}$ is a vector of cell-level controls. Cell-level controls include the three baseline controls shown in Table III as well as a large set of observable characteristics sourced from the Village Survey of the Population Census of 2001 including: literacy rate, distance to the nearest town, income per capita, agricultural labor share, share of irrigated agricultural land, telephones connections (per 1000 people), night light intensity and availability of a banking, education, medical facility.

Table V reports the first stage results. The estimated coefficient in column (1) indicates that cells covered by new SMIP towers experienced a 13 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 baseline controls district fixed effects: population, availability of power supply and terrain ruggedness. The magnitude of the estimated coefficient decreases from .13 to .08, and remains highly significant. Finally, in column (3), we add the remaining controls mentioned above. Consistent with the results presented in Table IV, the size of the point estimate is unaffected by including these additional controls. According to the specification in column (3), cells covered by new SMIP towers have, on average, 7.6 percentage points larger share of land with mobile phone coverage 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.

V.B The Effect of Mobile Phone Coverage on Technology Adoption

In this section we use the identification strategy described in section IV.B to estimate the effect of mobile phone coverage on the adoption of modern agricultural technologies. Table VI presents our main results when the outcome variable is adoption of high-yielding variety seeds. We report OLS, IV and Reduced Form coefficients for the sample of 6,562 cells potentially affected by the SMIP tower construction program.

Columns (1) and (2) report OLS estimates using the same specification as in Table II. The results are consistent with those obtained on the full sample of cells in the Agricultural Input Survey. In particular, the estimated coefficient in column (2) – which includes district fixed effects as well as all cell-level controls – suggests that cells with one standard deviation larger increase in area covered by mobile phones between 2007 and 2012 experienced around 0.4 percentage points larger increase in area farmed with HYV seeds.[25]

Columns (3) and (4) present IV estimates of the effect of mobile phone coverage on

regions.

[25] The magnitude of this estimated coefficient is between two and four times larger than the one shown in column (2) of Table II, which is obtained using data for the whole country. This is consistent with the effect of mobile coverage being larger in areas with no pre-existing coverage.

HYV seeds adoption between 2007 and 2012. The coefficient in column (4) is positive and precisely estimated. It indicates that cells with one standard deviation larger increase in mobile phone coverage experienced a 1.67 percentage points larger increase in area farmed with HYV seeds. This effect corresponds to a 9.8 percent increase in land cultivated with HYV seeds for the average cell in our sample.[26] One way to interpret the magnitude of this estimate is to compute the additional area farmed with HYV seeds for the additional coverage provided by one mobile phone tower. The towers constructed under the SMIP program provide mobile phone network to an area of approximately 80 squared kilometers. This implies that the coverage provided by one additional tower increases the area farmed with HYV seeds by 352 hectares.

The IV coefficients are around four times larger than the corresponding OLS estimates. One potential explanation for the downward bias in the OLS coefficients is unobservable farmers skills in cells experiencing higher increase in mobile phone coverage, which are not fully captured by our set of controls. In particular, high-skill farmers might already know and have adopted the best practices for their crops, or have a more informed network of farmers located in areas with coverage to whom to ask for agricultural advice. If that is the case, one would expect the OLS coefficient to display a smaller effect of mobile coverage on adoption relative to the IV coefficient.

Finally, columns (5) to (6) present the reduced form estimates of HYV seeds adoption on tower construction. The size of the estimated coefficient indicates that cells receiving coverage from a new SMIP tower experienced a 0.3 percentage points larger increase in the share of area farmed with HYV seeds.

One potential concern with the causal interpretation of the estimates in Table VI is that treated cells – those receiving coverage from new SMIP towers – may have been on a different trend of technology adoption in the period before the tower construction program started. To test the validity of this concern, we estimate equation (3) using as outcome variables the change in HYV seeds adoption in the periods 2002 to 2007, and 1997 to 2002. Table VII reports the results. As shown, cells where new SMIP towers were constructed after 2007 did not experience higher adoption of HYV seeds relative to the control group between 2002 and 2007, nor between 1997 and 2002. This indicates that our main results presented in Table VI are not driven by pre-existing trends across treatment and control cells in the 10 years preceding the mobile phone tower construction program.

Next, in Table VIII Panel A we estimate our IV specification using as outcome variable the share of land under chemical fertilizers. One important characteristic of HYV seeds is that they are highly respondent to fertilizers (Dalrymple et al., 1974). Thus, we expect adoption of HYV seeds by farmers to increase their demand for these complementary inputs of production. Column (1) of Table VIII shows that cells with a one standard

[26] The average share of HYV area across cells in our sample at baseline is 0.17.

deviation larger increase in mobile phone coverage experienced a 1.4 percentage points larger increase in area farmed using fertilizers. The magnitude of this estimate implies that the coverage provided by one additional mobile phone tower increases the area farmed with chemical fertilizers by 304 hectares. As shown in columns (2) and (3), the effect is entirely driven by increase in the use of fertilizers in cells that also use HYV seeds.

We also test for the effect of mobile coverage on 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 et al., 1974). Thus, we expect adoption of HYV seeds by farmers to also increase their demand for irrigation. We test this hypothesis in Panel B of Table VIII. We find positive but not statistically significant effects of mobile coverage on the increase in the share of land irrigated in a given cell, as shown in column (1). However, we do find an estimated IV coefficient of larger magnitude and close to statistical significance at standard levels when we focus on irrigation in areas farmed with HYV seeds relative to traditional seeds, as shown in columns (2) and (3).[27]

The results presented in this section are robust to a set of alternative specifications, which we report in Appendix C. In particular, they are robust to using the share of land covered by SMIP towers instead of an indicator variable as explanatory variable (Table C.6) or to include in the SMIP sample cells with positive mobile coverage at baseline (Table C.7). We also show that, consistently with the staggered construction of towers under Phase I of the SMIP program (Figure IV), the effect of tower construction on technology adoption is increasing in the time of exposure.[28] That is, cells that received mobile coverage in earlier stages of the program display a larger effect of tower construction on technology adoption relative to cells that received mobile coverage in later stages (see Table C.8).

Finally, we obtain results that are qualitatively and quantitatively similar to those presented in Tables VI and VIII by using a propensity score matching methodology to construct the control group. In this alternative identification strategy we match treated cells – e.g. those receiving mobile phone coverage under Phase I of SMIP – with control cells using an exact matching for location (i.e. treated and control cells have to be in the same district) and a propensity score matching for a large set of baseline covariates.[29]

[27] In unreported results available upon request we document statistically significant effects on irrigation for small and medium farms, while no effect on irrigation for large farms (which are more likely to have irrigation to start with).

[28] Notice that, while the adoption of HYV seeds, fertilizers and irrigation is only observed every five years in correspondence with the Agricultural Input Survey, tower construction is observable at monthly level.

[29] These covariates include: population, availability of power supply, ruggedness, share of labor force employed in agricultural sector, share of irrigated agricultural land, literacy rate, presence of educational facility, medical facility, banking facility, number of telephone connections per 1000 people, distance to nearest town (in km), night light intensity, and income per capita.

Figure C.2 reports the difference in standardized means between treatment and control cells along these covariates for both the overall sample and the matched sample. As shown, the matching absorbs a large fraction of baseline differences between treated cells and all other cells.[30] In Table C.10 we present reduced form results using this matched sample when the outcome variables are: change in area farmed with HYV seeds, change in area under chemical fertilizers, and change in area under irrigation. As shown, all results obtained with propensity score matching are consistent with those presented in Tables VI and VIII. In the next section we explore the potential mechanisms through which these effects arise.

V.C Mechanism

In section V.B we have documented that rural areas of India where coverage of the mobile phone network expanded faster also experienced faster adoption of modern agricultural technologies such as HYV seeds and chemical fertilizers. In this section we explore potential mechanisms through which this effect arises. We focus in particular on the role played by information diffusion over mobile phones, exploiting detailed data on the universe of mobile phone calls made by Indian farmers to KCC, a major call-center for agricultural advice.

We consider both the direct and indirect effects of information diffusion. First, farmers might lack information about the very existence of a new technology, or how to use it productively. In our context, farmers might not know which new seed varieties better meet their specific needs, or might not know the best practices to use them. In section V.C.1 we show that greater mobile phone coverage is associated with an increase in farmers' calls about high-yielding variety seeds, suggesting that information about the existence of new varieties and professional advice on how to use them can *directly* influence their adoption. Second, mobile phones may also temper other informational frictions that *indirectly* limit technology adoption. For example, farmers might not be aware of programs of subsidized credit that are available to them and could help them overcome financial constraints to adopt new agricultural technologies. In section V.C.2 we document an increase in farmers' calls regarding subsidized credit programs in areas experiencing faster increase in mobile phone coverage, and an associated increase in credit take-up in these areas.

We acknowledge that our empirical analysis cannot rule out that the increase in credit take up might be driven by an increase in credit demand from farmers adopting new agricultural technologies – regardless of the availability of mobile phone coverage. However, the finding that these areas also experience an increase in farmers' calls with questions

[30]Table C.9 shows balancedness between treated cells and matched control cells along all covariates. The only two variables displaying a statistically significant difference between treatment and control cells are population (treatment cells are approximately 5 percent larger than the control average) and telephone connections per 1000 people (treatment cells have marginally higher diffusion of phone connections per capita, although the diffusion is extremely low in both groups).

about subsidized credit programs – and that farmers seem to take up exactly the type of loans offered by such programs – is consistent with the existence of an underserved demand for information about credit programs that mobile phone coverage helps to serve.

V.C.1 Farmers' Calls About High-Yielding Variety Seeds

We start by investigating the relationship between the expansion of mobile phone coverage and the change in farmers' calls for agricultural advice. In particular, we use the identification strategy described in section IV.B and use as outcome variable the change in the number of farmers' calls originated from a given cell to Kisan Call Centers (in logs). The explanatory variable is the change in the share of land covered by the mobile phone network, instrumented by the variable $Tower$ from equation (3), while controlling for cell-level characteristics and district fixed effects.

Before presenting the results, let us describe in more detail how we construct our cell-level variable of calls for agricultural advice. Data from the Kisan Call Centers contain information on the district of origin of the call and the crop for which the caller is seeking information. In order to construct a measure of the number of farmers' calls originated in a given cell, we use an assignment rule similar to the one described in section IV.A. More specifically, we define:

$$Calls_{idt} \approx \sum_{c \in O_i} (Calls)_{cdt} \times \left(\frac{Area_{idc,t=2000}}{Area_{dc,t=2000}} \right) \tag{4}$$

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. 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.[31]

The results are reported in Table IX. Column (1) estimates the effect of mobile phone coverage on the change in the number of farmers' calls, irrespective of the question they ask. The estimated coefficient is 0.772 and precisely estimated. The magnitude indicates that cells with one standard deviation larger increase in mobile phone coverage experienced a 29.4 percent larger increase in total calls by farmers.

Crucially for our purposes, the call-level data reports the exact question asked by the farmer – as well as the answer provided by the agronomist. This allows us to distinguish between calls regarding new seeds varieties, fertilizers, irrigation, credit as well as other topics. For example, we classify as calls about new seed varieties those where farmers ask

[31] Since data on calls to Kisan Call Centers is available for the years 2006 to 2011, we construct the outcome variable for our empirical specification on calls as: $\Delta \log Calls_{idt} = \log\left(1 + \frac{1}{3}\sum_{t=09,10,11} Calls_{idt}\right) - \log\left(1 + \frac{1}{3}\sum_{t=06,07,08} Calls_{idt}\right)$.

advice on which seeds to use to improve yields for a given crop, those in which they ask information on how to use HYV seeds, and those in which they ask general advice on how to improve yields and the agronomist suggests to try specific HYV seed varieties.[32]

Column (2) reports the results of estimating our IV specification using as outcome variable the change in calls regarding new seed varieties. The estimated coefficient indicates that cells with one standard deviation larger increase in mobile phone coverage experienced a 12 percent larger increase in farmers' calls about seed varieties. In columns (3) and (4) we also find positive and significant effects of mobile phone coverage on the number of calls regarding fertilizers and irrigation, in line with the complementary nature of these inputs to HYV seed varieties discussed in the previous section.

