Technology Adoption and Access to Credit Via Mobile Phones*

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Abstract

We study the effect of mobile phone coverage on technology adoption and access to credit by Indian farmers. Our units of observation are 10×10 km cells for which we observe the evolution of mobile phone coverage, land use and agricultural inputs between 1997 and 2012. Our empirical strategy 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 towers were proposed but eventually not realized. We find that areas receiving mobile phone coverage experience faster adoption of high-yielding varieties of seeds, and higher increase in access to credit by small farmers. To explore how mobile phones can reduce farmers' information gap on new technologies and facilitate access to credit we analyze the content of 1.4 million geo-localized calls to a major call center for agricultural advice.

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I Introduction

Over the past two decades, the rapid spread of mobile phones across low-income countries has raised expectations about their potential to overcome informational barriers and provide economic opportunities to those previously unconnected (World Bank, 2016). One sector where mobile phones' transformative potential is especially relevant is agriculture. While 70 percent of the population in low-income countries still derive their livelihood from agriculture, limited access to information about optimal practices and inputs has traditionally constrained farmers' adoption of modern agricultural technologies (Foster and Rosenzweig, 1995; Conley and Udry, 2010; Jack, 2013). This has resulted in large gaps in crop yields: still in 2012, for example, yields of major crops such as wheat and rice in low-income countries were about half of those in high-income countries (FAO, 2017).

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.[1]

By making it possible to collect and deliver information to farmers at low cost, mobile phones can reduce the information frictions that prevent technology adoption in agriculture. Recent work using randomized controlled trials to study the effect of agricultural extension programs via mobile phones suggests that there is indeed a large demand for agricultural advice among farmers in developing countries, and that mobile-based services for agricultural advice affect agricultural practices and – in some instances – yields (Casaburi et al., 2014; Cole and Fernando, 2016).

In this paper we provide large-scale evidence on the effect of mobile phone coverage on technology adoption by farmers in India. To this end, we match detailed administrative 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 for the whole of India. Using variation across 10×10 km cells over the period 1997-2012, we document that areas with larger increase in mobile phone coverage experienced larger adoption of more advanced agricultural technologies – *i.e.*, use of high-yielding variety

[1] A large literature studies the determinants and obstacles to the adoption of modern agricultural technologies in developing countries. See Feder et al. (1985) for an early review 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; Asher and Novosad (2018), Shamdasani (2016), Aggarwal (2018) for recent evidence on the role of transport infrastructure on agricultural technology adoption.

(HYV) seeds. The relationship is concentrated in the late years of our sample – from 2007 onwards — when the mobile phone network expanded into rural areas of India and agricultural extensions accessible through mobile phones were introduced.

The level of geographical disaggregation of the data allows us to compare changes in the adoption of modern agricultural technologies across cells that are located within the same district but that experienced differential changes in mobile phone coverage. In this way, we account for time-invariant characteristics that are common within a narrowly defined geographical area. However, the concern remains that even within districts, agricultural technology and mobile phone adoption are correlated for reasons other than the causal effect of the latter on the former. For example, high-skill farmers might both adopt newer technologies and demand more mobile phone services. Additionally, areas with faster economic growth might experience both higher mobile phone penetration and faster technological upgrade. To overcome these challenges, we propose an identification strategy that exploits variation in the construction of new mobile-phone towers under a large government program: the Shared Mobile Infrastructure Program (SMIP). The program aimed at increasing mobile phone coverage in rural areas through the construction of more than seven thousand new mobile phone towers between 2007 and 2010. For identification, we compare cells where new towers were proposed *and* realized with similar and geographically near cells where new towers were proposed but eventually *not* realized, due to government budget considerations or logistical issues. Importantly, the two sets of locations have no initial mobile phone coverage, are observationally equivalent along many baseline characteristics and experienced similar trends in agricultural technology adoption during the previous decade.

The estimates from the identification strategy based on the SMIP sample confirm the impact of mobile phones on agricultural technology adoption. A one standard deviation increase in mobile phone coverage (38 percent of a cell area) is associated with a 1.6 percentage points larger increase in area farmed with HYV seeds. The magnitude of this estimate implies that a 80 km^2 increase in mobile phone coverage – approximately the coverage provided by one additional phone tower – would increase the area farmed with HYV seeds by 350 hectares.

Next, we investigate the mechanisms through which mobile phones affect agricultural technology adoption. We analyze both the direct effect of mobile phones in providing information about the existence and use of modern agricultural technologies, and the indirect effect they play by relaxing additional information frictions. We focus in particular on the existence of credit products available to farmers, which are known to limit adoption of HYV technology (Bhalla, 1979; Frankel, 2015) and for which we have detailed administrative data. To identify the information mechanisms linking mobile phone coverage to technology adoption, we analyze data from 1.4 million geo-located calls made by Indian farmers between 2006 and 2011 to Kisan Call Centers (KCC), a government-sponsored

and free-of-charge service for agricultural advice. The data report the location and topic of the call, the crop for which the farmer is seeking advice, as well as the answer provided by the agronomist. This level of detail allows us to distinguish between calls about new agricultural technologies (*i.e.*, HYV seeds, fertilizers, irrigation) and calls about credit products available to farmers.

The call-level data indicate a substantial demand for information about modern agricultural technologies by Indian farmers, with advice on seed varieties sought in 13 percent of the calls. At the same time, farmers also actively seek information about credit: 2.2 percent of the calls refer to advice on how to get a loan, and farmers often appear to be unaware of existing programs offering subsidized credit and how to participate in them. Exploiting variation in tower construction in the SMIP sample, we show that mobile phones relax both direct and indirect information frictions, helping farmers to overcome these obstacles to technology adoption. In particular, we find that a one standard deviation increase in coverage is associated with a 11.2 percent increase in mobile phone calls about new seeds. This allows us to calculate the elasticity of HYV seeds adoption to mobile phone calls about this technology. Our estimates indicate that a 1 percent increase in mobile phone calls about HYV seeds translates into a 0.87 percent increase in their actual adoption.

