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-by-10 kilometer 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 tower construction was 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.

Keywords: ICT, Credit Card, Agriculture, HYV Seeds.
JEL Classification: G21, Q16, E51

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I Introduction

The adoption of new technologies proceeds at different speeds in different countries. One sector where such differences are large and fairly well measurable is agriculture. In 2012, for example, only 60 percent of all soybean land in India was farmed with high-yielding varieties (HYV) of seeds.[1] In the same year, US farmers used genetically engineered seeds – a more advanced version of HYV seeds – on 93 percent of soybean land.[2] The limited take-up of advanced technologies by farmers in less-developed countries is one potential explanation for the large observed differences in agricultural productivity across countries. For example, in 2012, the average soybean yields in India were 1.3 tons per hectare, around half of those observed in the United States.[3] Studying the frictions that slow down or prevent the take-up of new technologies in developing countries is therefore of first-order importance for our understanding of productivity differences across countries.

Limited adoption of new technologies has been associated with limited access to information (Foster and Rosenzweig 1995, Conley and Udry 2010). For example, farmers might not know which new seed varieties, pesticides or fertilizers are available to better meet their specific needs, or might simply not know how to use these new technologies. 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 their financial constraints or smooth their consumption. Similarly, limited access to information on market prices or weather forecasts can limit risk-taking and adoption of new technologies.[4]

Over the last decade, the rapid spread of mobile phones has raised expectations about their potential to overcome informational barriers that prevent technology adoption, making it possible to collect and deliver information to farmers at low cost. Recent work using randomized controlled trials to study the effect of agricultural extension programs via mobile phones has shown that there is indeed a large demand for agricultural advice among farmers, and that these services affect agricultural practices and – in some instances – increase 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 and access to credit by farmers in India. To this end, we match

[1] High-yielding variety seeds are traditionally obtained by cross-breading of plants with desirable traits and, more recently, through genetic modification.

[2] The Figure for India is computed from micro-data of the Agricultural Input Survey of India of 2012. According to the USDA, Economic Research Service National Agricultural Statistics Service, US farmers used Herbicide-Tolerant varieties of soybean in 93 percent of all planted soybean land in 2012.

[3] FAOSTAT reports that, in 2012, average soybean yields were 1.353 tons per hectare in India, 2.687 tons per hectare in the US. Between 1961 and 2016, average soy yields in India have been consistently between 25 and 50 percent of those observed in the US.

[4] Of course, there are other frictions that do not strictly depend on access to information. One example is the lack of proper infrastructure such as roads or railroads (Asher and Novosad 2018, Shamdasani 2016, Aggarwal 2018).

data on the diffusion of mobile phone coverage at fine geographical level with detailed administrative data on agricultural inputs used by Indian farmers, including seed varieties, use of pesticides and fertilizers, and credit. To study the mechanism through which coverage affects technology adoption, we analyze data from 1.4 million geo-localized calls made by Indian farmers to call centers for agricultural advice. This data allows us to trace the location of the caller, the question asked by the farmer and the answer provided by the call center. Using variation across 10-by-10 km cells we show that areas with larger increase in mobile phone coverage experienced larger increase in farmers' calls for agricultural advice and larger adoption of more advanced agricultural technologies. This correlation is concentrated in the late years of our sample – 2007 to 2012 — when the mobile phone network started expanding into rural areas of India and agricultural advice services via mobile phones were introduced.[5] Using more aggregate variation, we also show that districts with larger increase in mobile phone coverage experienced larger increase in the share of agricultural establishments with access to credit. These effects are concentrated among small-to-medium establishments (those below 2 hectares in size, which constitute 83 percent of farms and 41 percent of agricultural area in India) and short-term loans, consistently with the observed increase in calls about credit cards offering short-term credit to small farmers.

The correlations described above cannot be interpreted as evidence of a causal link between mobile phone coverage and adoption of new agricultural technologies. 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, or SMIP. The Phase I of SMIP 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 cells where new towers were proposed but eventually *not* realized due to government budget considerations or logistical issues. Importantly, proposed locations are observationally equivalent along many baseline characteristics and experienced similar trends in agricultural technology adoption during the previous decade.[6] In addition, they have a large share of population working in agriculture and no initial coverage by the mobile phone network.

We find a positive and strong effect of mobile phone coverage on adoption of high-yielding seed varieties. Our most conservative IV estimates indicate that land cells with

[5]Our sample spans the years 1997 to 2012, covering the four most recent waves of the Agricultural Input Survey of the Indian Ministry of Agriculture.

[6]The main significant differences are in terms of population and availability of power supply. All our results are unchanged when we control for these observables.

a one standard deviation larger increase in mobile phone coverage experienced a 1.6 percentage points larger increase in area farmed with HYV seeds. The magnitude of this estimate indicates that a 10 square km increase of mobile phone coverage in rural areas would increase the area farmed with HYV seeds by approximately 43 hectares. We can use this estimated elasticity to derive aggregate implications for India as a whole. Our estimates suggest that the expansion of mobile phone coverage in India as a whole between 2007 and 2012 can explain around 11 percent of the observed increase in land farmed with HYV seeds during the same period.