Overall, the results presented in Table IX are consistent with mobile phone coverage affecting technology adoption via the diffusion of information about the existence and use of new technologies. Using this estimate along with the estimate reported in Table VI allows us to calculate the elasticity of HYV seeds adoption to mobile phone calls about this technology. In practice, to compute this elasticity we divide the estimated percentage increase in area farmed with HYV seeds for a standard deviation larger increase in coverage (9.8 percent) by the estimated percentage increase in farmers' calls regarding this technology for a standard deviation larger increase in coverage (12 percent). The obtained elasticity indicates that a 1 percent increase in mobile phone calls about HYV seeds translates into a 0.82 percent increase in their actual adoption.

V.C.2 Farmers' Calls about Credit and Growth in Agricultural Lending

In this section we explore an indirect mechanism through which mobile phone coverage can affect technology adoption: the diffusion of information about credit programs. When new technologies require an initial fixed investment, credit constraints can limit their adoption. Adopting HYV seeds, for example, requires an initial investment in more expensive seed varieties, higher use of fertilizers, and securing a more reliable irrigation system.[33] In many developing countries, governments offer subsidized credit programs to farmers in order to facilitate this type of investments. In India, for example, farmers can access credit at a subsidized rate through special cards called Kisan Credit Cards. However, an analysis of farmers' questions recorded in our call-level data indicates that farmers are often unaware of how this subsidized credit program works. Thus, an expansion of mobile phone coverage can foster the diffusion of information about credit programs. This, in turn, can facilitate technology adoption via increased access to external finance.

In this section we provide evidence consistent with this mechanism. First, we study

[32]See Appendix A for a detailed description of the keywords used to classify calls in different categories as well as several examples for calls about seeds, fertilizers, irrigation and credit.

[33] As discussed in Feder et al. (1985), several studies have found that limited access to credit can significantly limit the adoption of HYV technology even when the size of the initial investment required for adoption is not large.

whether diffusion of mobile phone coverage is associated with an increase in calls regarding credit programs available to farmers. Second, we study whether diffusion of mobile coverage explains actual credit growth to Indian farmers.

We start by studying the relationship between mobile phone coverage and farmers' calls about credit. We classify as calls about credit those where farmers ask how to obtain a loan to buy a specific input (e.g. a tractor, an irrigation system, a buffalo), as well as calls where farmers inquire about how they can obtain credit via one of the subsidized credit programs offered by the government. Appendix A provides a detailed description of the exact keywords used to classify calls regarding credit as well as several examples. In 2.2 percent of the 1.4 million calls to Kisan Call Centers, farmers ask question regarding credit. In 25 percent of calls about credit farmers ask specifically about how to obtain a Kisan Credit Card. Kisan Credit Cards offer short-term credit to farmers at relatively low interest rates (7 to 9 percent per year, depending on the issuing bank). Loans are usually taken during the planting season and repaid after harvesting. In case of a bad harvest, farmers have the option to rollover the debt. Importantly, most banks operating in rural areas offer Kisan Credit Cards. Bista et al. (2012) show that up to 40 percent of credit to farmers coming from cooperative banks, regional rural banks or commercial bank is issued through Kisan Credit Cards. Thus, access to information about this specific type of credit card is a potential determinant of access to credit, especially for small farmers.

Differently from questions about seeds, questions about credit do not require the farmer to mention the specific crop for which she plans to use the loan.[34] This implies that crop information is missing for the vast majority of calls about credit in our data. As described in section V.C.1, information on the crop farmed by the caller is essential to assign calls to specific cells within a given district. In absence of crop-information, we can only rely on the location of the caller at the district level. Thus, we start by presenting a set of basic correlations between the expansion in mobile phone coverage and the change in farmers' calls about credit, as well as actual credit take up, at the district level. The results of this analysis are reported in Table X. The outcome variable in column (1) is the change in the number of calls about credit by farmers located in a given district (in logs). The estimated coefficient on change in mobile phone coverage is positive and statistically significant, suggesting that districts with a one standard deviation larger increase in mobile phone coverage experienced a 14.5 percent larger increase in farmers' calls about credit. In columns (2) to (4) we estimate the same regression using as outcome variable the change in agricultural credit per hectare at district level. Data on credit to agricultural establishments is collected in the Agricultural Input Survey and contains information on loan size, loan maturity, size of the borrower, and type of lender.[35] Our results suggest

[34] More generally, calls about meteorologic conditions and credit tend not to report crop information. On the other hand, calls about market prices, pesticides, seeds and fertilizers report crop information.

[35] Lenders are classified into four main categories: commercial banks, rural regional banks, agricultural credit societies (PACS) and land development banks.

that districts with higher increase in mobile coverage also experienced higher increase in credit take up per hectare, and that such increase is driven by short-term loans.

The analysis reported in Table X documents basic correlations at district level. In what follows, we use the identification strategy presented in section IV.B to estimate the effect of mobile coverage on credit to farmers at cell-level. While data on calls about credit cannot be assigned to different cells within a district, we can construct a proxy of credit to farmers in a given cell using information on the size of the borrower. Using an assignment rule along similar lines to the one described in section IV.A we construct a measure of total agricultural credit in a given cell as follows:

$$Credit_{it} = \sum_{s \in H_i} (Credit)_{sdt} \times \left(\frac{Area_{ids,t=2001}}{Area_{ds,t=2001}} \right) \tag{5}$$

Notice that the second element of the product inside the summation captures the share of cultivated area in cell i that is farmed by agricultural establishments of size s over the total area farmed by agricultural establishments of size s in district d. Thus, the product of the two terms inside the summation is our measure of total credit to establishments of size s in cell i and year t ($Credit_{ist}$). Summing over all holding sizes (H_i) gives a measure of total agricultural credit to farmers operating in a given cell. Finally, we divide the above measure of total credit by the area of the cell to get the amount of agricultural credit per hectare.[36]

Table XI reports the results on the effect of mobile phone coverage on credit outcomes. We start by documenting the effect of mobile coverage on total credit per hectare, including credit of all maturities, borrowers of all sizes, and lenders of all types. The point estimate in column (1) of Panel A is positive and large in magnitude – around 390 Rupees per hectare – suggesting a positive effect of coverage on total credit per hectare, although the effect is imprecisely estimated and not different from zero at standard levels of significance. Columns (2) and (3) show that the positive effect is driven by an increase in short term credit, i.e. credit with maturity lower than 18 months. This is consistent with mobile phones facilitating diffusion of information about subsidized credit programs, and Kisan Credit Cards in particular.[37]

In columns (4) to (8) we then focus on short term credit and split borrowers by farm size. Size categories reported by the Agricultural Input Survey include: very small farms

[36] As a sanity check, Appendix Table C.11 shows that the above measure of credit is correlated with standard determinants of credit that we observe at cell-level such as: number of bank branches and distance from the nearest town for the cell. Column (1) of Table C.11 shows that an additional bank branch in a cell is associated with 162 Rupees more credit per hectare in that cell. This amounts to 9 percent higher credit relative to the mean. Column (2) of Table C.11 shows that cells that are one standard deviation away from the town (32.7 km) have 145 Rupees lower credit per hectare. This translates into 8 percent lower credit relative to the mean. Column (3) - (6) shows that these effects hold for both short-term credit and long-term credit.

[37] Short term credit accounts for 60 percent of total credit to farmers recorded by the Agricultural Input Survey in 2007.

(below 1 hectare), small farms (1 to 2 ha), small-medium farms (2 to 4 ha), medium farms (4 to 10 ha) and large farms (10 and above ha).[38] We find that the effect of mobile phone coverage on short term credit per hectare is monotonically decreasing in farm size, and statistically significant for very small and small farms. In terms of magnitude, the coefficients reported in columns (4) and (5) indicate that very small and small farms operating in cells with a one standard deviation larger increase in mobile phone coverage experienced – respectively – a 14.3 percent and 9.7 percent larger increase in credit per hectare. The finding that the effect of coverage on credit is concentrated among small farmers and in short-term credit is consistent with the information mechanism described above. Small farmers are the primary beneficiaries of subsidized credit programs such as Kisan Credit Cards, and these programs focus on offering short-term credit.

Next, in Panel B of Table XI we replicate the results of Panel A focusing exclusively on credit to farmers originated by Commercial Banks. The rationale is that Commercial Banks are the primary issuer of Kisan Credit Cards. According to Bista et al. (2012), as of 2010-2011, Commercial Banks had issued 55 percent of Kisan Credit Cards in India and originated 69 percent of total credit to farmers lent via Kisan Credit Cards. As shown, when we focus on credit originated by commercial banks, the effect of coverage on credit per hectare becomes more precisely estimated. In terms of magnitudes, the coefficients reported in column (1) and (2) suggest that cells that experienced a one standard deviation increase in mobile phone coverage experienced a 20 percent and 34 percent larger increase in total and short term credit, respectively. Consistent with Panel A, the effect is driven by short term credit to very small and small agricultural establishments. The coefficients reported in columns (4) and (5) indicate that very small and small farms operating in cells that experienced a one standard deviation larger increase in mobile phone coverage experienced – respectively – a 36 percent and 16 percent larger increase in credit per hectare.

VI Concluding Remarks

Mobile phones have experienced a widespread and fast diffusion in both developed and developing countries over the last 20 years. The benefits – as well as the costs – of this diffusion are still to be understood, especially in previously unconnected areas, such as rural areas of developing countries. In this paper we study the effect of mobile phone coverage on technology adoption by Indian farmers. To this end, we exploit data at a very fine-level of geographical variation: our data allows to observe, at 10×10 km level, the diffusion of the mobile phone network, the content of around 1.4 million farmers' phone

[38] According to the Agricultural Input Survey of 2007, and as reported in Figure XI, very small farms constitute the vast majority (63.7 percent) of agricultural holdings in India, followed by small farms (18.7 percent). Even in terms of area farmed, as of 2007 very small farms constitute around 20.7 percent of agricultural land, small farms constitute 20.4 percent.

calls to one of the major providers of agricultural advice, and the actual adoption of agricultural technologies in India between 1997 and 2012. To the best of our knowledge, this is the first paper to analyze the effect of mobile phone coverage on technology adoption at this level of variation and with administrative data covering a significant share of Indian farmers.

In terms of identification, we propose a new empirical strategy that exploits variation in the construction of mobile phone towers under a large government program aimed at increasing mobile coverage in rural areas. In particular, we compare cells covered by new towers with similar cells where new tower construction was proposed but eventually not realized.

Our findings indicate that areas receiving mobile phone coverage experienced faster adoption of modern agricultural technologies, such as high-yielding varieties of seeds, and of complementary inputs of production, such as fertilizers and irrigation. We argue that this effect is driven by increased access to information by farmers, and present evidence consistent with this argument using detailed data on farmers' calls. We show in particular that farmers in areas covered by mobile phones have greater access to direct information about the existence or optimal use of modern technologies, and to information about credit programs that can help them overcome financial constraints, which may further indirectly foster technology adoption.

Although nowadays the mobile phone network covers almost the entirety of India, advancements have been made in recent years towards the expansion of the 3G/4G mobile services and universal availability of broadband Internet. These ICT enhancements have been contemporaneously met with rise in social media, online information-sharing websites and smart-phone applications. These digital platforms can further help the diffusion of information among farmers. We leave the question of how advancements in digital ICT foster technological adoption for future research.