Similarly, we investigate whether access to additional information on the existence of credit programs translates into actual access to credit, by using data from the Agricultural Input Survey on access to credit by agricultural establishments. We find that areas with greater mobile phone coverage and higher phone calls about credit also experience larger increases in access to credit to agricultural establishments. The effects are concentrated on short-term loans and among very small and small establishments, consistent with the observed increase in calls about credit cards offering short-term credit to small farmers.[2]

Overall, our results imply that the diffusion of mobile phone coverage in rural areas – coupled with the introduction of call-centers for agricultural advice – has a large and positive effect on the adoption of modern agricultural technologies. We can use the estimated elasticities presented in this paper to derive aggregate implications on the role played by the expansion of mobile phone coverage on technology adoption in India as a whole. 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.[3]

[2] Very small agricultural establishments are those below 2 hectares in size, which constitute 83 percent of farms and 41 percent of agricultural area in India.

[3] 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. During this period, land farmed with HYV seeds increased by 32 percent,

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. Previous research has shown that social networks are a powerful tool for information diffusion across farmers. 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).

More recent literature has focused on whether mobile phones can amplify information diffusion about agricultural practices and impact farmers' behavior. The answer coming from several RCTs seems to be "yes": mobile phone messaging programs or call centers for agricultural advice can affect farmers adoption of new techniques and, in some instances, increase yields. For example, preliminary findings in Casaburi et al. (2014) show 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 around 800 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.[4]

There is, instead, 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

from approximately 81.8 million ha to 108.3 million ha. Our estimate 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.

[4] 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.

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 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).

We think that our paper contributes to the existing literature in three ways. To the best our knowledge, it is the first study to analyze the effect of mobile phone coverage on technology adoption in agriculture using large administrative datasets that cover a large share of Indian farmers.[5] Our data allows to observe, at relatively fine geographical level (10×10 km cells) the diffusion of the mobile phone network, the content of farmers' phone calls to one of the major providers of agricultural advice, and the actual adoption of agricultural technologies. Second, our paper provides 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. Finally, the nature of the data allows us to study heterogeneous effects across agricultural establishments of different sizes, while the existing literature on this topic has focused mostly on small holdings.

The paper is organized as follows. Section II provides the background details on the expansion of mobile coverage and introduction of agricultural extension services in India. Section III describes the data. Section IV presents the baseline correlations in the data and describes the empirical strategy. Section V presents the results and provides evidence on the mechanism, and Section VI concludes.

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.[6]

[5] The data used in our OLS specifications based on all cells with available data in India cover 64 million farmers and 146 million people working in agriculture (including farmers and dependent workers). The data used in our IV specifications focusing on the sample of cells potentially affected by new mobile phone towers under the SMIP program cover 19 million farmers and 31 million people working in agriculture. The totals for India as of 2001 are: 102 million farmers and 226 million people working in agriculture. These numbers are obtained from the 2001 Population Census of Indian Villages, described in more detail in Section III, which reports the number of people whose primary occupation is agriculture.

[6] We use data from the Gridded Population of the World, Version 4. We assume that population is

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 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.[7] 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 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.[8] 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.

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.

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

[8] 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.

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.[9] 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.

III Data description

In this section we describe the four main data sources used in the empirical analysis: (i) the geo-located data on mobile phone coverage from GSMA, (ii) the administrative data on input use by Indian farmers from the Agricultural Input Survey (AIS), (iii) the location of mobile phone towers under the SMIP program obtained from the Department of Telecommunications of India, and (iv) the proprietary data on farmers' calls obtained 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.[10]

[9] Other early development extensions, like aAQUA and NanoGanesh, established in 2003 and 2004 respectively, focused on aquaculture, fishery and advice for irrigation techniques. 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).

[10] 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.

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).

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.[11] 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.[12]

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

[12] 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

Data from the AIS is aggregated and made available by the Ministry of Agriculture at the district-crop-farm size level.[13] 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.[14]

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.[15]

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 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. The towers were constructed between 2007 and 2010, with most of them being built in 2008 and 2009. 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.

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

2013, 47 new varieties have been introduced covering different oilseeds, cereals and vegetables including rice, groundnut, wheat, millet, soy and cotton.

[13] 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.

[14] 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 1st July, 1996 to 30th June, 1997. This terminology applies to all four waves.

[15] To cross-validate our data sources on agricultural production, we aggregated the FAO-GAEZ dataset at the district level and tested the correlation in area farmed with a given crop in a given district as reported in the AIS relative to the FAO-GAEZ dataset. The correlation between the two datasets for the four main crops in India (rice, wheat, maize and soy) ranges between 0.6 and 0.73. These results are available from the authors upon request.

made, and the response provided by the agronomist.[16] The department maintains record of these calls starting from 2006. Figure IV shows the total number of calls to Kisan Call Centers in the period 2006 to 2011. As shown, the number of calls increases exponentially starting in 2009, going from a few hundreds to around four hundred thousands per year, and reaching over half a million in 2011.

Almost fifty percent of the calls to Kisan Call Centers are about pests and how to deal with them. Farmers usually receive detailed advice on which pesticide (if any) they should use to deal with the pest, as well as information on dosage (grams per liter) and number of applications. The second most represented category is questions about how to improve yields or – more specifically – which varieties of seeds to use in order to obtain higher yields. 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 (5.3 percent), advice for field preparation (4.5 percent), market price information (3.6 percent), credit information (2.2 percent), and irrigation (1 percent).[17]

Many of the calls asking for "credit information" are in fact questions regarding a specific program of subsidized credit available to Indian farmers, which 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 – 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

[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] 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.

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.[18] 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, school, banking facility, number of telephone connections), measures of socio-economic development (night lights, literacy rate, income per capita, expense 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, share of cultivable land used for agriculture, percentage of irrigated land) as well as cell-specific measures of changes in agricultural technology adoption over time. Table A.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. 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

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

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 land farmed with crop c. It is observed at district-crop level and sourced from the Agricultural Input Survey. This variable captures technology adoption rate 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-crop level and sourced from the FAO-GAEZ dataset. This variable captures the initial allocation of land in a cell across crops, and it is observed 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.[19] 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 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) of suggest that, between 2007 and 2012, a 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

[19] An example might help to clarify our measure of the share of land farmed with a given agricultural technology in a given cell. 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: $(0.2 \times 0.4) + (0.5 \times 0.6) = 0.38$.

comparing cells within the same district.[20]

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 areas in India, documented in Figure II, and with the introduction of agricultural extension programs provided via mobile phones, which, as shown in Figure III, have been widely available to farmers in India only starting from the mid-2000s. Thus, in the remainder of the empirical analysis, we focus on the post-2007 period to identify the effect of mobile phone coverage and agricultural extension programs on the adoption of modern agricultural technologies.