Our data also allows to investigate heterogeneous response to information provision across crops. It is plausible to expect heterogeneous returns to information across crops, both because of their nature (e.g. different sensitivity to weather shocks) and because of heterogeneous movements in the technological frontier (i.e. creation of new varieties of seeds). We plan to explore these sources of heterogeneity in the next iteration of the paper.

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 high-yielding varieties of 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)).

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) randomly provide 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.[7]

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 via a mobile phone based system on risk sharing. They find that households using this mobile phone system are better able to smooth consumption when facing negative income shocks. Karlan et al. (2016) show that reminders from banks sent via SMS help clients achieve their saving goals, which in turn can have positive effects on their income growth (Dupas and Robinson 2013, Karlan et al. 2014). Text messages are 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 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 the majority of Indian farmers. Our data allows to observe, at relatively fine geographical level (10-by-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 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 their actual take-up of credit. Finally, large administrative dataset allow us to study heterogeneous effects across agricultural establishments of different size, across crops, and across regions with different characteristics.

II Institutional Background

In this section we provide institutional details about the diffusion of mobile phones in India and the government programs used in our empirical analysis – namely, the Kisan Call Centers for agricultural advice and the Shared Mobile Infrastructure Program.

According to data from the GSMA – described in detail in section III – India had virtually no mobile phone coverage until the end of the 1990s. The area covered by the mobile phone network increased exponentially starting from the early 2000s, as shown in Figure I. According to the Department of Telecommunications, mobile cellular subscriptions per 100 people in India went from 0.34 in 2000, to 61.1 in 2010, up to 87.3 in

[7]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.

2017.[8] Diffusion of mobile phones can benefit agricultural establishments by providing: information on new technologies and how to use them, advice on land allocation, information on crop prices, weather reports, information on pests and how to deal with them, information on credit. Figure VI shows the timing of introduction of the largest Indian providers of agricultural advice. Notice that Kisan Call Centers for agricultural advice – described in detail below – were introduced in 2004 and were the first providers of general agricultural advice via mobile phone calls.[9] Other providers of general agricultural advice via mobile phones entered into the market only from 2010. [10]

II.A Agricultural Extension Program through Mobile Phones: Kisan Call Centers

Access to reliable information on agricultural practices and technologies could play an important role for agricultural productivity. For example, in absence of expert advice, farmers rely on knowledge of neighboring farmers and agricultural input dealers, who may be either poorly informed or misinform farmers due to misaligned incentives (Anderson and Birner 2007). Additionally, providing the required localized and specific information requested by farmers who use the service is problematic. Moreover, willingness of farmers to pay for the service could be low even when the returns from using the service are high (Cole and Fernando 2016).

With the objective to provide information to farmers on demand for free, the Indian Ministry of Agriculture established 25 Kisan Call Centers (KCC) in January 2004.[11] These call centers are spread across all states and allow farmers to call a toll-free number to get answers to their queries. The calls are picked by representatives who are trained agricultural graduates. When a call is received by a KCC representative, the query is answered based on representative's knowledge and on the suggested answer provided by the computer. The response to the query is then answered in the local language by the representative. 98% 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.[12]

[8] Data from Department of Telecommunications (DOT). Ministry of Communications and Information Technology. Sourced from `data.worldbank.org/`.

[9] aAQUA focuses mostly on aquaculture and fishery and works via SMS, while NanoGanesh focuses mostly on advice for irrigation techniques.

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

[11] As per the Reserve Bank of India, the Government of India spent $300 million on agricultural research and a further $60 million on public extension programs in 2010.

[12] In the very few cases in which the senior expert is unable to answer, the query is forwarded by email to further experts and the answers are passed on to the farmers by post or returned through a phone call.

II.B USOF Program and SMIP

The Universal Service Obligation Fund (USOF) was initiated by the Government of India in 2003. The primary objective of the fund was to provide access to telecommunications services to all uncovered areas, including rural areas, at affordable prices. The necessary funds were generated through taxes levied on the telecom operator's revenue.

As part of meeting its objective, USOF scheme implemented the Shared Mobile Infrastructure Program (SMIP) in 2007. The program provided subsidies to telecommunication service providers for setting up and maintaining 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 identified to set up the towers. Uncovered villages or cluster of uncovered villages with population of at least 2000 were prioritized for the installation of towers under the scheme. Telecom operators were responsible for installing and maintaining the towers between 2007 and 2013. [13] Of the 7,871 proposed towers under Phase-I, 7,353 towers were eventually constructed.

III Data description

In this section we describe the main data sources used in the empirical analysis. Namely: the Agricultural Input Survey (AIS) from the Indian Ministry of Agriculture, the Indian Population Census, the FAO-GAEZ Land Use Database, the GSMA data on mobile phone coverage, the Kisan Call Centers data on farmers' calls, and the mobile-phone tower construction data under the SMIP program.