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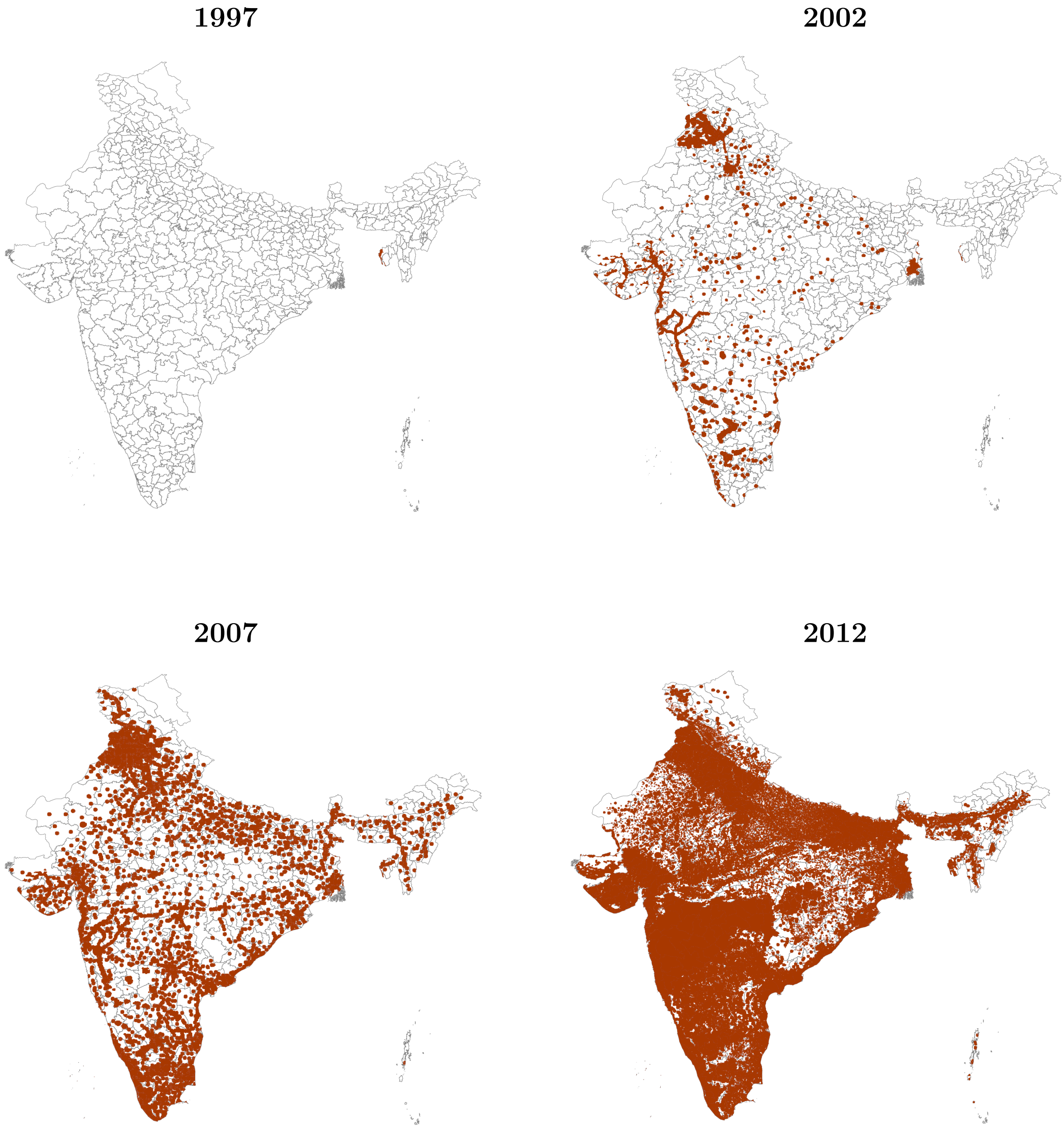
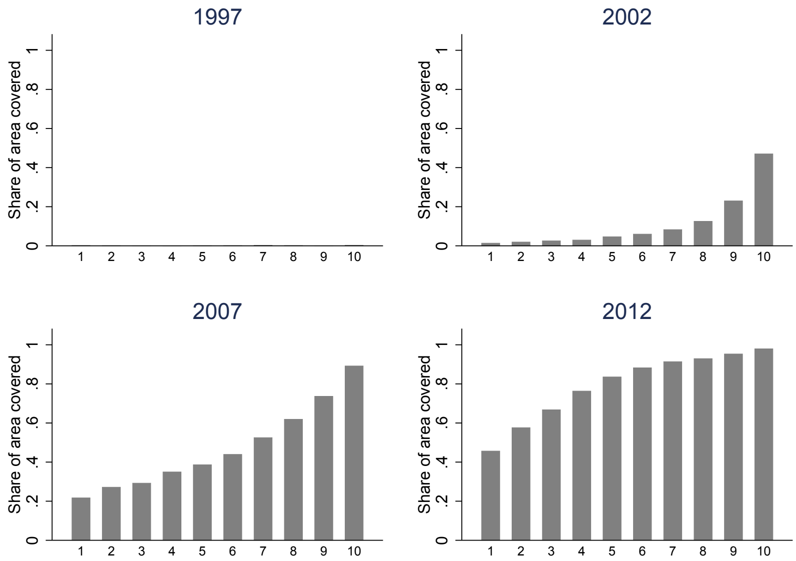
Figures and Tables

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



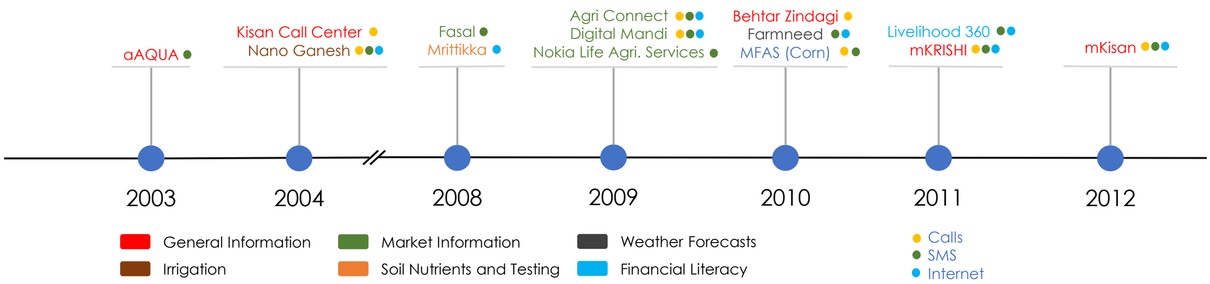
Notes: The figure reports geo-referenced data on mobile phone coverage for all of India at five-year intervals between 1997 and 2012. Source: GSMA.

Figure II: Mobile Phone Coverage by Night Light Intensity



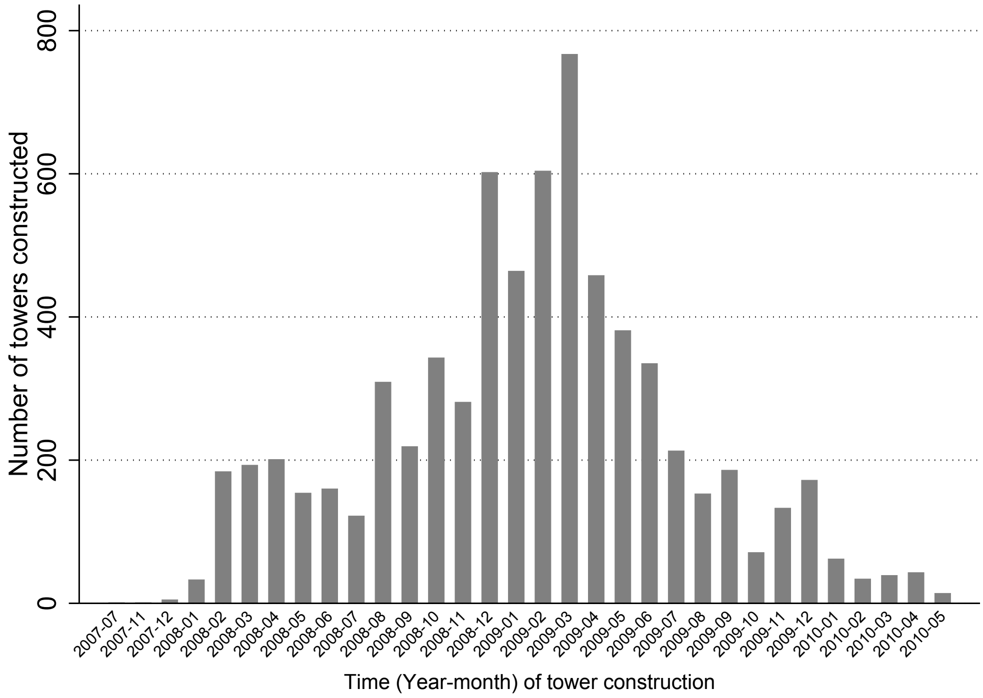
Notes: The average share of land with mobile phone coverage in each decile is calculated for the 4 years in which the Agricultural Input Survey was conducted: 1997, 2002, 2007 and 2012. Night Light Intensity data refers to 1996.

Figure III: Indian Providers of Agricultural Advice Services: A Timeline



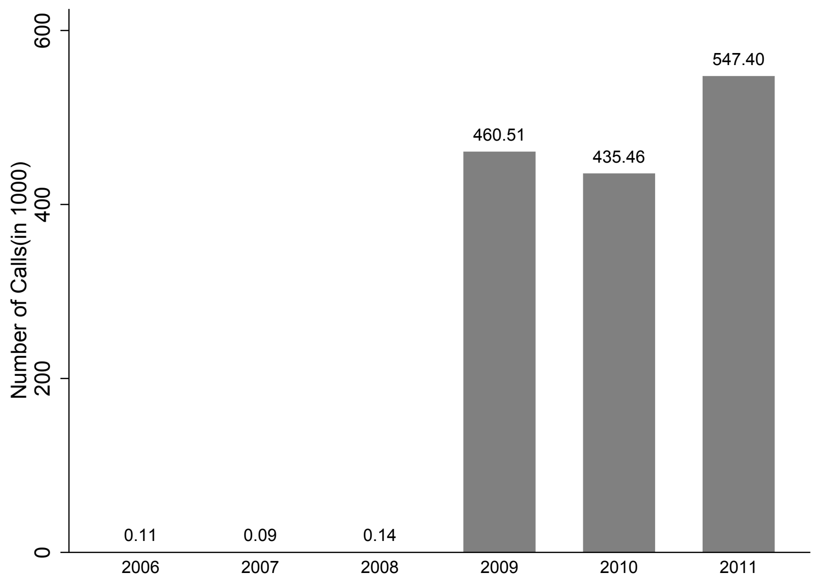
Notes: Source: GSMA mAgri Deployment Tracker

Figure IV: Timeline of tower construction under SMIP Phase I



Notes: Source: Department of Telecommunications, India

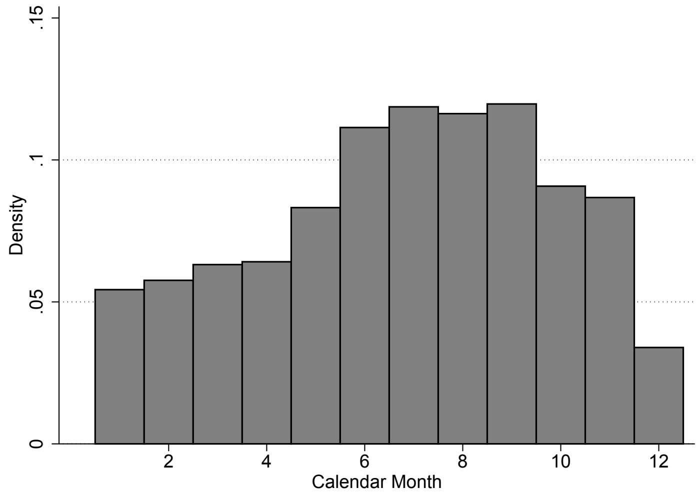
Figure V: Total Number of Calls to Kisan Call Centers: 2006-2011