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.

Thus, in this section, we present an identification strategy that aims at generating plausibly exogenous variation in mobile phone coverage across cells. This allows us to identify the effect of mobile phone coverage on technology adoption. To this end, 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 minimum threshold of 2,000 inhabitants or 400 households. This makes the areas potentially covered by new towers an ideal setting to study the impact of mobile phone coverage on agricultural technology adoption: rural areas where the majority of the population is employed in agriculture and with no previous mobile phone

[20] 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.

coverage.

In our empirical strategy, we focus on cells that potentially receive mobile phone coverage from SMIP towers. We compute potential coverage assuming that each tower has a 5 km radius of coverage around its centroid. 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.[21]

For identification purposes, we exploit the fact that not all towers were eventually constructed in their originally proposed location. In some cases, towers were not constructed and postponed to a later phase of the program. In others, the towers were constructed but in a different location with respect to the one initially proposed. To identify the effect of mobile phone coverage on technology adoption we thus compare cells where towers were *proposed and constructed* (treatment) to cells where towers were *proposed but eventually not constructed* (control), either because canceled or relocated. This is captured by an indicator variable $Tower$, which is equal to one for cells in the treatment group and zero otherwise.[22] Figure V provides a visual example of how we classify cells into treatment and control group based on tower location.

Among the 6,562 cells in our final sample, 4,761 cells are in the treatment group (in red) and 1,801 cells in the control group (in blue). This is shown in Figure VI, which reports the geographical distribution of treatment and control cells in our final sample across India as a whole. Figure VII zooms into Rajasthan — the largest Indian state by area — superimposing the lattice of grid cells, as well as the administrative boundaries for the 32 districts of the state. Our identification exploits within-district variation in treatment and control status across SMIP cells. There are on average 27 SMIP-sample-cells per district across the whole of India.

Although all proposed locations share common characteristics, the decision not to construct a tower or to relocate a tower is not randomly assigned across initially proposed locations. In Table III 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. As shown, some observable characteristics are significantly correlated with $Tower$ in the univariate regression (column 3). As expected,

[21] 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. The results are reported in Table A.6 of Appendix. The 15,197 sample, however, is more unbalanced in terms of observable initial cell characteristics between treatment and control cells. Thus, in the main empirical analysis we prefer to focus on cells with no initial mobile coverage.

[22] Our results are robust to using the share of land covered by SMIP towers instead of a dummy variable.

given the government objective to maximize the scope of the program while minimizing logistical issues, the relocation of towers targeted more populous areas with better infrastructures, in particular with access to the electricity grid and reliable power supply.[23] Indeed, once we control for district fixed effects as well as initial population and availability of power supply (column 5) most of the correlation with local characteristics is absorbed. In particular, treatment and control cells are no longer statistically different in terms of income measures, such as night light intensity and average income per capita, nor in terms of presence of local infrastructures. In both treatment and control cells around 60 percent of workers are employed in agriculture. Importantly, we find no significant difference in the percentage of agricultural land that is irrigated, nor different pre-existing trends in the adoption of HYV seeds. On the other hand, treatment cells seems to have slightly higher literacy rate (0.6 percentage points), and shorter distance to the nearest town (3.8 km). In our main estimating equation we control for a large set of cell-level characteristics, including all those that are statistically different at baseline.

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 SMIP tower construction and GSMA mobile phone coverage. Next, we exploit geographical variation in the construction of new mobile phone towers and the identification strategy presented in section IV.B to estimate the effect of mobile coverage on technology adoption. Finally, in section V.C, we explore the mechanisms that can rationalize our results. In particular, we attempt to answer the question: why do increases in mobile phone coverage lead to larger adoption of modern agricultural technologies such as HYV seeds? We argue that information diffusion via mobile phones is a potential mechanism, and we test it using data on farmers' calls to Kisan Call Centers for agricultural advice. We start by testing the effect of mobile phone coverage on the diffusion of information about modern seed varieties, fertilizers and irrigation. Next, we test the effect of coverage on the diffusion of information about credit programs via mobile phones as well as the effect of coverage on actual access to credit by farmers. To the extent that access to credit enables farmers to adopt modern agricultural technologies, this is another – indirect – channel through which mobile coverage facilitates technology adoption.

V.A First Stage

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

[23] This is also consistent with our conversations with the Department of Telecommunications: tower relocation was often driven by maximizing the size of the population covered or logistical issues such as presence or absence of reliable power supply.

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

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 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 from the Population Census of 2001. Cell-level controls include observable characteristics that are statistically different between treatment and control cells at baseline such as population, availability of power supply, literacy rate, and distance to the nearest town. Additionally we control for income per capita, agricultural labor share, share of irrigated agricultural land and availability of a banking facility.

Table IV reports the first stage results. The estimated coefficient in column (1) indicates that cells covered by new SMIP towers experienced a 28 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 district fixed effects, thus comparing cells where new towers were constructed to others in the same district where towers were proposed but eventually not constructed. The estimates suggest that treated cells experienced a 13 percentage points higher increase in mobile phone coverage relative to the control group. The large and statistically significant effect persists when we include additional baseline characteristics in columns (3) and (4). According to our most conservative specification, cells covered by new SMIP towers have, on average, 8 percentage points larger share of land covered by mobile phones in 2012 relative to the control group. Below the regressions we also report the Kleibergen and Paap (2006) first stage F-statistics for the validity of the instrument. We can safely reject that the first stage is weak in all specifications.

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 V 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

[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 regions.

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 HYV seeds adoption between 2007 and 2012. The coefficient in column (4) is very precisely estimated and indicates that cells with a 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] 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 V 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 VI 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 V are not driven by pre-existing trends across treatment

[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.

[26] We compute the estimated percentage increase in area farmed with HYV seeds by dividing the estimated coefficient reported in column (4) of Table V (0.044) by the average share of HYV area across cells in our sample at baseline (0.17).

and control cells in the 10 years preceding the mobile phone tower construction program.

Next, in Table VII 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 VII shows that cells with a one standard deviation larger increase in mobile phone coverage experienced a 1.4 percentage points larger increase in area farmed using fertilizers. 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.