Since the datasets mentioned above report information at different levels of aggregation, the empirical analysis is based on a common geographical unit of observation to which all these datasets could be matched. This unit of observation is a square with sides of approximately 10 km that we constructed by super-imposing a grid to the map of India in ArcGIS. We refer to this unit of observation as a cell.[14] Figure II shows a map of India divided into the 41,495 cells that we use as our unit of observation.[15]

[13] 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.

[14] Cell dimensions are 0.0833333333 by 0.0833333333 degrees, which correspond approximately to 10-by-10 km. However, not all cells are of equal size. For example, cells in coastal areas or at the border with neighboring countries will have a smaller size.

[15] Notice that the data from the Agricultural Input Survey – described below – covers 26,537 cells (or 64 percent of all those in our grid 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 – as discussed above – do not consistently participate in the Agricultural Input Survey. To cross-validate our data sources we tested the correlation in area farmed with a given crop in a given district as reported in the FAO-GAEZ dataset relative to the Agricultural Input Survey. The results are reported in Figure A1 for the four main crops by area harvested in India (rice, wheat, maize and soy). As shown, the correlation between the two datasets ranges between .6 and .73.

Another challenge is that some of data sources – such as the Agricultural Input Survey – report information at Indian district level, and Indian districts have been changing shape or were created or dissolved during the period under study. Thus, in order to have unit of observation that is consistent over time, we created minimum comparable areas (MCAs) encompassing one or more districts that cover the same geographical space between 1997 and 2012.[16]

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

III.A Agricultural Input Survey of India

The Agricultural Input Survey (AIS) conducted by the Ministry of Agriculture collects information on input use by Indian farmers at 5-year intervals. Under the survey, all operational holdings from a randomly selected 7% sample of all villages in a sub-district are interviewed about their input use. Information is collected on the use of high-yielding variety seeds, chemical fertilizers, organic manures and pesticides, agricultural machinery and agricultural credit availed. The data for each crop is then aggregated at the district-level.[17] Thus, our data on input use is at the district-crop level. We use the last 4 waves of the AIS covering the period from 1997 to 2012.[18] The AIS covers the entire country in 2012 but the survey was not conducted in the states of Bihar and Maharastra before 2012. Thus, we exclude these states from our analysis.

III.B FAO-GAEZ Land Use

We obtain data on land use at very fine geographical level (10-by-10 km cell) 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 of this paper 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 aggregate data, area harvested with these 10 crops amounts to 135.5 million hectares and accounts for 76 percent of total area harvested in India in 2000.

[16] 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 another districts. However, there are exceptions. For example, the Baska district in the state of Assam was created by carving out parts of three other districts: Barpeta, Nalbari and Kamrup. In this case, the MCA is the union of Baska and the three districts from which it was carved out.

[17] The data also provides the information broken down by operational holding size. Size categories include: 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). This allows us to explore the heterogeneous effects of changes in mobile coverage on technological adoption by holding size.

[18] 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.

III.C GSMA Mobile Coverage Data

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.

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 Report). 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. This allows us to measure the adoption of mobile phone technology at a very disaggregated geographical level. The data we have access to collate submissions from all member operators. 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 same GSMA data as used in this paper to study the effects of mobile coverage expansion on political mobilization in Africa.

III.D Tower Location Data

Our data on proposed towers under the SMIP Phase I comes from the Center for Department of Telematics (C-DoT) - the consulting arm of the Department of Telecommunications, India. The center provided us with geographical coordinates of the 7,871 towers proposed for expanding rural mobile coverage under the program.

We also obtained the geographical coordinates of 7,353 towers that were finally constructed under the program. Other relevant information includes the date these towers became operational and the names of telecom operators sharing the towers. Institutional details related to the coverage radius of the towers comes from our conversations and documents obtained from the C-DoT officials responsible for the Phase I implementation. The information on precise location of both the proposed and constructed towers allows us to map the towers to our 10-by-10 km cells. Figure VII shows the location of both proposed as well as finally constructed towers. The figure demonstrates the scope of the SMIP program - both proposed and constructed towers spanned all Indian states.

III.E Kisan Call Centers Data

Data on farmer's queries is from the Department of Agriculture, Cooperation and Farmers Welfare. For every call received in one of the 25 call centers, the representative collects basic information on the farmer (name, location and contact information), crop for which the query is made, date and time of the call, the description of the query and the response provided. The department maintains record of these calls starting from 2006.

Table II reports the main topics farmers ask when calling Kisan Call Centers. As shown, almost fifty percent of the calls 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. Questions about pesticides are followed by questions regarding 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 ask about fairly consistently are: fertilizers (10.4 percent of calls), weather conditions (5.2 percent), advice for field preparation (4.53 percent), market price information (3.6 percent), and credit information (1.9 percent).[19] Interestingly, many of the calls that we classify as "credit" are specific questions regarding "kisan credit cards". This credit card was introduced in 1998 by the Reserve Bank of India as a mechanism to provide access to small loans to farmers, and it is 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.