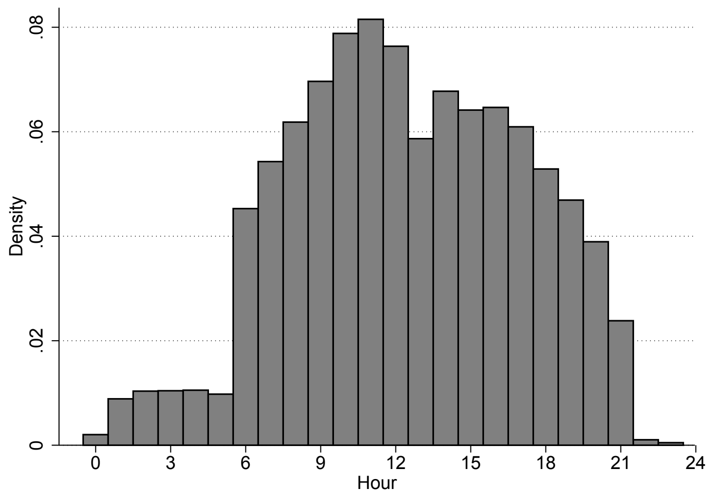
Notes: Source: Kisan Call Center, Ministry of Agriculture

Figure VI: Distribution of calls made to kisan call center

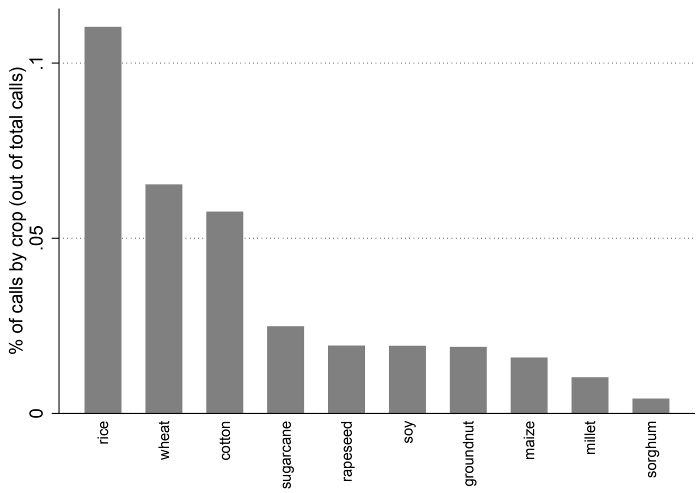
(a) Calls by Calendar Month



(b) Calls by Time of Day



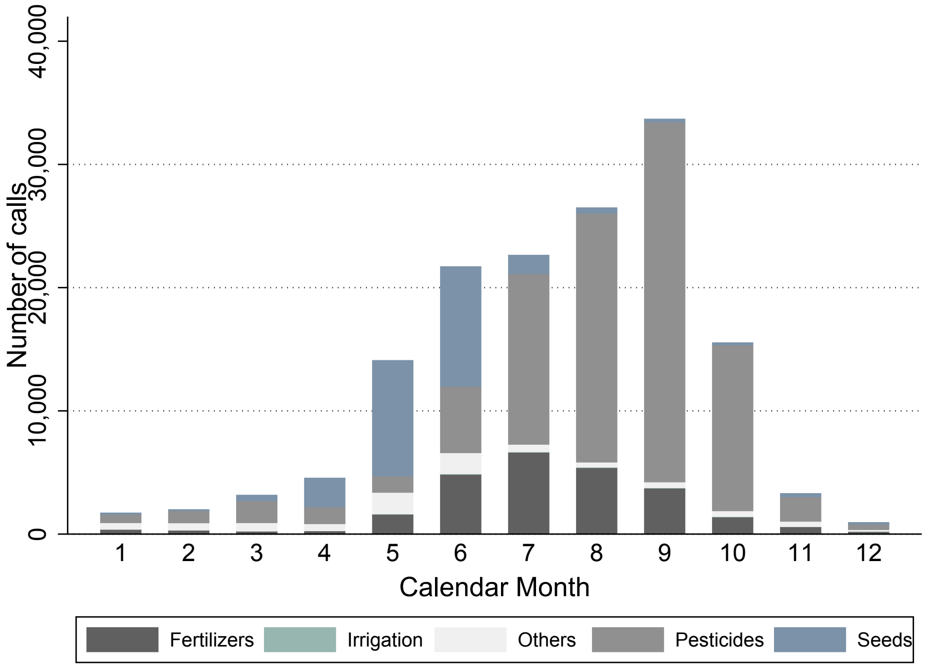
(c) Calls by Crop



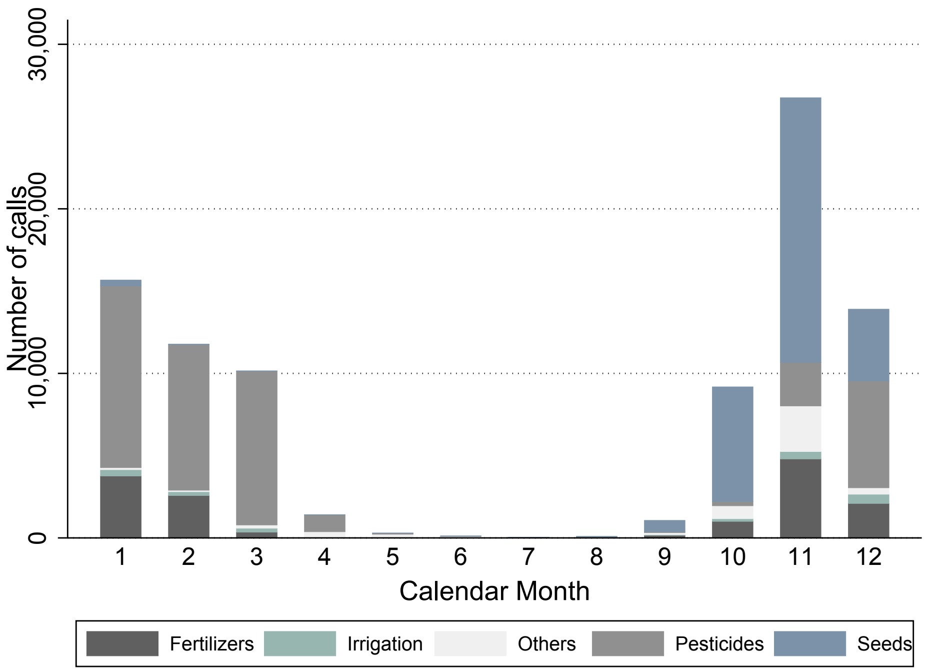
Notes: Source: Kisan Call Center, Ministry of Agriculture

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

(a) Rice

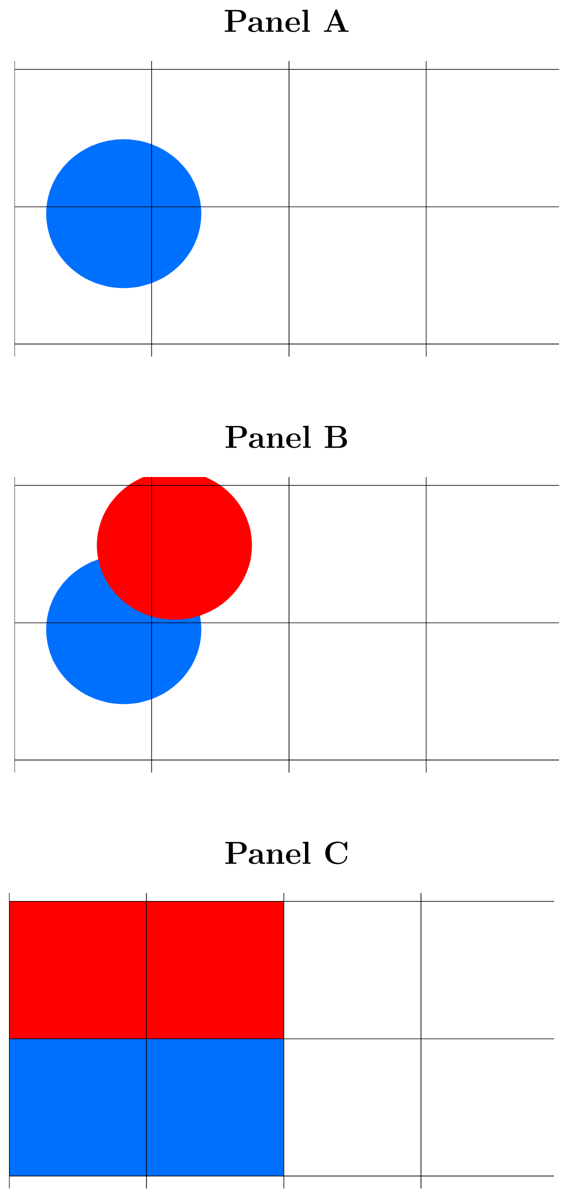


(b) Wheat



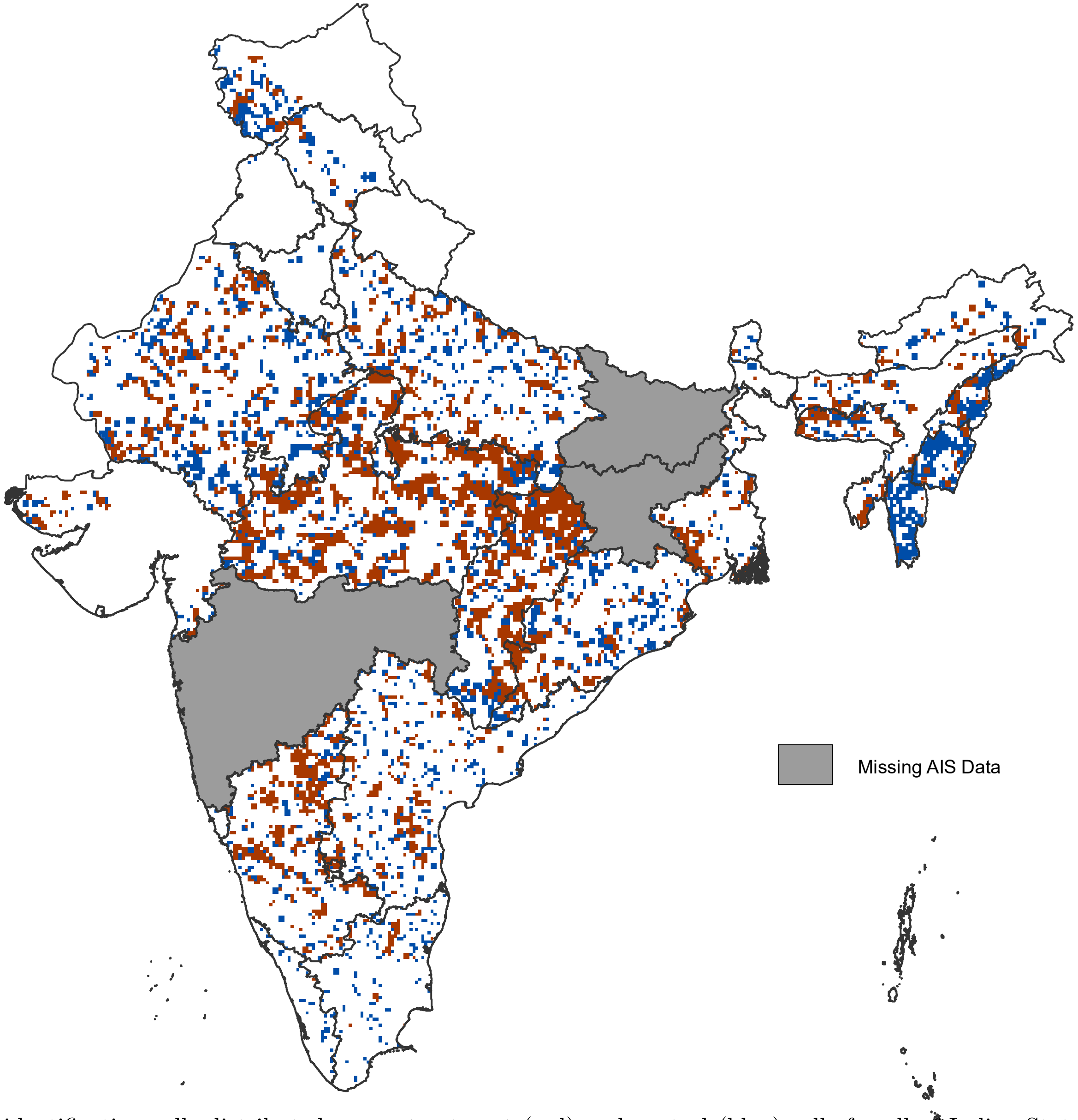
Notes: Source: Kisan Call Center, Ministry of Agriculture