Finally, we 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 VII. 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]

Overall, the results on fertilizers and irrigation presented in Table VII are consistent with a positive effect of mobile phone coverage on adoption of HYV seeds. In the next section we explore the mechanism through which this effect arises.

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. Here we try to disentangle the 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 to an increase in farmers' calls about high-yielding variety seeds, suggesting that information about the existence of new

[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).

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.

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

In this section we investigate 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.[28]

The results are reported in Table VIII. 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 0.753 and precisely estimated. The magnitude indicates that cells with one standard deviation larger increase in mobile phone coverage experienced a 28.6 percent larger increase in total calls by farmers.

[28] 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: $\Delta \log Calls_{idt} = \log\left(1 + \frac{1}{3}\sum_{t=09,10,11} Calls_{idt}\right) - \log\left(1 + \frac{1}{3}\sum_{t=06,07,08} Calls_{idt}\right)$.

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 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. Appendix A provides 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.

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 11.2 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 VIII 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 V 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 (11.2 percent). The obtained elasticity indicates that a 1 percent increase in mobile phone calls about HYV seeds translates into a 0.87 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.[29] 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

[29] 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.

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 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.[30] 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 IX. 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

[30] 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.

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.[31] Our results suggest 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 IX 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.[32]

Table X 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 350 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

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

[32] As a sanity check, Appendix Table A.7 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 A.7 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 A.7 shows that cells that are one standard deviation away from the town (32.4 km) have 143 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.

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.[33]

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 (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).[34] 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 13.5 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 X 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 18 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 37 percent and 16 percent larger increase in credit per hectare.

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

[34] According to the Agricultural Input Survey of 2007, and as reported in Figure VIII, 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.

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 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. In particular, we argue that increased access to information can affect technology adoption in two ways. First, directly, through the dissemination of information about the very existence or the use of new technologies. Second, indirectly, through the dissemination of information about credit programs that can help farmers overcome financial constraints.

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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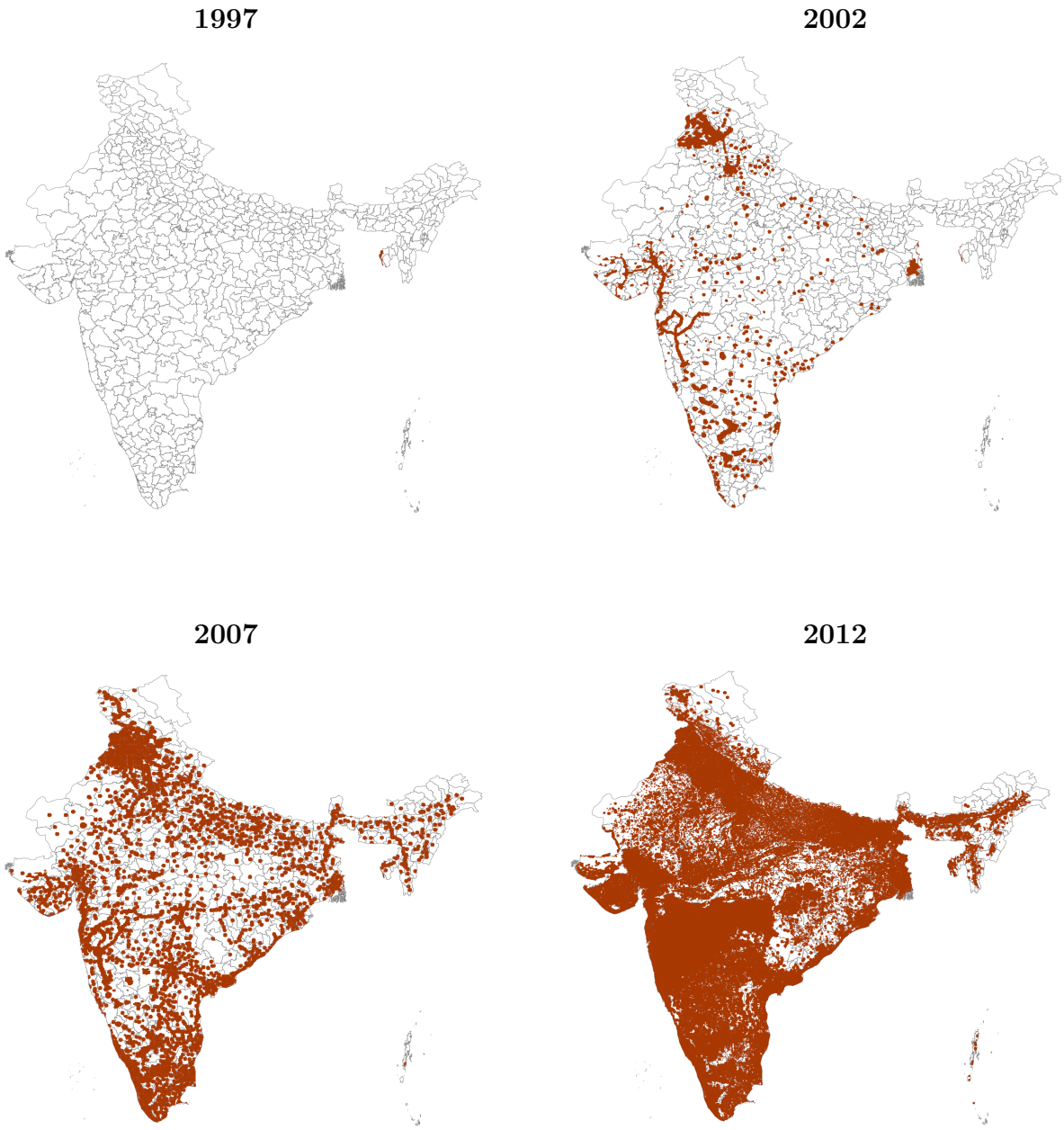
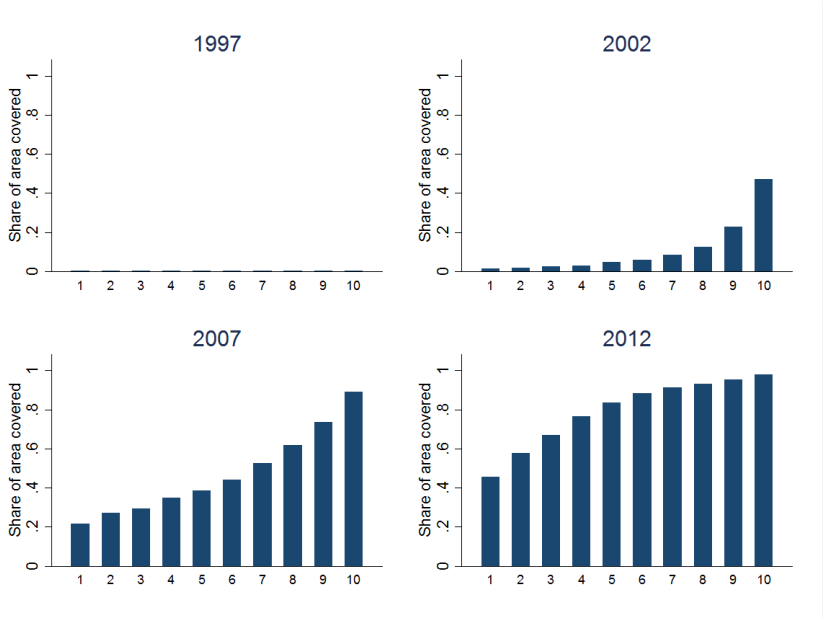
Figures and Tables