Table III shows the main crops farmers have questions about when calling Kisan Call Centers.

Figure III shows the total number of calls to Kisan Call Centers in the period 2006 to 2012. As shown, the number of calls to Kisan Call Centers exponentially increase after 2009, going from a few hundreds to around seven hundred thousands a year, and more than one million a year starting in 2012.

IV Empirics

In this section we describe our empirical strategy to study the effect of mobile phone coverage on technology adoption in agriculture. We start by presenting the specification used to estimate a set of basic correlations in the data. Next, we describe the empirical challenges we face and present an identification strategy that addresses them. The empirical results are then described in section V.

[19]Notice that we have enough information on the content of the call to classify 90.6 percent of the calls to Kisan Call Centers between 2006 and 2011.

IV.A Baseline Specification

In our baseline specification we study the correlation between change in area with mobile phone coverage and change in area farmed with a given agricultural technology. The agricultural technologies we focus on are: high-yielding seed varieties, fertilizers, and pesticides. To this end, we estimate the following equation in first differences:

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

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

As described in section III, data on technology adoption from the Agricultural Input Survey is not available at cell-level. Thus, 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 described in section III. 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 dataset described in Section III. 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. For example, if data from the Agricultural Input Survey shows that 20 percent of land farmed with rice in a district is farmed using technology k, we assign that share of adoption to all cells within that district.[20]

[20] 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 seed varieties. 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

Since $Area_{i,t=2000}$ – the size of a cell – does not depend on crops farmed in that cell we can rewrite equation (2) as:

$$\left(\frac{Area^k}{Area}\right)_{it} \approx \frac{\sum_{c \in O_i} \left(\frac{Area^k}{Area}\right)_{cdt} \times (Area_{idc,t=0})}{Area_{id,t=2000}}$$

This definition holds under the neutral assignment rule described above, and the additional assumption that crop shares in a given cell are relatively stable over time. Under this definition, the coefficient β in equation (1) has an easy interpretation: it is the percentage point change in area farmed with technology k for one percentage point change in area covered by mobile phone signal.

Different types of bias can arise when estimating the coefficient β in equation (1). First, reverse causality: farmers adopting new agricultural technologies could demand more mobile phone services. Second, omitted variable bias: certain areas within a district experience faster economic development than others. Faster development might push higher mobile phone penetration and favor farmers adoption of new technologies, for example to serve an increase in local demand. Due to these potential biases, the estimates obtained estimating equation (1) cannot be interpreted as evidence of a causal link between mobile phone coverage and adoption of new agricultural technologies.

Even if changes in mobile phone coverage were randomly assigned across cells within each district and had a positive effect on technology adoption, an additional challenge would be to disentangle the actual mechanism through which this effect arises. One hypothesis is that mobile phone coverage makes information available to farmers in terms of existence and use of new agricultural technologies, weather, prices, access to credit. Another possibility is that technology adoption by farmers is driven by general equilibrium effects of mobile phone coverage. An exogenous shock to mobile phone coverage can create economic opportunities also in "urban" sectors such as manufacturing and services. Higher income in urban areas could increase demand for non-tradable goods, including agricultural output. Farmers might then decide to switch to newer technologies to cater this increase in local demand. Notice that this is not a concern in terms of identification – as technology adoption is driven by mobile coverage – but it is a concern in terms of disentangling the mechanism through which such effect takes place.

In section IV.B we present an identification strategy that aims at generating plausibly exogenous variation in mobile phone coverage across cells in India. In order to provide evidence on the mechanism we will then rely on detailed data on more than 1.4 million phone calls that farmers made through a large government-sponsored call center program.

with wheat. Under our neutral assignment rule, we assign 38 percent of land in cell i to high-yielding varieties. This comes from $(0.2 \times 0.4) + (0.5 \times 0.6) = 0.38$.

IV.B Identification Strategy

In this section we present our empirical strategy to identify the effect of mobile phone coverage on technology adoption. To this end, we exploit variation across areas in the construction of mobile phone towers under the Shared Mobile Infrastructure Program (SMIP). As described in section II, in the first phase of this program, 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 into the mobile phone network, the proposed locations share several common characteristics. First, proposed locations are in rural areas with no pre-existing mobile phone coverage at the time of the program. Second, in order to maximize the impact on the program, proposed tower locations were chosen in order 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 coverage.

In our empirical strategy, we focus on the cells containing the location of proposed mobile phone towers under Phase I of the SMIP. For identification purposes, we exploit the fact that not all the new towers were eventually constructed in their initially proposed locations. 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. As reported in section III.D, out of 7,871 proposed locations, 7,353 towers were eventually constructed between 2007 and 2010. Out of the constructed towers, around 70 percent were constructed in the same cell of the initially proposed location. The remaining 30 percent were either not constructed or constructed in a different cell than the one initially proposed.