Figure VIII: An example of classification of cells into treatment and control groups



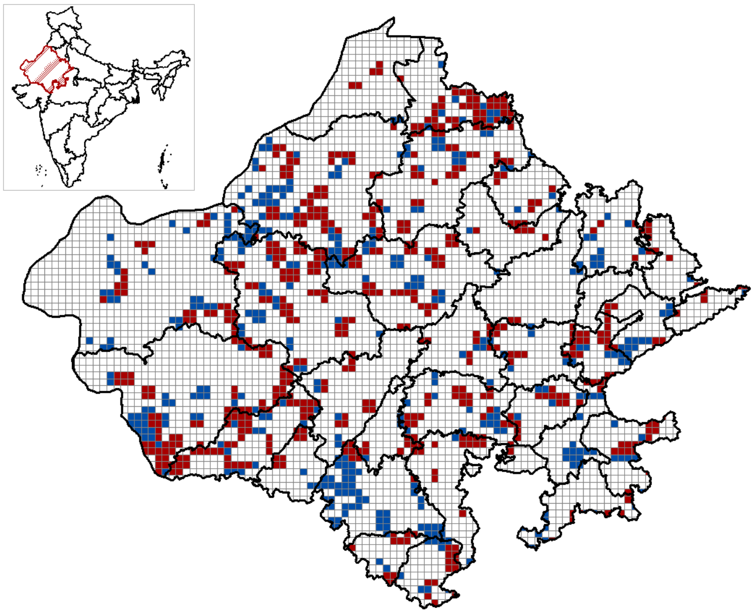
Notes: The figure provides an illustration of classification of cells into treatment(red) and control(blue) group. Panel A shows area covered by a *proposed* tower under SMIP. Panel B shows the area covered by an *actual* tower eventually constructed. Panel C shows the assignment of cells into treatment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

Figure IX: Treatment and Control cells under SMIP



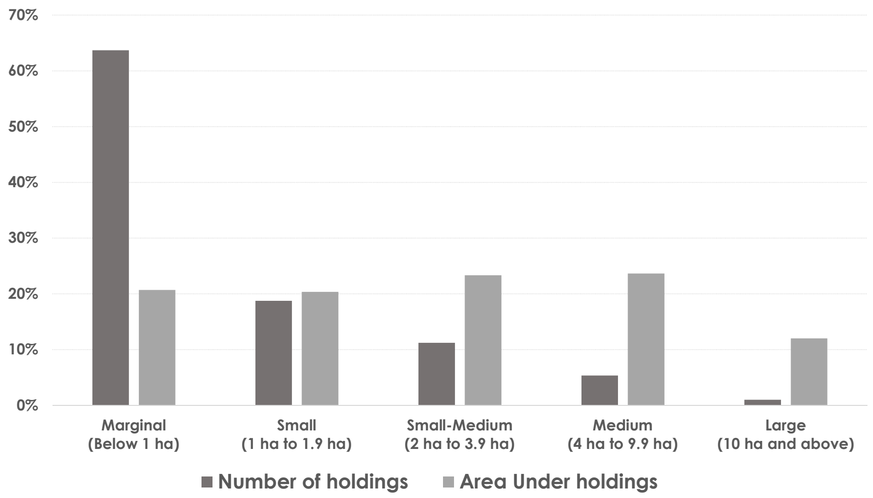
Notes: The figure shows the 6,562 identification cells distributed across treatment (red) and control (blue) cells for all of India. State borders are marked in black. Treatment cells are those that are both proposed *and* covered by mobile tower under SMIP Phase I. Control cells are those that are proposed *and not* covered by mobile towers under SMIP Phase I. Grey areas represent states with missing AIS information.

Figure X: Treatment and Control Cells
(Rajasthan State)



Notes: 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 SMIP Phase I. Control cells are those that are proposed *and not* covered by mobile tower under SMIP Phase I.

Figure XI: Distribution of number of holdings and area under cultivation , by size of holdings



Notes: Distribution of number of holdings and farmed area under various holding sizes. Source : Agricultural Input Survey.

Table I: Summary Statistics

	Mean	Median	Standard Deviation	N
All India				
Δ Coverage	0.283	0.096	0.437	26537
Δ HYV Share	0.024	0.007	0.06	26537
SMIP sample				
Δ Coverage	0.621	0.757	0.38	6562
Δ HYV Share	0.035	0.015	0.069	6562
Δ Fertilizer Share	0.027	0.018	0.064	6552
Δ Irrigation Share	0.012	0.003	0.04	6562
Δ Log ($\text{Calls}_{\text{All}}$)	0.928	0.802	0.767	6562
Δ Log ($\text{Calls}_{\text{Yield}}$)	0.299	0.149	0.396	6562
Δ Log ($\text{Calls}_{\text{Fertilizers}}$)	0.217	0.11	0.299	6562
Δ Log ($\text{Calls}_{\text{Irrigation}}$)	0.057	0.017	0.097	6562
Credit (per hectare):				
Δ Total Credit_{All}	767.05	163.47	1273.78	6562
Δ Total Credit_{ST}	655.82	173.89	1009.67	6562
Δ Total Credit_{LT}	32.84	0	387.68	6562
Δ Bank Credit_{All}	404.66	13.85	780.83	6562
Δ Bank Credit_{ST}	319.32	4.65	504.89	6562
Δ Bank Credit_{LT}	2.56	0	200.26	6562
District-level variables				
Δ Coverage	0.235	0.249	0.232	419
Δ Log ($\text{Calls}_{\text{Credit}}$)	0.341	0.288	0.456	419
Δ Total Credit_{All}	1028.8	382.89	2323.77	419
Δ Total Credit_{ST}	620.05	175.78	1564.59	419
Δ Total Credit_{LT}	455.38	0	1422.64	419

Notes: Changes in variables are calculated over the interval of five years from 2007-2012. Unit of observation is a cell, unless specified. Only cells with non-missing Δ HYV values considered. SMIP sample includes all cells used for identification. Credit variables are in Rupees per hectare.

Table II: Basic Correlations: HYV Share and Mobile Coverage

	2007-2012		2002-2007		1997-2002	
	(1)	(2)	(3)	(4)	(5)	(6)
Δ Coverage	0.021***	0.004***	-0.004	0.000	-0.005	0.002
	[0.005]	[0.001]	[0.003]	[0.001]	[0.006]	[0.002]
Observations	26,537	26,537	26,537	26,537	26,537	26,537
R-squared	0.023	0.837	0.001	0.808	0.000	0.835
District f.e.		✓		✓		✓

Notes: Changes in dependent variables are calculated over the interval of five years *i.e.* waves (1997-2002, 2002-2007, 2007-2012). The unit of observation is a 10-by-10 *km* cell. Δ Coverage is the change in the share of cell area covered under GSM mobile coverage calculated over the five years corresponding to the wave. For each wave, Column (1), (3) and (5) reports correlation without district-fixed effects and Column (2), (4) and (6) reports correlations with the district-fixed effects. Only cells with non-missing Δ HYV value across all waves considered. Standard errors clustered at district level are reported in brackets. Significance level: *** p<0.01, ** p<0.05, * p<0.1 .

Table III: Determinants of Tower Relocation/Cancellation

Dependent variable:	𝟙 (Tower)			
	(1)	(2)	(3)	(4)
Population (1000's)	0.007***			0.005***
	[0.001]			[0.001]
Power Supply		0.181***		0.113***
		[0.037]		[0.035]
Ruggedness			-0.090***	-0.068***
			[0.014]	[0.015]
Observations	6,562	6,562	6,562	6,562
R-squared	0.229	0.225	0.229	0.239
District f.e.	✓	✓	✓	✓

Notes: The table reports the correlations of main determinants of tower relocation or cancellation i.e. cell's population, the availability of power supply and average ruggedness with probability of being covered by a tower under SMIP Phase I (𝟙 (Tower)). Column (1)-(3) report the coefficients from a univariate OLS regression of probability of being covered by a tower under SMIP Phase I (𝟙 (Tower)) on each determinant of tower relocation or cancellation. Column (4) reports the coefficient from a multivariate OLS regression of 𝟙 (Tower) on the determinants of tower relocation or cancellation. All specifications control for district fixed effects. 𝟙 (Tower) is a dummy variable that takes the value of 1 if a cell is both proposed *and* covered by a tower (Treatment) under SMIP Phase I and takes the value of 0 if a cell is proposed *and not* covered (Control). The sample includes all cells with zero cell phone coverage in 2006. Standard errors clustered at district level are reported in brackets. Significance level: *** p<0.01, ** p<0.05, * p<0.1 .

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

Dependent variable:	coeff.	R^2
	(1)	(2)
Agri. Workers/Working Pop.	0.010	0.344
	(0.006)	
Percent Irrigated	0.001	0.616
	(0.009)	
Literacy Rate	0.005	0.594
	(0.004)	
Education Facility	0.003	0.475
	(0.006)	
Medical Facility	-0.003	0.426
	(0.010)	
Banking Facility	-0.005	0.183
	(0.004)	
# Phone conn. per 1000 people	-0.226	0.105
	(0.382)	
Dist. to nearest town(kms)	-2.916	0.561
	(1.832)	
Night Lights (2006)	-0.077	0.488
	(0.054)	
Income per capita	-0.387	0.152
	(12.902)	

Notes: The table reports the differences in the correlation of cell-characteristics across treatment and control cells. Column (1) reports the coefficient from a univariate OLS regression of each dependent variable on probability of being covered by a tower under SMIP Phase I ($\mathbb{1}$ (Tower)) controlling for district fixed effects, and determinants of tower relocation *i.e.* cell's population, the availability of power supply and average ruggedness. Column (2) reports the R^2 of the regression. The treatment variable $\mathbb{1}$ (Tower) is a dummy variable that takes the value of 1 if a cell is both proposed *and* covered by a tower (Treatment) under SMIP Phase I and takes the value of 0 if a cell is proposed *and not* covered (Control). The sample includes all cells with zero cell phone coverage in 2006. Standard errors clustered at district level are reported in brackets. Significance level: *** p<0.01, ** p<0.05, * p<0.1 .

Table V: First Stage

Dependent variable:	Δ GSMA Coverage(2007-2012)		
	(1)	(2)	(3)
𝟙 (Tower)	0.131***	0.080***	0.076***
	[0.016]	[0.013]	[0.013]
Population (1000's)		0.011***	0.008***
		[0.001]	[0.001]
Power Supply		0.215***	0.125***
		[0.026]	[0.026]
Ruggedness		-0.085***	-0.067***
		[0.012]	[0.010]
Observations	6,562	6,562	6,562
Number of districts	286	286	286
F-stat	68.00	35.78	35.45
Other Controls			✓
District f.e.	✓	✓	✓

Notes: This table reports first-stage regression of Δ GSMA Coverage on treatment variable 𝟙 (Tower). The unit of observation is a 10-by-10 *km* cell. Δ GSMA Coverage is change in the share of cell area under mobile coverage from 2007 to 2012, based on the data provided by telecom companies to GSMA. 𝟙 (Tower) is a dummy variable that takes the value of 1 if a cell is both proposed *and* covered by a tower under SMIP 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 GSMA Coverage on treatment variable. Column (2) includes baseline controls of cell's 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, literacy rate, access to a educational facility, access to a medical facility, access to a banking facility, number of telephones connections per 1000 people, distance to nearest town (in *kms.*), night light intensity, income per capita (in rupees). The sample includes all cells with zero cell phone coverage in 2006. 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. Significance level: *** p<0.01, ** p<0.05, * p<0.1.