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



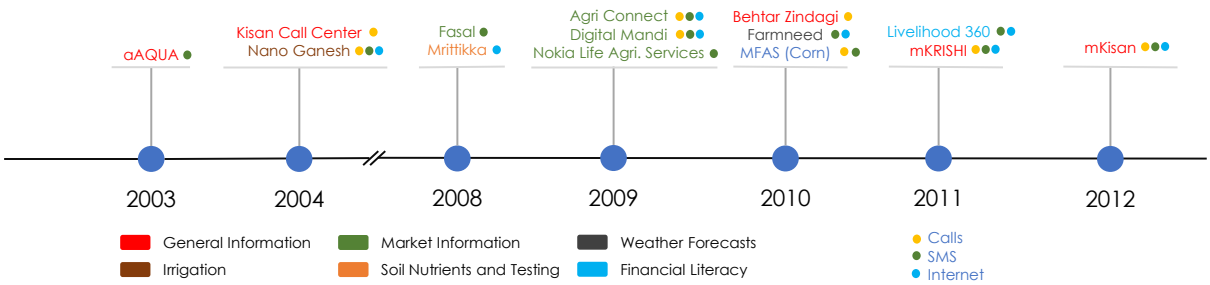
Notes: The figure reports geo-referenced data on mobile phone coverage for all of India at five-year intervals between 1997 and 2012. Source: GSMA.

Figure II: Mobile Phone Coverage by Night Light Intensity



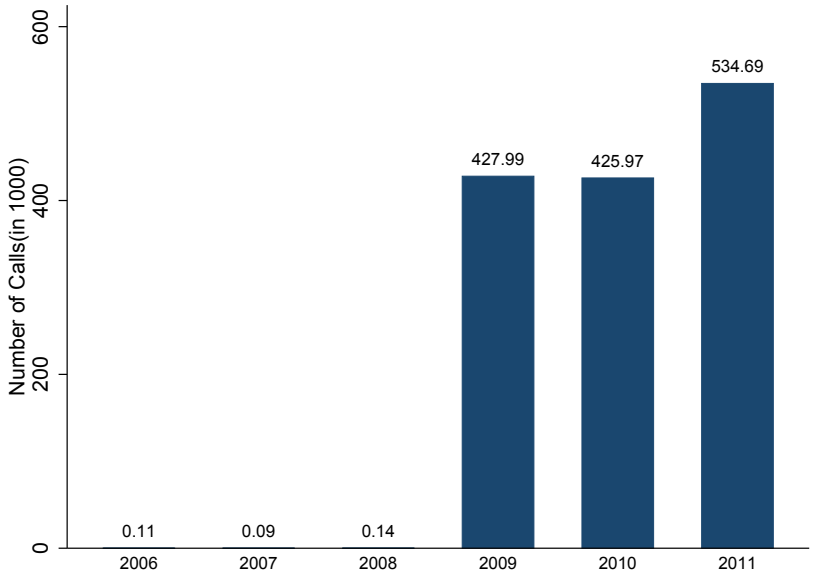
Notes: The average share of land with mobile phone coverage in each decile is calculated for the 4 years in which the Agricultural Input Survey was conducted: 1997, 2002, 2007 and 2012. Night Light Intensity data refers to 1996.

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



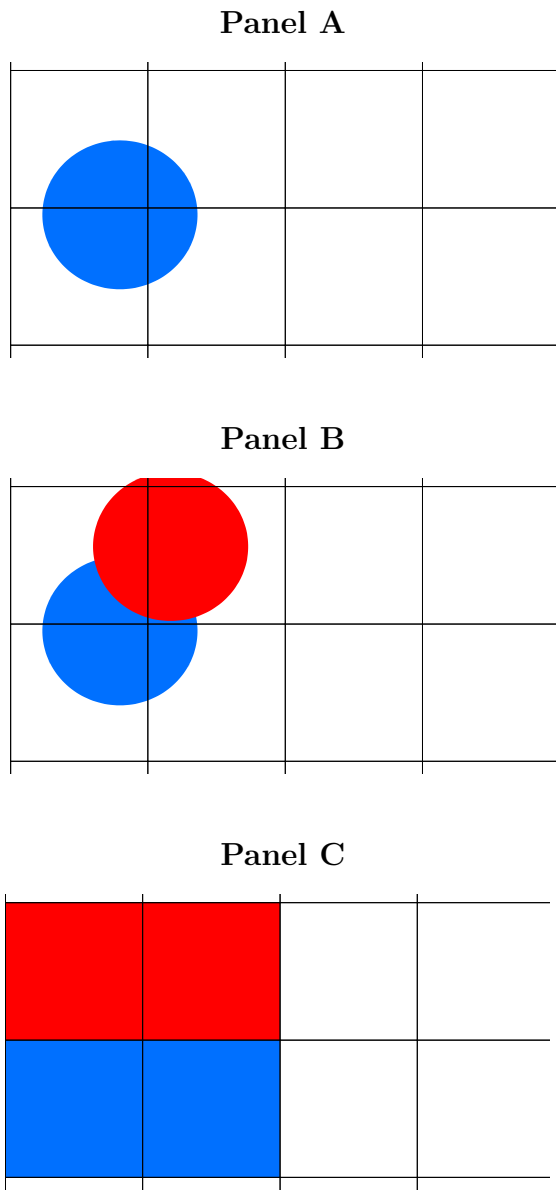
Notes: Source: GSMA mAgri Deployment Tracker