Figure VII shows the geographical distribution of proposed and actual locations of mobile phone towers under Phase I of the SMIP program across India. The blue triangles indicate initially proposed locations, while the red circles indicate the actual locations of towers eventually constructed under the SMIP program. The map shows the wide scope of the program, which encompasses rural areas across all India. Figure VIII and IX show the geographical distribution of proposed and actual areas covered by new mobile phone towers within a given state and a given district respectively. Given technical specifications of new towers, we use a circle with a 5 km radius centered on the tower location as an approximation of the area covered by the tower. The Figures also report the grid of 10-by-10 km cells used as our unit of observation, as well as village boundaries. The area covered by a tower is approximately equivalent to the area of a cell.[21]

[21] For this identification strategy we focus on cells with greater than zero potential coverage from towers under Phase I. We assume that each tower has a 5km radius of coverage around the centroid based on

To identify the effect of mobile phone coverage on technology adoption we 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. Although all proposed locations share common characteristics, the decision not to construct a tower or to re-locate a tower is not randomly assigned across initially proposed locations. Table VIII compares treated and control cells on a large set of observable characteristics, all observed in 2001 and sourced from the Population Census.[22] In particular, columns (1) and (2) report means in treatment and control for the set of observables, column (3) reports the estimated coefficient of a univariate regression of each observable characteristics on the treatment dummy; column (4) reports the R squared of that regression. As shown, cells in the treatment group have significantly larger population than those in the control group (around 5,300 more relative to a mean of approximately 9,400 in the control group). Cells in the treatment group also have an 11.5 percent higher probability of having power supply. Our conversations with people familiar with the SMIP program suggest that tower relocation or cancellation was often driven by maximizing the size of population covered or logistical issues such as presence or absence of reliable power supply. Indeed, once we control for district fixed effects as well as initial population and availability of power supply, differences in observable characteristics between treatment and control group become very small and not statistically significant, as shown in column (3) of Table VIII. In particular, treatment and control cells are not statistically different in terms of income measures such as night light intensity and average income per capita, nor in terms of presence of different facilities such as: schools, hospitals, post office, banks or credit society. In both treatment and control cells around 40 percent of workers are employed in agriculture, and around 60 percent of cultivable area is devoted to agriculture. We find no significant difference in the percentage of agricultural land that is irrigated, while treatment cells seems to have a slightly higher level of adoption of HYV seeds at baseline (around 1 percentage point), slightly higher literacy rate (0.7 percentage points), and slightly shorter distance to the nearest town (3.8 km). Thus, in the empirical analysis we augment our main estimating equation with cell-level controls

technical characteristics of mobile phone towers under SMIP. In our dataset there are 20,454 cells with greater than zero potential coverage from towers under Phase I. The median initial coverage of these cells is 8% in 2006, with 44 percent of them having zero mobile coverage in that year. This is consistent with the fact that SMIP targeted areas previously without coverage. Notice that village size usually smaller than cell size. Thus, even cells with positive coverage might contain villages with zero coverage targeted by the program. In the empirical analysis we focus on cells with zero mobile coverage in 2006 and non-missing information on technology adoption from the Agricultural Input Survey. This gives us a final sample of 6,582 cells: 4,776 cells in the treatment group and 1,806 cells in the control group.

[22] We assign villages to our 10 km $\times$ 10 km cells based on the geographical co-ordinates for the centroid of that village . Specifically, the centroids for 2001 Census villages were obtained from `http://india.csis.u-tokyo.ac.jp`. A village is then assumed to belong completely to the cell if its centroid falls inside that cell. Data on demographics, land usage and amenities for the villages is obtained from 2001 Primary Census Abstract and 2001 Village Directory. We have alternatively assigned villages to cell using data on village boundaries and obtain similar results.

for all those observable characteristics where significant differences arises at baseline as follows:

$$\Delta\left(\frac{Area^k}{Area}\right)_{idt} = \alpha_d + \beta\,\mathbb{1}\,(Tower)_{id,t-1} + \gamma X_{id,t=2001} + u_{idt} \tag{3}$$

The outcome variable in equation (3) is the change in the share of land farmed with a given agricultural technology k between 2007 and 2012 in cell i, district d. The main coefficient of interest is β, which captures the effect of tower construction under SMIP. Notice that new towers were constructed between 2007 and 2010, the vast of majority of them in 2008 and 2009. Finally, $X_{id,t=2001}$ is a vector of cell-level controls observed in the Population Census year 2001 and including: population, availability of power supply, literacy rate, income per capita, agricultural labor share, share of irrigated agricultural land, availability of agricultural credit society facility, availability of banking facility and distance to the nearest town.