TABLE VI: HYV SHARE AND MOBILE COVERAGE (2007-2012)

	OLS		IV-2SLS		Reduced Form	
	(1)	(2)	(3)	(4)	(5)	(6)
Δ Coverage	0.011***	0.009***	0.043***	0.044***		
	[0.003]	[0.003]	[0.015]	[0.015]		
$\mathbb{1}$ (Tower)					0.003***	0.003***
					[0.001]	[0.001]
Observations	6,562	6,562	6,562	6,562	6,562	6,562
R-squared	0.854	0.855	0.841	0.841	0.853	0.855
District f.e.	✓	✓	✓	✓	✓	✓
Baseline Controls	✓	✓	✓	✓	✓	✓
Other Controls		✓		✓		✓

Notes: The dependent variable is the change in share of area cultivated under HYV between 2007-2012. The unit of observation is a 10-by-10 *km* cell. ΔCoverage is the change in the share of cell area covered under GSM mobile coverage between 2007-2012. $\mathbb{1}$ (Tower) is a dummy variable that takes the value of 1 if a cell is both proposed *and* covered by a tower under SMIP Phase I and takes the value of 0 if a cell is proposed *and not* covered. Column (1)-(2) reports the OLS coefficients; Column (3)-(4) reports coefficients from IV-2SLS where we instrument Δ Coverage using $\mathbb{1}$ (Tower); and Column (5)-(6) reports reduced form results. All columns controls for district fixed effects. Odd columns include baseline controls for cell's population, the availability of power supply and average ruggedness. Even columns also include other controls for the cell including share of labor force employed in agricultural sector, share of agricultural land that is irrigated, literacy rate, access to a educational facility, access to a medical facility, access to a banking facility, number of telephones connections per 1000 people, distance to nearest town (in *kms.*), night light intensity, income per capita (in rupees). The sample includes all cells with zero cell phone coverage in 2006. Standard errors clustered at district level are reported in brackets. Significance level: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table VII: HYV Share and SMIP Tower Placements: Pre-Existing Trends

	2007-2012		2002-2007		1997-2002	
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{1}$ (Tower)	0.003***	0.003***	0.000	0.000	0.002	0.001
	[0.001]	[0.001]	[0.001]	[0.001]	[0.003]	[0.003]
Observations	5,223	5,223	5,223	5,223	5,223	5,223
R-squared	0.865	0.868	0.854	0.855	0.881	0.883
District f.e.	✓	✓	✓	✓	✓	✓
Baseline Controls	✓	✓	✓	✓	✓	✓
Other Controls		✓		✓		✓

Notes: This table tests for pre-existing trends in the change in HYV coverage between all consecutive waves of Agricultural Input Survey and the probability of being covered by SMIP Phase I towers ($\mathbb{1}$ (Tower)). The unit of observation is a 10-by-10 *km* cell. Changes in dependent variables are calculated over 2007-2012 in Column (1)-(2); 2002-2007 in Column (3)-(4) and 1997-2002 in Column (5)-(6). $\mathbb{1}$ (Tower) is a dummy variable that takes the value of 1 if a cell is both proposed *and* covered by a tower under SMIP Phase I and takes the value of 0 if a cell is proposed *and not* covered. All columns controls for district fixed effects. Odd columns include baseline controls for cell's population, the availability of power supply and average ruggedness. Even columns also include other controls for the cell including share of labor force employed in agricultural sector, share of agricultural land that is irrigated, literacy rate, access to a educational facility, access to a medical facility, access to a banking facility, number of telephones connections per 1000 people, distance to nearest town (in *kms.*), night light intensity, income per capita (in rupees). The sample includes all cells with zero cell phone coverage in 2006. Standard errors clustered at district level are reported in brackets. Significance level: *** p<0.01, ** p<0.05, * p<0.1.

Table VIII: Technology Adoption and Mobile Coverage: 2SLS (2007-2012)

	A. Δ Share of Area under Fertilizers		
	Total Area	Area under HYV	Area not under HYV
	(1)	(2)	(3)
Δ Coverage	0.034*	0.048**	-0.011
	[0.019]	[0.019]	[0.012]
Observations	6,552	6,552	6,552
R-squared	0.821	0.834	0.879
District f.e.	✓	✓	✓
Baseline Controls	✓	✓	✓
Other Controls	✓	✓	✓
	B. Δ Share of Area Irrigated		
	Total Area	Area under HYV	Area not under HYV
	(1)	(2)	(3)
Δ Coverage	0.012	0.023	-0.011
	[0.013]	[0.016]	[0.008]
Observations	6,562	6,562	6,562
R-squared	0.757	0.788	0.799
District f.e.	✓	✓	✓
Baseline Controls	✓	✓	✓
Other Controls	✓	✓	✓

Notes: The table reports the IV-2SLS estimates of effect of mobile coverage on share of area under fertilizers (Panel A) and share of area irrigated (Panel B) between 2007-2012. The unit of observation is a 10-by-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 SMIP Phase I and takes the value of 0 if a cell is proposed *and not* covered. Column (1) shows the estimates for total area; Column (2) reports the estimates for area cultivated with HYV seeds and Column (3) reports the estimates for area not cultivated with HYV seeds. All columns include district fixed effects. Baseline controls include cell's 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, literacy rate, access to a educational facility, access to a medical facility, access to a banking facility, number of telephones connections per 1000 people, distance to nearest town (in *kms.*), night light intensity, income per capita (in rupees). The sample includes all cells with zero cell phone coverage in 2006. Standard errors clustered at district level are reported in brackets. Significance level: *** p<0.01, ** p<0.05, * p<0.1 .

Table IX: Farmers' Calls and Mobile Coverage: 2SLS

	Δ log (Calls)			
Calls on:	All	Seeds	Fertilizers	Irrigation
	(1)	(2)	(3)	(4)
Δ Coverage	0.772***	0.317**	0.201***	0.077***
	[0.214]	[0.138]	[0.074]	[0.027]
Observations	6,562	6,562	6,562	6,562
R-squared	0.813	0.825	0.851	0.771
District f.e.	✓	✓	✓	✓
Baseline Controls	✓	✓	✓	✓
Other Controls	✓	✓	✓	✓

Notes: The table reports the IV-2SLS estimates of effect of change in mobile coverage on change in (log) calls received at KCC. The unit of observation is a 10-by-10 *km* cell. Changes are calculated over 2007-2012. 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 SMIP Phase I and takes the value of 0 if a cell is proposed *and not* covered. Column (1) includes all calls for which crop information is available; Column (2) includes only calls on crop-yields; Column (3) includes only calls on fertilizers and Column (4) includes only calls on irrigation. All columns include district-fixed effects. Baseline controls include cell's 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, literacy rate, access to a educational facility, access to a medical facility, access to a banking facility, number of telephones connections per 1000 people, distance to nearest town (in *kms.*), night light intensity, income per capita (in rupees). The sample includes all cells with zero cell phone coverage in 2006. Standard errors clustered at district level are reported in brackets. Standard errors clustered at district level are reported in brackets. Significance level: *** p<0.01, ** p<0.05, * p<0.1 .

Table X: Baseline Correlations:
Agricultural Credit and Mobile Coverage

	Calls	**Credit**		
	Δ log(Calls)$_{\text{Credit}}$	ΔCredit$_{\text{Total}}$ (per hectare)	ΔCredit$_{\text{ST}}$ (per hectare)	ΔCredit$_{\text{LT}}$ (per hectare)
	(1)	(2)	(3)	(4)
Δ Coverage	0.630***	876.500*	899.674***	-254.241
	[0.095]	[455.919]	[299.525]	[296.125]
Observations	419	419	419	419
R-squared	0.103	0.008	0.018	0.002

Notes: Changes in dependent variables are calculated over 2007-2012. The unit of observation is a district. ΔCoverage is the change in the share of district area covered under GSM mobile coverage between 2007-2012 . Column (1) is the change in log of number of calls about credit; Column (2) is the change in total agricultural credit per hectare; Column (3) is the change in short-maturity agricultural credit per hectare and Column (4) is the change in long-maturity agricultural credit per hectare. Short-maturity is defined as credit with maturity less than or equal to 18 months and long-maturity credit represents credit with maturity of greater than 18 months. Calls data is from Kisan Call Center (KCC) and agricultural credit data is from Agricultural Input Survey (AIS). Credit outcomes are winsorized at 10% level and are reported in rupees per hectare. Standard errors clustered at district level are reported in brackets. Significance level: *** p<0.01, ** p<0.05, * p<0.1.

Table XI: Credit and Mobile Coverage: 2SLS

	Panel A: Δ **Total Credit (per hectare)**							
	Credit by maturity			*Short-maturity credit by holding size*				
	Total	Short	Long	Very-Small	Small	Small-Medium	Medium	Large
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δ Coverage	392.791	325.811	-88.293	129.974*	75.710	73.107	43.112	7.014
	[283.583]	[245.552]	[65.747]	[72.269]	[45.888]	[46.678]	[32.299]	[4.454]
Observations	6,562	6,562	6,562	6,562	6,562	6,562	6,562	6,562
R-squared	0.900	0.895	0.926	0.935	0.918	0.918	0.916	0.914
District f.e.	✓	✓	✓	✓	✓	✓	✓	✓
Baseline Controls	✓	✓	✓	✓	✓	✓	✓	✓
Other Controls	✓	✓	✓	✓	✓	✓	✓	✓
	Panel B: Δ **Commercial Bank Credit (per hectare)**							
	Credit by maturity			*Short-maturity credit by holding size*				
	Total	Short	Long	Very-Small	Small	Small-Medium	Medium	Large
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δ Coverage	218.138*	221.061**	27.053	69.748*	28.900	8.551	3.208	1.712*
	[125.797]	[87.892]	[38.470]	[41.747]	[18.215]	[8.568]	[3.565]	[1.010]
Observations	6,562	6,562	6,562	6,562	6,562	6,562	6,562	6,562
R-squared	0.926	0.920	0.941	0.936	0.938	0.950	0.956	0.930
District f.e.	✓	✓	✓	✓	✓	✓	✓	✓
Baseline Controls	✓	✓	✓	✓	✓	✓	✓	✓
Other Controls	✓	✓	✓	✓	✓	✓	✓	✓

Notes: The table reports the IV-2SLS estimates of effect of mobile coverage on credit outcomes between 2007-2012. The unit of observation is a 10-by-10 *km* cell. Panel A shows the change in total agricultural credit. Panel B shows the change in total agricultural credit provided by commercial banks. Column (1) is the change in total agricultural credit per hectare; Column (2) is the change in short-maturity agricultural credit per hectare and Column (3) is the change in long-maturity agricultural credit per hectare. Column (4)-(8) breaks down short-maturity credit by holding sizes - very small (below 1 hectare), small (1 to 2 ha), small-medium (2 to 4 ha), medium (4 to 10 ha) and large (10 and above ha). Short-maturity is defined as credit with maturity less than or equal to 18 months and long-maturity represents credit with maturity of greater than 18 months. The agricultural credit data is from Agricultural Input Survey (AIS). All credit outcomes are winsorized at 10% level. Baseline and other controls are as described in Table IX. The sample includes all cells with zero cell phone coverage in 2006. Standard errors clustered at district level are reported in brackets. Significance level: *** p<0.01, ** p<0.05, * p<0.1.

Appendix

A Kisan Call Center Calls

In this section we describe our methodology used to clean the farmer's call received in Kisan Call Centers (KCC) to extract crop information and type of query made by farmers. In only less than 10% of the cases, both the correct information on crop and category of query is recorded in the data by the agronomist. In the remaining cases when information on any of these fields are missing, we use the details recorded in two text fields available in the KCC data i.e. farmer's query and agronomist's answer, to obtain the information. To illustrate this better, consider the following calls received in 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 in the KCC data information on crop is missing under the "Crop" field but is clearly available when one reads the text of the query. Similarly in Call 2, the farmer inquires how to control termites (which is incorrectly recorded as "temites" in QueryText) for Soyabean crop. Similar to previous call both the crop information and category of call is missing in the recorded data. We use the information in "QueryText" to deduce the crop for the call is *Soyabean*. We also use the information in "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 query or KCC answer to the query. In many cases, crops names are recorded in the 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.[39] Here we describe in detail the assignment of main query categories used in the paper - calls on seeds, fertilizers, irrigation and credit.