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



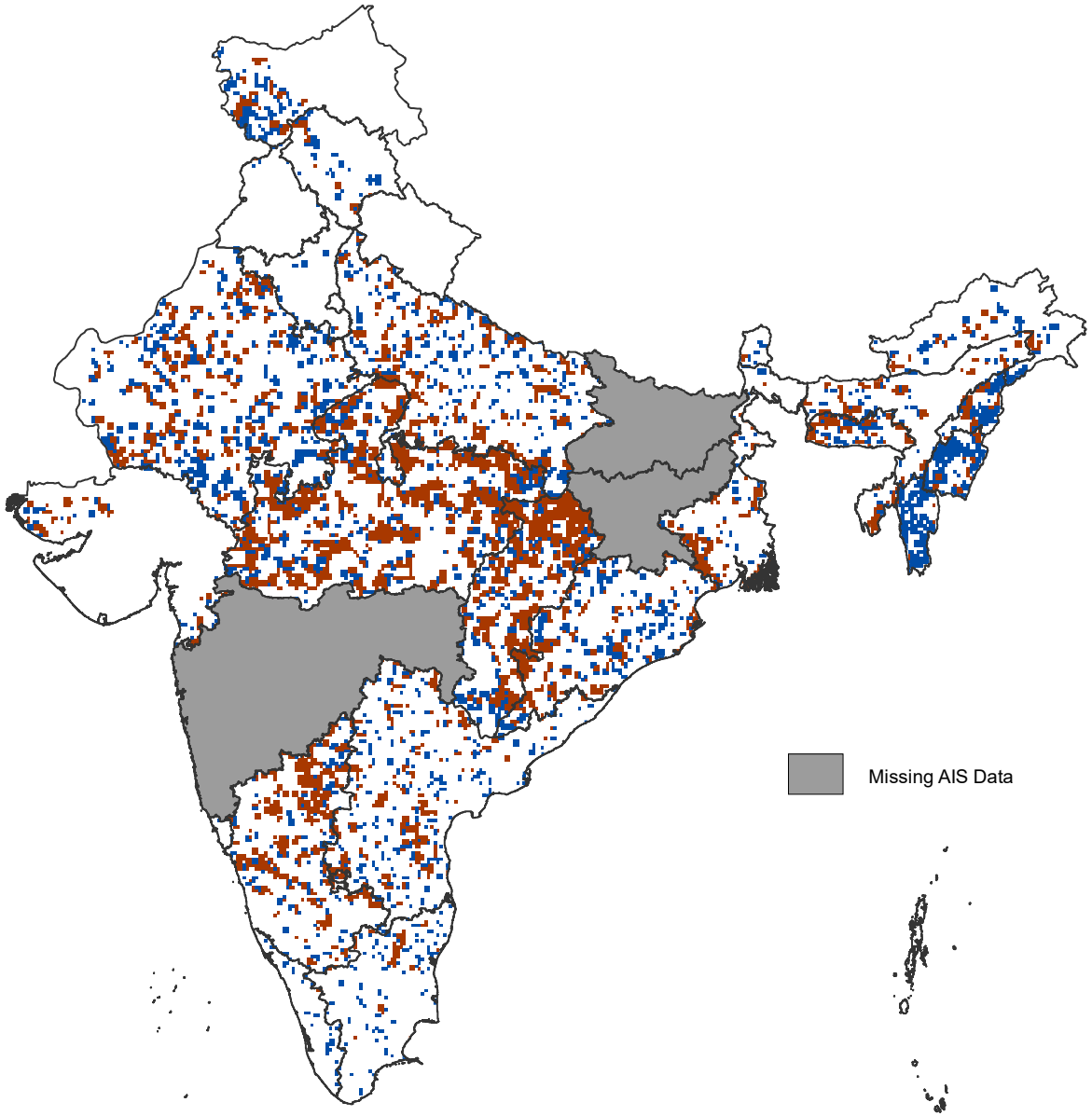
Notes: Source: Kisan Call Center, Ministry of Agriculture

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



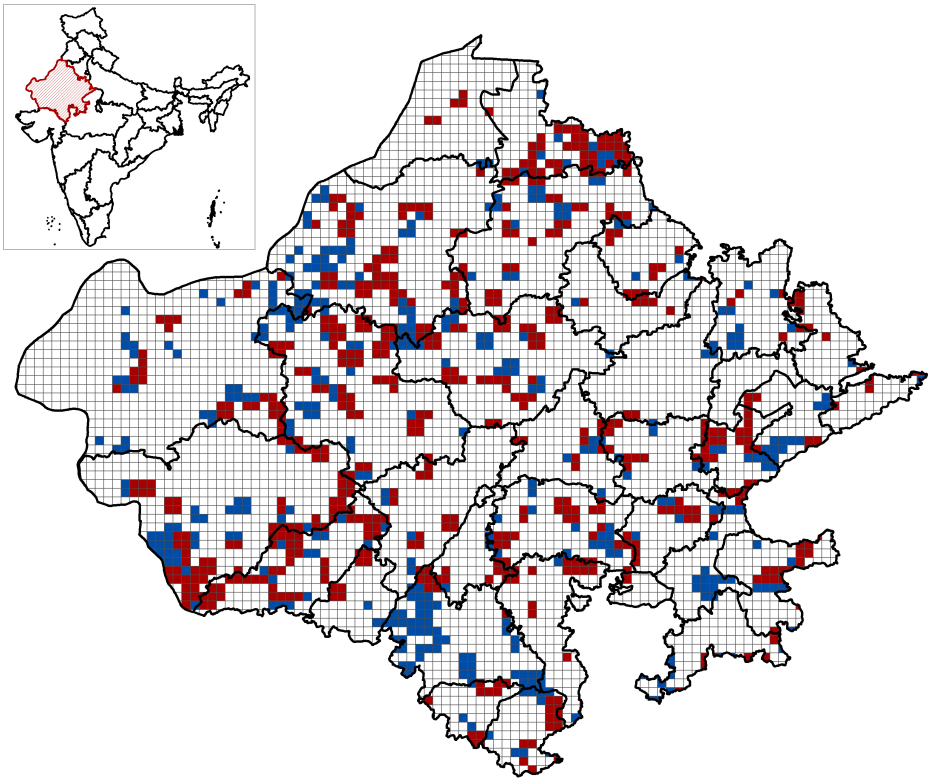
Notes: The figure provides an illustration of classification of cells into treatment(red) and control(blue) group. Panel A shows area covered by a *proposed* tower under SMIP. Panel B shows the area covered by an *actual* tower eventually constructed. Panel C shows the assignment of cells into treatment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