Table IX presents the first stage results. In the first stage, we use variation in tower construction under SMIP across comparable cells to explain changes in mobile phone coverage between 2007 and 2012. In reading these coefficients it is important to keep in mind that the tower construction program we use for identification is not the only way in which mobile phone coverage can reach these regions. During the same period, private companies have built mobile phone towers across India to extend their services and expand their market shares, potentially also in these previously non-covered areas. Thus, we do not expect tower construction under SMIP to be the sole source of variation in change in coverage, even in rural regions. Notice that the outcome of the first stage is not the assumed coverage derived from tower location and range, but the actual coverage as reported by Indian telecommunication companies to the GSMA. Thus, it includes new coverage provided by SMIP towers as well as new coverage provided by other providers. As shown in columns (3) and (4) – which include all controls – we find a strong first stage: cells covered by new SMIP towers have, on average, 14 percentage point larger share of land covered by mobile phones in 2012 relative to the control group (8 percentage points when focusing on within-district variation). The F-stat on the first stage in our most demanding specification is 50.66 (see column (4)). The R-squared without controls is 0.105 (see column (1)).

V Results

V.A Baseline Correlations in the Data: Technology Adoption

In this section we explore a first set of correlations between mobile phone coverage and adoption of new technologies in agriculture. We start by estimating equation (1) when the outcome variable is the change in share of land farmed with high-yielding varieties (HYV) of seeds between waves of the Agricultural Input Survey. The explanatory variable is the change in the share of land covered by mobile phone network. The unit of observation is a 10-by-10 km cell in India.

Table IV reports the results. In the first column we pool together data on all waves of the Agricultural Input Survey (1997, 2002, 2007 and 2012). As shown, the estimated coefficient on mobile phone coverage is positive and statistically significant. The magnitude suggests that a 10 percentage points increase in the area covered by mobile phones in a given cell corresponds to .07 percentage points increase in area farmed with HYV seeds in the same cell.

In columns (2) to (4) of Table IV we estimate equation (1) separately for each 5-year period across waves of the Agricultural Input Survey: 1997 to 2002, 2002 to 2007 and 2007 to 2012. As shown, variation in mobile phone coverage is strongly correlated with technology adoption between 2007 and 2012, while the coefficient is an order of magnitude smaller and not statistically significant in the periods 1997 to 2002, and 2002 to 2007. In terms of magnitude, the result in column (2) suggests that cells with a one standard deviation higher increase in the area covered by mobile phones between 2007 and 2012 experienced a 1 percentage points larger increase in area farmed with HYV seeds during the same years (0.2 percentage points when adding district fixed effects). One way to think about this magnitude is in terms of additional coverage of a new mobile phone tower like those constructed under SMIP. The standard SMIP tower provides coverage to a circle of 5km radius around its location, or an area of approximately 80 square km. This means that, between 2007 and 2012, the coverage coming from one additional phone tower is associated with around 160 additional hectares of land farmed with HYV seeds. [23]

To sum up, Table IV shows that the positive correlation between mobile phone coverage and agricultural technology adoption is driven by the 2007-2012 period, while there is no correlation before 2007. Notice that HYV seeds have been available in India starting with the Green Revolution of the 1960s, so the timing of the effect cannot be driven by the timing of introduction of this technology. There are two potential explanations for this result.

First, mobile phone coverage might not have reached rural areas until after the mid-2000s. Figure IV shows evidence consistent with a pattern of diffusion of the mobile phone network that initially covers densely populated urban areas, and only afterwards expands to rural ones.[24] The Figure reports the average share of land covered by mobile phones

[23] To avoid selection driving differences across waves, this specification restricts 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 26,756 cells out of 41,495 cells in India. Point estimates are very similar in size if we were to remove this restriction. Without this restriction, the number of cells in column (2) would be 34,155, the point estimate 0.018, statistically significant at the 1 percent level.

[24] Notice that in this part of the analysis we use data from all regions of India, independently from the intensity of local agricultural production.

across cells by initial level of urbanization. As a proxy of urbanization we use night light intensity, which is available at cell level from satellite data. Higher night light intensity captures higher urbanization. As shown, there was virtually no mobile phone coverage in India in 1997, our baseline year. After 1997, the speed of diffusion has been different 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.[25] 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 above 40 percent by 2012. We also study the correlation between 5-year changes in mobile phone coverage and initial night light intensity. Figure V reports this correlation for each of the three periods used in the empirical analysis: 1997 to 2002, 2002 to 2007, and 2007 to 2012. As shown, growth in mobile phone coverage is positively correlated with night light intensity up to 2007, which indicates that more urban areas initially experienced faster increase in coverage. The relationship is instead negative after 2007, when rural areas started catching up with urban ones that had already reached full coverage.[26]

A second reason why the positive correlation between mobile phone coverage and agricultural technology adoption only manifests itself after the mid-2000s is the availability of agricultural advice programs provided via mobile phones. As we discussed in section II, only starting from the mid-2000s agricultural advice via mobile phones has been widely available to farmers in India. These services can be used by farmers to get information on prices, weather, credit and, of course, agricultural practices including which seed varieties deliver higher yields for a given crop in a given region. As shown in Figure VI, most providers started their services in the mid-2000s. The Kisan Call Centers, which we will use in the empirical analysis and that are part of one of the major programs of agricultural information diffusion for farmers, were launched by the Indian government only in 2004 and the total number of calls they received was extremely modest until 2010. In the next section we show some basic stylized facts based on proprietary call data from the Kisan Call Centers.