[39]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 provide are associated with 90% of the calls. We collapse all categories with lower than 1% calls into a combined category of "Others" which in total makes up about 10% of the calls.

Calls on Seeds: We classify calls made to obtain information on hybrid seed varieties or calls made to inquire about seed varieties as calls on seeds by farmers. We use the following keywords in either text of query or agronomist's answer to classify 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 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: In order to classify calls on fertilizers, we identify the use of following keywords in either of farmer's queries or agronomist's replies: (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 farmer's 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 first two calls farmers ask about the suitable time for particular stages of irrigation. In the last case, farmer seeks information on 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 Credit: We use the following keywords in either text of query or text of agronomist's answer to classify calls on credit: (i) calls seeking information on Kisan Credit Card [40] (ii) calls asking about process to obtain a loan (iii) calls about various government subsidies (iv) calls related to information on specific bank's address or contact information (v) inquiries about Kisan Mela [41]. Table A.4 below provides few examples of calls on credit after applying our methodology described above. As can be seen in the Table, and described in Section V.C.2, information on crops is missing for majority of queries on credit.

Table A.4: Sample calls on Credit

Sno	Date	State	District	Crop	QueryType	QueryText	Answer
1	10/13/2009	Rajasthan	Alwar	-	Credit	How to get Kisan Credit Card	Contact your nearest bank
2	07/13/2010	Andhra Pradesh	Kapada	-	Credit	Asked about Agri. Loans	Provided details as per data
3	07/29/2010	Orissa	Baragarh	Groundnut	Credit	Subsidy on Oilseed	Answer given in details
4	12/18/2010	Uttar Pradesh	Buland- -shahar	-	Credit	Info. related to SBI Bank	Contact toll-free # 1-800-425-3800
5	09/17/2011	Haryana	Hisar	-	Credit	Kisan Mela Date in Hisar	18-19th September

[40]Keywords for detecting Kisan Credit Cards include Kisan Card, KCC Card, Credit Card

[41]Kisan Mela *i.e.* farmer's gathering is an initiative by State Bank of India — the largest state-owned bank by assets in India — to educate farmer's about their rights and the bank's credit initiatives.

B Data Validation: HYV Adoption

In this section we propose a validation of our main measure of technology adoption at cell level, i.e. share of cell area farmed under HYV seeds. Recall from Section IV.A that we observe HYV seeds adoption at district-crop level and we use a neutral assignment rule to construct a proxy of adoption at cell-level within each district. Thus, it is important to validate whether this measure captures actual adoption at fine geographical level using publicly-available data on HYV seeds adoption.

We should emphasize that information on the use of HYV seeds at fine geographical level is seldom available. Two publicly available survey data that report such information at the village level are ICRISAT Village Dynamics in South Asia (VDSA) and Tamil Nadu Socioeconomic Mobility Survey (TNSMS) conducted by the Economic Growth Center at Yale University. Both surveys collect information on cultivation practices (including use of HYV seeds) from a randomly selected sample of Indian households in a limited number of villages.

For this validation exercise we will focus on the VDSA data. This is because VDSA reports village identifiers, allowing us to match each village with one of the 10×10 km cells used in our empirical analysis. On the other hand, TNSMS does not provide village identifiers in its publicly available version. The VDSA survey covers 17 villages spanning five Indian states (Andhra Pradesh, Gujarat, Karnataka, Madhya Pradesh and Maharashtra).[42]

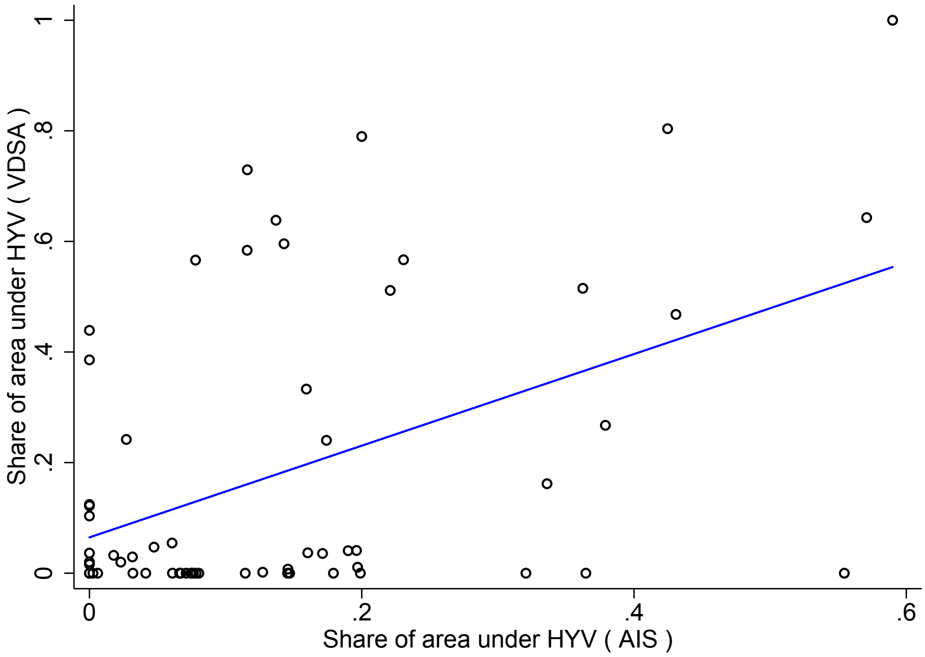
We start by calculating the share of land farmed with HYV seeds by crop in villages located in a given cell. Our sample for this test is composed by 61 cell-crop observations across 17 cells. This implies there is a unique matching between villages and cells, and that we have information on HYV adoption for 3.6 crops on average for each village. Next, we compute the correlation at cell-crop-level between the measure of share of land farmed with HYV seeds used in the empirical analysis of the paper and the one extracted from the VDSA data.

Figure B.1 reports the results. Panel (a) of Figure B.1 shows that our measure of technology adoption is strongly and positively correlated with the measure extracted from the VDSA survey: the slope of the line is 0.83 and statistically significant (t = 3.15). The relationship remains positive and significant if we drop all zeros across both the measures (slope = 1.06 and t = 4.33) , as shown in Panel (b). Although based on a very small sample, the positive and significant correlation between the two variables suggests that our measure of HYV share well captures variation in the actual share of area farmed under HYV seeds across cells.

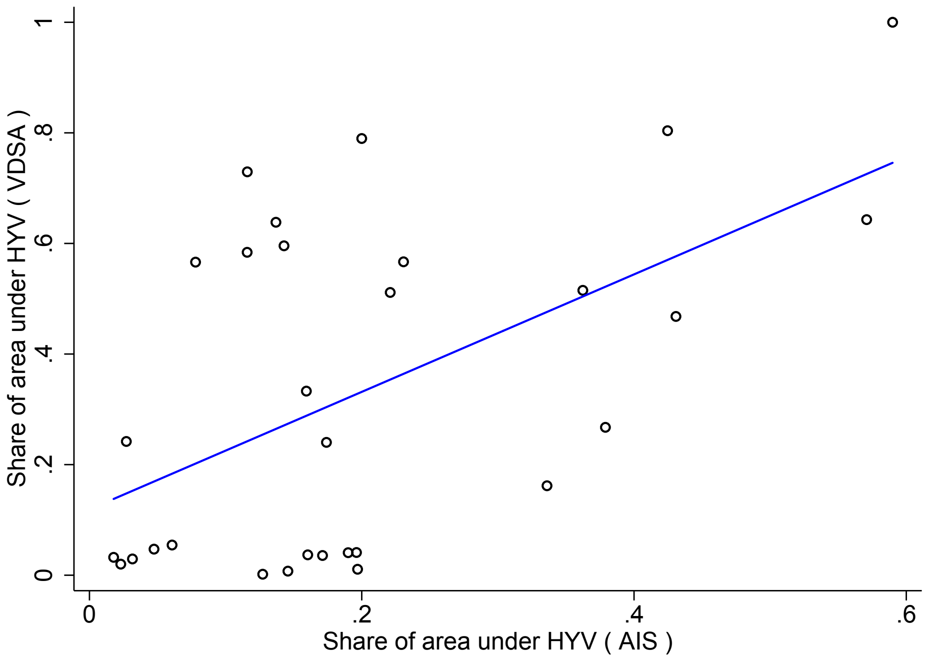
[42]VDSA only covers six villages consistently between 2002-2012. Four of these villages are in the state of Maharashtra. This limits our ability to compare our measure of *changes* in share of area under HYV seeds as AIS does not cover Maharashtra until 2012. We therefore only compare the *levels* of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

Figure B.1: Data Validation: HYV Adoption

(a) All observations (N=61)



(b) Excluding zeros (N=30)



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. Panel (a) has 61 observations and the slope of the line is 0.83 (t = 3.15). Panel (b) has 30 observations and the slope of the line is 1.06 (t = 4.33).

C Empirics: Additional Results

Table C.5: Summary Statistics on Cell Characteristics (SMIP Sample)

	Mean	**Median**	**Standard Deviation**	**N**
Population	13187	10177	12498	6562
Power Supply	0.777	0.967	0.318	6562
Ruggedness	0.841	0.302	1.405	6562
Δ HYV Share (2002-2007)	0.018	0.01	0.049	5256
Δ HYV Share (1997-2002)	0.023	0.014	0.1	5223
Agri. Workers/Working Pop.	0.578	0.584	0.159	6562
Percent Irrigated	0.249	0.147	0.274	6562
Literacy Rate	0.423	0.428	0.133	6562
Education Facility	0.866	0.944	0.189	6562
Medical Facility	0.344	0.286	0.283	6562
Banking Facility	0.059	0	0.117	6562
# phone conn. per 1000 people	1.379	0.255	7.137	6562
Dist. to nearest town(kms)	37.91	29.00	32.30	6562
Night Lights (2006)	1.119	0.27	1.684	6562
Income per capita	81.45	7.56	399.93	6562

Table C.6: Robustness to continuous measure (2SLS) (2007-2012)

	First Stage	**Δ Technology Adoption**			**Δ log (Calls)**				**Δ $\text{Credit}_{\text{ST}}$ (per hectare)**	
	Δ Coverage	HYV	Fertilizer and HYV	Irrigated and HYV	All	Seeds	Fertilizers	Irrigation	Total	Bank
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
% covered by SMIP	0.183***									
	[0.022]									
Δ Coverage		0.028**	0.022**	0.014*	0.438***	0.127**	0.080**	0.030***	136.796	91.696*
		[0.011]	[0.010]	[0.008]	[0.108]	[0.062]	[0.034]	[0.010]	[117.572]	[48.703]
Observations	6,562	6,562	6,552	6,562	6,562	6,562	6,562	6,562	6,562	6,562
F-stat	67.18									
R-squared		0.851	0.852	0.794	0.848	0.853	0.872	0.798	0.901	0.928
Baseline Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Other Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
District f.e.	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

Notes: Unit of observation is a 10-by-10 *km* cell. The tables reports robustness of our IV-2SLS estimates by using share of land covered by SMIP towers instead of an indicator variable as the treatment variable. Column (1) reports the first-stage regression of Δ GSMA Coverage on independent variable of area of cell covered by SMIP tower (% covered by SMIP). For Columns (2)-(10), ΔCoverage is the change in the share of cell area covered under GSM mobile coverage between 2007-2012 instrumented using % covered by SMIP. Columns (2)-(4) estimates the effect of change in mobile coverage on change in share of land under HYV seeds (Column 2), share of land under fertilizers and HYV seeds (Column 3) and share of irrigated land under HYV seeds (Column 4). Columns (5)-(8) estimates the effect of change in mobile coverage on change in number of (log) calls to the KCC. Column (5) estimates the effect on total calls, Column (6) estimates the effect on calls about seeds, Column (7) estimates the effect on calls about fertilizers and Column (8) estimates the effect on calls about irrigation. Columns (9)-(10) estimates the effect of change in mobile coverage on change in short-maturity credit per hectare. Column (9) estimates the effect on total short-maturity credit. Column (10) estimates the effect on short-maturity credit originated by commercial banks. Short-maturity is defined as credit with maturity less than or equal to 18 months. All columns include baseline controls, other controls and district fixed effect. Baseline controls include cell's 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, literacy rate, access to a educational facility, access to a medical facility, access to a banking facility, number of telephones connections per 1000 people, distance to nearest town (in *kms.*), night light intensity, income per capita (in rupees). Standard errors clustered at district level are reported in brackets. Significance level: *** p<0.01, ** p<0.05, * p<0.1.