Figure VI: 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 VII: 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 VIII: 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 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: SMIP coverage ($\mathbb{1}$ (Tower)) and cell characteristics (Balance Test)

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	**mean**		**univariate OLS**		**FE & controls**	
	Treatment	Control	coeff.	R^2	coeff.	R^2
Population	14,633.408	9,377.612	5,255.795***	0.035		
	(677.114)	(627.305)	(604.043)			
Power Supply	0.808	0.695	0.113***	0.025		
	(0.017)	(0.024)	(0.021)			
Agri. Workers/Working Pop.	0.575	0.585	-0.010	0.001	0.010	0.344
	(0.007)	(0.011)	(0.011)		(0.006)	
Agri. Land/Cultivable Area	0.613	0.527	0.086**	0.000	-0.167	0.147
	(0.059)	(0.037)	(0.042)		(0.200)	
Percent Irrigated	0.263	0.198	0.065***	0.012	0.003	0.630
	(0.018)	(0.017)	(0.017)		(0.008)	
Δ HYV Share (2006)	0.019	0.014	0.005	0.002	0.000	0.854
	(0.004)	(0.003)	(0.003)		(0.001)	
Literacy Rate	0.430	0.404	0.026**	0.008	0.006*	0.593
	(0.007)	(0.014)	(0.011)		(0.003)	
Education Facility	0.872	0.851	0.021**	0.003	0.004	0.475
	(0.009)	(0.011)	(0.011)		(0.006)	
Medical Facility	0.351	0.325	0.026*	0.002	-0.004	0.426
	(0.014)	(0.017)	(0.015)		(0.010)	
Banking Facility	0.061	0.054	0.007	0.001	-0.005	0.183
	(0.004)	(0.005)	(0.004)		(0.004)	
#Phone conn. per 1000 people	1.423	1.331	0.091	0.000	-0.207	0.105
	(0.144)	(0.362)	(0.327)		(0.369)	
Dist. to nearest town(kms)	34.213	49.852	-15.639***	0.049	-3.771**	0.569
	(1.879)	(3.377)	(2.950)		(1.749)	
Night Lights (2001)	1.562	1.023	0.539***	0.015	-0.079	0.493
	(0.115)	(0.108)	(0.104)		(0.065)	
Income per capita	86.089	71.832	14.257	0.000	0.662	0.152
	(12.305)	(18.542)	(17.739)		(13.041)	
Expense per capita	74.753	66.938	7.815	0.000	-5.409	0.187
	(9.831)	(18.207)	(16.868)		(11.135)	

Notes: The table reports the mean of cell-characteristics in the treatment and control cells (Column 1 & 2) and their correlation with the treatment variable $\mathbb{1}$ (Tower) (Column 3 & 4). 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. Columns (3)-(4) report the coefficient and R2 of the univariate OLS regression of each variable on probability of being covered by a tower under SMIP Phase I. Columns (5)-(6) adds district fixed effects, and control of baseline covariates of cell's population and the availability of power supply. Standard errors clustered at district level are reported in brackets. Significance level: *** p<0.01, ** p<0.05, * p<0.1 .

Table IV: First Stage

Dependent variable:	Δ GSMA Coverage(2007-2012)			
	(1)	(2)	(3)	(4)
𝟙 (Tower)	0.276***	0.131***	0.091***	0.079***
	[0.019]	[0.016]	[0.014]	[0.013]
Population (1000's)			0.013***	0.010***
			[0.001]	[0.001]
Power Supply			0.238***	0.132***
			[0.028]	[0.026]
Agri. workers/Working Pop.				0.016
				[0.036]
Literacy Rate				0.481***
				[0.056]
Distance to nearest Town(kms)				-0.002***
				[0.000]
Land irrigated/Agri land				0.132***
				[0.026]
Banking Facility				0.018
				[0.031]
Income per Capita				0.000*
				[0.000]
Observations	6,562	6,562	6,562	6,562
Number of districts	286	286	286	286
F-stat	202.15	68.00	44.70	35.58
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. Column (1) reports estimates of regression of Δ GSMA Coverage on treatment variable. Column (2) includes district fixed effects. Column (3) includes baseline controls of cell's population and the availability of power supply. Column (4) includes other controls for the cell including share of labor force employed in agricultural sector, literacy rate, distance to nearest town (in *kms.*), share of agricultural land that is irrigated, access to a banking facility and 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 V: HYV Share and Mobile Coverage (2007-2012)

	OLS		IV-2SLS		Reduced Form	
	(1)	(2)	(3)	(4)	(5)	(6)
Δ Coverage	0.012***	0.010***	0.041***	0.044***		
	[0.003]	[0.003]	[0.014]	[0.015]		
𝟙 (Tower)					0.004***	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	0.842	0.841	0.852	0.854
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. 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 𝟙 (Tower); and Column (5)-(6) reports reduced form results. The sample includes all cells with zero cell phone coverage in 2006. All columns controls for district fixed effect. Odd columns include controls for cell's population and the availability of power supply. Even columns also include other controls for the cell including share of labor force employed in agricultural sector, literacy rate, distance to nearest town (in *kms.*), share of agricultural land that is irrigated, access to a banking facility and 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 VI: HYV Share and SMIP Tower Placements: Pre-Existing Trends

	2007-2012		2002-2007		1997-2002	
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{1}$ (Tower)	0.004***	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	0.867	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. The sample includes all cells with zero cell phone coverage in 2006. All columns controls for district fixed effect. Odd columns include controls for cell's population and the availability of power supply. Even columns also include other controls for the cell including share of labor force employed in agricultural sector, literacy rate, distance to nearest town (in *kms.*), share of agricultural land that is irrigated, access to a banking facility and 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 VII: Technology Adoption and Mobile Coverage: 2SLS (2007-2012)