V.B Baseline Correlations in the Data: Access to Credit

Data on credit to agricultural establishments collected by the AIS contains detailed information on the size of the establishment receiving credit, the maturity of the loan and – for short-term loans – the objective of the loan. The survey does not, however,

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

[26]This stylized fact is robust to using alternative measures of urbanization, such as share of population in rural villages over total population, or agricultural labor share.

report the specific crop farmed by the agricultural establishment that received credit.[27] Thus, when studying the relationship between mobile coverage and credit outcomes, the analysis is at district-level instead of at cell-level.

In this section we study the correlation between changes in mobile phone coverage and access to credit by estimating a version of equation (1) where the outcome variable is the change in the share of agricultural establishments with access to credit in a given districts. The AIS contains information on four main sources of credit: commercial banks, rural regional banks, agricultural credit societies (PACS) and land development banks. In what follows we consider access to credit as having access to loans from any of these four different types of lenders.

Table V reports the results for the period 2007 to 2012. The estimated coefficient on the change in mobile phone coverage is positive and significant, indicating that districts with larger increase in coverage experienced larger increase in access to credit by agricultural establishments. Column (1) use data on establishments of all sizes. The magnitude of the coefficient suggests that districts with a 1 standard deviation higher increase in the share of land covered by mobile phones experienced a 2.8 percentage points higher increase in the share of agricultural establishments with access to credit. In columns (2) to (6) we estimate the same regression using as outcome the change in the share of establishment of a given size with access to credit. Size categories include: 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). According to the Agricultural Input Survey of 2007, very small holdings constitute the vast majority (63.7 percent) of agricultural holdings in India, followed by small holdings (18.7 percent).[28] The effects of mobile phone coverage are monotonically decreasing in farm size, and not statistically different from zero for large farms.[29]

Although the correlations presented in Table V do not establish a causal link between mobile phone coverage and access to credit by small and medium agricultural establishments, we can speculate on potential mechanisms linking coverage to credit using the content of mobile phone calls regarding credit. As shown in Table II, in around 2 percent of the 1.4 million calls to Kisan Call Centers farmers ask question regarding credit. Farmers ask, for example, how to obtain a loan to acquire a tractor, an irrigation system, or even a buffalo or a goat. A large share of the calls about credit – around one-quarter of those asked in English – is 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 annum, depending on the issuing bank). Loans are usually taken during the planting

[27] Most establishments farm multiple crops. Also, differently from other inputs, credit is not crop specific.

[28] Even in terms of area farmed, as of 2007 very small holdings occupy around 20.7 percent of agricultural land, small holdings occupy 20.4 percent.

[29] Table A2 in the Appendix shows that districts with higher increase in mobile phone coverage in the 2007-2012 period did not experience faster access to finance in the previous decade. This is consistent with mobile phone networks reaching rural areas mostly after 2007, as shown in section V.A.

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) shows that a large share (15 to 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, access to information about this specific type of credit card seems an important determinant of access to credit, especially for small farmers. Although these cards have been available since the end of the 1990s, the large amount of farmers' questions on this topic suggest there is still an informational gap that mobile phones can help to bridge.

In section V.C we will present results using call data, and focus specifically on calls regarding credit tools available to farmers. In terms of credit outcomes, to test whether access to information about Kisan Credit Cards might have played a role in explaining the increase in access to credit associated with mobile phone coverage, we study the correlation between change in coverage and increase in loans of different maturities. The AIS contains information on the total monetary value of existing loans by maturity and farm size, but not on the share of agricultural establishments using those loans. Thus, for this outcome we focus on the change in total value of loans of a given maturity between 2007 and 2012. The results are reported in Table VI. As shown, districts with larger increase in mobile phone coverage experienced larger increase in short-term lending, i.e. loans with maturity of one year or less. The magnitude of the coefficient in column (1) of Panel B suggests that districts with a 1 standard deviation higher increase in the share of land covered by mobile phones experienced a 22 percent higher increase in short term credit. The effects are concentrated among small and very small farmers. Instead, we find no effect of change in coverage on long-term loans, independently from the size of agricultural establishment.

V.C Baseline Correlations in the Data: Farmers' Calls

In this section we study the relationship between extension in mobile phone network and number of mobile phone calls. To this end, we use data on the universe of mobile phone calls made by farmers to the Kisan Call Centers across India. As discussed in section II, the Kisan Call Centers program was launched in 2004 but was not diffused among farmers until 2009-10. Aggregate data published by the Ministry of Agriculture shows that there were virtually no calls to Kisan Call Centers as of 2007. Between 2007 and 2012, the number of calls has increased up to 1.23 million per year (Figure III). Thus, in this section we focus on the period between the last two waves of the Agricultural Input Survey (2007 to 2012) and study the relationship between increase in mobile phone coverage and increase in calls at cell-level.