Table C.7: Robustness: All cells under SMIP program (2SLS) (2007-2012)

	First Stage	**Δ Technology Adoption**			**Δ log (Calls)**				**Δ Credit$_{\mathbf{ST}}$ (per hectare)**	
	Δ Coverage	HYV	Fertilizer and HYV	Irrigated and HYV	All	Seeds	Fertilizers	Irrigation	Total	Bank
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
𝟙 (Tower)	0.059***									
	[0.011]									
Δ Coverage		0.056***	0.045***	0.034**	0.578***	0.223**	0.136*	0.051**	229.409	153.704*
		[0.016]	[0.017]	[0.013]	[0.200]	[0.103]	[0.076]	[0.022]	[185.992]	[78.855]
Observations	15,197	15,197	15,156	15,197	15,197	15,197	15,197	15,197	15,197	15,197
F-stat	28.09									
R-squared		0.755	0.808	0.727	0.853	0.889	0.893	0.853	0.917	0.926
District f.e.	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Baseline Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Other Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

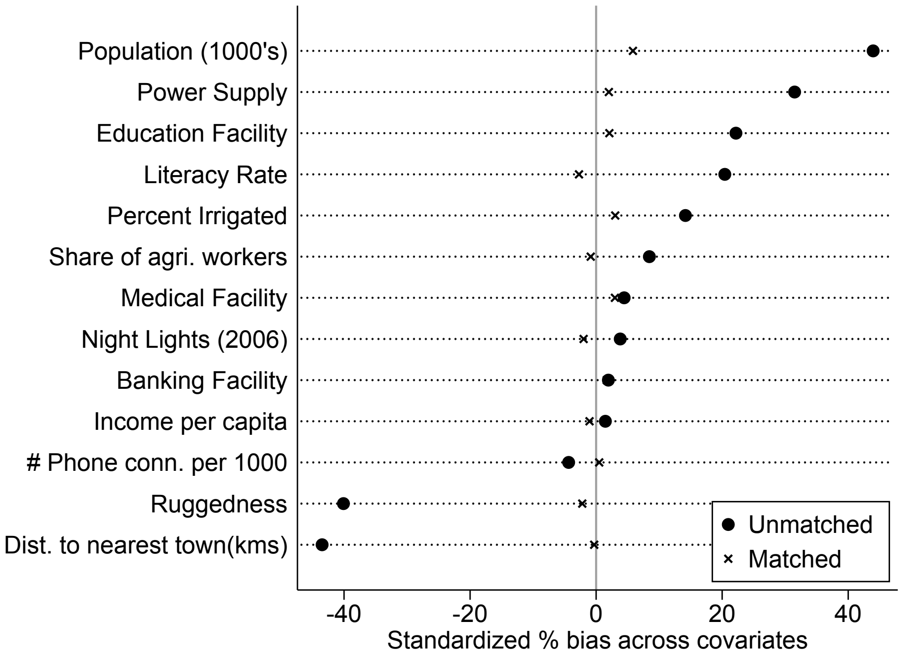
Notes: Unit of observation is a 10-by-10 *km* cell. The tables reports robustness of our IV-2SLS estimates by including all cells exposed to the SMIP program. Specifically, we no longer restrict our analysis to only cells with zero coverage in the year 2006. Column (1) reports the first-stage regression of Δ GSMA Coverage on treatment variable 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 SMIP Phase I and takes the value of 0 if a cell is proposed *and not* covered. For Columns (2)-(10), ΔCoverage is the change in the share of cell area covered under GSM mobile coverage between 2007-2012 instrumented using 𝟙 (Tower). Columns (2)-(4) estimates the effect of change in mobile coverage on change in share of land under HYV seeds (Column 2), share of land under fertilizers and HYV seeds (Column 3) and share of irrigated land under HYV seeds (Column 4). Columns (5)-(8) estimates the effect of change in mobile coverage on change in number of (log) calls to the KCC. Column (5) estimates the effect on total calls, Column (6) estimates the effect on calls about seeds, Column (7) estimates the effect on calls about fertilizers and Column (8) estimates the effect on calls about irrigation. Columns (9)-(10) estimates the effect of change in mobile coverage on change in short-maturity credit per hectare. Column (9) estimates the effect on total short-maturity credit. Column (10) estimates the effect on short-maturity credit originated by commercial banks. Short-maturity is defined as credit with maturity less than or equal to 18 months. All columns include baseline controls, other controls and district fixed effect. Baseline controls include cell's 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, literacy rate, access to a educational facility, access to a medical facility, access to a banking facility, number of telephones connections per 1000 people, distance to nearest town (in *kms.*), night light intensity, income per capita (in rupees). Standard errors clustered at district level are reported in brackets. Significance level: *** p<0.01, ** p<0.05, * p<0.1.

Table C.8: Heterogeneous effects based on exposure time

	Δ Technology Adoption			Δ log (Calls)
	HYV	Fertilizer and HYV	Irrigated and HYV	All calls
	(1)	(2)	(3)	(4)
𝟙 (Tower) × Lowest exposure quintile	0.002	0.002	0.001	0.041***
	[0.002]	[0.002]	[0.002]	[0.015]
𝟙 (Tower) × Second exposure quintile	0.002*	0.002	0.002	0.036**
	[0.001]	[0.002]	[0.001]	[0.015]
𝟙 (Tower) × Third exposure quintile	0.004*	0.005**	0.004**	0.053***
	[0.002]	[0.002]	[0.002]	[0.016]
𝟙 (Tower) × Fourth exposure quintile	0.004**	0.004**	0.002	0.046**
	[0.002]	[0.002]	[0.001]	[0.019]
𝟙 (Tower) × Highest exposure quintile	0.005*	0.005***	0.001	0.109**
	[0.003]	[0.002]	[0.002]	[0.054]
Observations	6,562	6,552	6,562	6,562
R-squared	0.855	0.854	0.797	0.863
Baseline Controls	✓	✓	✓	✓
Other Controls	✓	✓	✓	✓
District f.e.	✓	✓	✓	✓

Notes: Unit of observation is a 10-by-10 *km* cell. The table reports the heterogeneous effects of tower construction across cells based on their time under tower coverage. Cells are divided into exposure quintiles, with cells covered by last (first) 20% of SMIP towers belonging to the lowest (highest) exposure quintile. 𝟙 (Tower) is a dummy variable that takes the value of 1 if a cell is both proposed *and* covered by a tower under SMIP Phase I and takes the value of 0 if a cell is proposed *and not* covered. Columns (1)-(3) estimates the effect on change in share of land under HYV seeds (Column 1), share of land under fertilizers and HYV seeds (Column 2) and share of irrigated land under HYV seeds (Column 3). Column (4) estimates the effect on change in number of (log) calls to the KCC. All columns include baseline controls, other controls and district fixed effect. Baseline controls include cell's 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, literacy rate, access to a educational facility, access to a medical facility, access to a banking facility, number of telephones connections per 1000 people, distance to nearest town (in *kms.*), night light intensity, income per capita (in rupees). Standard errors clustered at district level are reported in brackets. Significance level: *** p<0.01, ** p<0.05, * p<0.1.

Figure C.2: Balancedness in the Unmatched and Matched (PSM) Samples



Notes: The graph reports the standardized percentage bias for the unmatched and the matched samples. The standardized percentage bias is the percentage difference in sample means between treated and control groups as a percentage of the square root of the average of the sample variances in the treated and control groups (Rosenbaum and Rubin (1985)). In the matched sample we impose exact matching in terms of district between treatment and control cells.

Table C.9: Balancedness in Matched Sample

Cell characteristic	Mean Treated	Control	$p > \|t\|$
Population (1000's)	14.3710	13.6720	0.008
Power Supply	0.8092	0.8024	0.265
Ruggedness	0.6318	0.6664	0.125
Agri. Workers/Working Pop.	0.5752	0.5767	0.624
Percent Irrigated	0.2638	0.2553	0.129
Literacy Rate	0.4297	0.4334	0.147
Education Facility	0.8739	0.8692	0.210
Medical Facility	0.3508	0.3418	0.121
Banking Facility	0.0614	0.0593	0.365
# Phone conn. per 1000 people	1.4012	1.2432	0.023
Dist. to nearest town(kms)	33.8390	33.9530	0.841
Night Lights (2006)	1.2287	1.2653	0.306
Income per capita	85.4640	90.9280	0.521

Table C.10: Technology Adoption and Mobile Coverage: Propensity Score Matching (2007-2012)

Dependent variables:	Δ HYV Area Share	Δ Fertilizers Area Share		Δ Irrigated Area Share	
		HYV	not HYV	HYV	not HYV
	(1)	(2)	(3)	(4)	(5)
$\mathbb{1}$ (Tower)	0.0049**	0.0036*	-0.0024	0.0031**	-0.0013
	[0.0023]	[0.0022]	[0.0018]	[0.0016]	[0.0009]
Observations (on support)	12,411	12,322	12,322	12,411	12,411
R-squared	0.033	0.027	0.003	0.007	0.002

Notes: The table reports the estimates obtained with propensity score matching. The variable $\mathbb{1}$ (Tower) is a dummy that takes the value of 1 if a cell is both proposed *and* covered by a tower under SMIP Phase I. In this case, a cell is considered as treated. Control cells are identified imposing exact matching for district and using propensity score matching for a large set of baseline covariates, including: population, availability of power supply, ruggedness, share of labor force employed in agricultural sector, share of irrigated agricultural land, literacy rate, presence of educational facility, medical facility, banking facility, number of telephone connections per 1000 people, distance to nearest town (in km), night light intensity, and income per capita (in rupees). The sample includes all cells with zero cell phone coverage in 2006. Robust standard errors are reported in brackets. Significance level: *** p<0.01, ** p<0.05, * p<0.1 .

Table C.11: Correlations: Agricultural Credit in Cell and Credit Facilities

	Credit_{All} (Rs. per hectare)		Credit_{ST} (Rs. per hectare)		Credit_{LT} (Rs. per hectare)	
	(1)	(2)	(3)	(4)	(5)	(6)
# Bank Branches	162.625***		93.947***		68.678***	
	[27.779]		[15.006]		[16.169]	
Distance to nearest Town(kms)		-4.411***		-3.067***		-1.344***
		[0.876]		[0.665]		[0.246]
Observations	150,232	150,232	150,232	150,232	150,232	150,232
R-squared	0.431	0.430	0.475	0.474	0.317	0.316
Wave f.e.	✓	✓	✓	✓	✓	✓
District f.e.	✓	✓	✓	✓	✓	✓

Notes: The unit of observation is a 10-by-10 *km* cell. The table reports correlation between total credit in cell (based on equation (5)) and bank branches (odd columns); distance to nearest town in *kms*. (even columns) for the cell. Columns (1)-(2) is total agricultural credit per hectare; Column (3)-(4) is total short-maturity agricultural credit per hectare and Column (5)-(6) is total long-maturity agricultural credit per hectare. Short-maturity is defined as credit with maturity less than or equal to 18 months and long-maturity credit represents credit with maturity of greater than 18 months. All columns include district and wave fixed effects. Agricultural credit data is from Agricultural Input Survey (AIS). Standard errors clustered at district level are reported in brackets. Significance level: *** p<0.01, ** p<0.05, * p<0.1.