	A. Δ Share of Area under Fertilizers		
	Total Area (1)	Area under HYV (2)	Area not under HYV (3)
Δ Coverage	0.036**	0.047***	-0.008
	[0.018]	[0.018]	[0.011]
Observations	6,552	6,552	6,552
R-squared	0.819	0.834	0.879
District f.e.	✓	✓	✓
Baseline Controls	✓	✓	✓
Other Controls	✓	✓	✓
	B. Δ Share of Area Irrigated		
	Total Area (1)	Area under HYV (2)	Area not under HYV (3)
Δ Coverage	0.012	0.022	-0.011
	[0.012]	[0.015]	[0.008]
Observations	6,562	6,562	6,562
R-squared	0.756	0.787	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. The sample includes all cells with zero cell phone coverage in 2006. All columns include district fixed effects. Baseline controls include cell's population and the availability of power supply. Other controls for the cell include share of labor force employed in agricultural sector, literacy rate, distance to nearest town (in *kms.*), share of agricultural land that is irrigated, access to a banking facility and 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 VIII: Farmers' Calls and Mobile Coverage: 2SLS

	Δ log (Calls)			
Calls on:	All	Seeds	Fertilizers	Irrigation
	(1)	(2)	(3)	(4)
Δ Coverage	0.753***	0.295**	0.193***	0.072***
	[0.206]	[0.127]	[0.071]	[0.025]
Observations	6,562	6,562	6,562	6,562
R-squared	0.815	0.829	0.853	0.774
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 effect. The sample includes all cells with zero cell phone coverage in 2006. Baseline controls include cell's population and the availability of power supply. Other controls for the cell include share of labor force employed in agricultural sector, literacy rate, distance to nearest town (in *kms.*), share of agricultural land that is irrigated, access to a banking facility and income per capita (in rupees). 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 IX: Baseline Correlations: Agricultural Credit and Mobile Coverage

	Calls	**Credit**		
	$\Delta \log(\text{Calls})_{\text{Credit}}$	$\Delta\text{Credit}_{\text{Total}}$ (per hectare)	$\Delta\text{Credit}_{\text{ST}}$ (per hectare)	$\Delta\text{Credit}_{\text{LT}}$ (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 X: Credit and Mobile Coverage: 2SLS

	Panel A: Δ **Total Credit (per hectare)**							
	Credit by maturity			*Short-maturity credit by holding size*				
	Total (1)	Short (2)	Long (3)	Very-Small (4)	Small (5)	Small-Medium (6)	Medium (7)	Large (8)
Δ Coverage	352.530	301.338	-86.828	122.753*	75.808*	67.992	40.620	6.263
	[264.591]	[228.848]	[60.375]	[68.772]	[44.293]	[43.579]	[30.601]	[4.182]
Observations	6,562	6,562	6,562	6,562	6,562	6,562	6,562	6,562
R-squared	0.901	0.896	0.926	0.935	0.918	0.919	0.917	0.915
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 (1)	Short (2)	Long (3)	Very-Small (4)	Small (5)	Small-Medium (6)	Medium (7)	Large (8)
Δ Coverage	204.753*	217.477**	19.368	71.958*	29.904*	8.337	3.235	1.517
	[119.643]	[84.189]	[35.678]	[40.050]	[17.782]	[8.250]	[3.536]	[0.936]
Observations	6,562	6,562	6,562	6,562	6,562	6,562	6,562	6,562
R-squared	0.927	0.919	0.941	0.936	0.937	0.950	0.956	0.931
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. 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.[35] Here we describe in detail the assignment of main query categories used in the paper - calls on seeds, fertilizers, irrigation and credit.

[35]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 2nd 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 [36] (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 [37]. 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	18-19*th* September

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

[37] 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.

Table A.5: Summary Statistics on Cell Characteristics

	Mean	Median	Standard Deviation	N
All India				
Population	19660	14016	18330	24611
Power Supply	0.834	1	0.281	24611
Main Agri. Workers/Working Pop.	0.539	0.55	0.179	24611
Agri. Land/Cultivable Area	0.595	0.798	7.665	23488
Percent Irrigated	0.37	0.295	0.321	24611
Δ HYV Share (2006)	0.013	0.005	0.048	26537
Literacy Rate	0.459	0.462	0.137	24611
Education Facility	0.855	0.938	0.202	24611
Medical Facility	0.421	0.333	0.313	24611
Banking Facility	0.102	0.037	0.182	24611
# phone conn. per 1000 people	4.314	0.663	27.034	24611
Dist. to nearest town(kms)	29.038	19.667	29.438	24611
Night Lights (2001)	3.583	2.285	5.312	26471
Income per capita	98.89	11.58	2173.13	24611
Expense per capita	80.81	11.00	1680.78	24611
SMIP Sample				
Population	13190	10177	12501	6562
Power Supply	0.777	0.967	0.318	6562
Main Agri. Workers/Working Pop.	0.578	0.584	0.159	6562
Agri. Land/Cultivable Area	0.592	0.724	2.692	6082
Percent Irrigated	0.245	0.142	0.27	6562
Δ HYV Share (2006)	0.018	0.01	0.049	5256
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)	38.522	29.327	31.628	6562
Night Lights (2001)	1.414	0.485	1.961	6562
Income per capita	81.46	7.56	399.93	6562
Expense per capita	71.97	7.08	321.89	6562

Table A.6: Robustness: All cells under SMIP program (2SLS)
(2007-2012)

	First Stage	**Δ Technology Adoption**			**Δ log (Calls)**				**Δ Credit$_{ST}$ (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)	0.072***									
	[0.011]									
Δ Coverage		0.048***	0.039***	0.028***	0.516***	0.189**	0.128**	0.042**	205.140	138.515**
		[0.012]	[0.013]	[0.011]	[0.157]	[0.082]	[0.060]	[0.018]	[148.437]	[63.752]
Observations	15,197	15,197	15,156	15,197	15,197	15,197	15,197	15,197	15,197	15,197
F-stat	42.95									
R-squared		0.780	0.821	0.749	0.864	0.897	0.895	0.862	0.918	0.929
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 and the availability of power supply. Other controls for the cell include share of labor force employed in agricultural sector, literacy rate, distance to nearest town (in *kms.*), share of agricultural land that is irrigated, access to a banking facility and 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 A.7: 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.