Our data covers all calls made by farmers to Kisan Call Centers between 2006 and 2011. For each call, the dataset contains information on both the district of the caller, and the crop the farmer asks information about. Thus, as in the Agricultural Input Survey, data on calls is at district-crop level. Using an assignment rule similar to the one described in section IV.A we construct a measure of the number of calls originated in a given cell as follows:

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

Notice that the second element of the product inside the summation 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, if 10 percent of the area farmed with rice in district d is farmed in cell i, we assign to cell i 10 percent of the calls about rice received from farmers located in district d. Using the measure described in equation (4), we estimate a version of equation (1) for the period 2007 to 2012 where the outcome variable is defined as:

$$\Delta \log Calls_{idt} = \log \left(1 + \frac{1}{3} \sum_{t=09,10,11} Calls_{idt} \right) - \log \left(1 + \frac{1}{3} \sum_{t=06,07,08} Calls_{idt} \right) \tag{5}$$

The results are reported in Table VII. Columns (1) and (2) of Panel A show that cells with larger increase in mobile phone coverage experienced a larger increase in total number of calls to Kisan Call Centers. The magnitude in column (1) suggests that cells with a one standard deviation higher increase in mobile phone coverage between 2007 and 2012 experienced a 16.5 percent larger increase in total number of farmers' calls (3.1 percent when we exploit variation across cells within a district). As shown in column (3) and (4), we find a positive and significant effect of coverage also when we use change in calls per agricultural worker in a given cell.

In Panels B and C of Table VII we focus specifically on calls regarding seed varieties and ways to improve yields (Panel B), and calls asking information about how to access a loan or how to obtain the Kisan Credit Card described above (Panel C). We find positive and significant effects for both types of calls.

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

In this section we study the effect of mobile phone coverage on adoption of agricultural technologies. To this end, we use the identification strategy described in section IV.B. Our identification exploits variation in mobile-phone tower construction across Indian cells that were initially proposed as potential sites for new towers under a large government program. As discussed in section IV.B, treatment and control cells are located in rural areas and have no mobile phone coverage at the beginning of the program (2007). In addition, treatment and control cells are largely comparable in terms of baseline observable characteristics after adjusting for differences in population and availability of power supply, the main drivers of tower relocation. Whenever significant differences in observable characteristics arises, we show that our results are robust to controlling for such differences.

In terms of outcome variables, in this section we focus on adoption of the agricultural technologies covered by the Agricultural Input Survey (AIS). The AIS covers the main inputs used by farmers in India, which can be classified into the following categories: seed varieties, pesticides, and fertilizers. In this section we focus on the share of land farmed with high-yield seed varieties (HYV) – as opposed to traditional seeds – as our main outcome. HYV seeds are new varieties or hybrid seeds developed to increase crop yields.[30]

Table X presents our main results on adoption of HYV seeds. The Table focuses on the 6,582 cells potentially affected by the tower construction program and whose characteristics at baseline are described in Table VIII. Table X reports OLS, IV and Reduced Form coefficients. Changes in mobile phone coverage and HYV adoption are 5-year differences between 2007 and 2012. Tower construction is captured by a dummy equal to 1 if a cell is covered (in total or in part) by new towers constructed under the Shared Mobile Infrastructure Program between 2007 and 2010. Our results are robust to using the share of land covered by SMIP towers instead of a dummy variable. In what follows we discuss our results step by step.

First, we present OLS estimates from the same specification as Table IV, but focusing exclusively on the sample of cells used in our identification strategy. As shown, the estimates are consistent with those in Table IV. The estimated coefficient in column (2) suggests that a 10 percentage points increase in the area covered by mobile phones between 2007 and 2012 (approximately 10 square km) corresponds to around .35 percentage points increase in area farmed with HYV seeds in the same cell.[31] The magnitude of the estimated coefficient on change in mobile phone coverage is 75 percent larger than the one shown in Table IV 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.

In columns (4) to (6) we present the estimated IV coefficients on the effect of mobile phone coverage on HYV adoption between 2007 and 2012. The estimated coefficient in column (5) indicates that cells with a one standard deviation larger increase in mobile phone coverage experienced a 4 percentage points larger increase in area farmed with HYV seeds (1.6 percentage points if using within-district variation, see column (6)). As shown, our IV coefficients are between three and four times larger than the corresponding OLS estimates presented in columns (2) and (3) for the same sample of cells. What is the source

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

[31] Or .11 percentage points if using within-district variation across cells, see column (3).

of downward bias for the OLS coefficients? One potential explanation is unobservable farmers skills in cells experiencing higher increase in mobile phone coverage, which is not fully captured by literacy rate, distance to nearest town or initial HYV adoption. These 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, we expect the OLS coefficient to display a smaller effect of mobile coverage on adoption relative to the IV coefficient.

Finally, in columns (7) to (9) we present our reduced form estimates of HYV adoption on tower construction. The size of the estimated coefficient indicates that cells receiving coverage from a new SMIP tower experienced a 1.4 percentage points larger increase in the share of their area farmed with HYV seeds.

One potential concern is that treated cells – those receiving coverage from new towers – were in 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 adoption in the period 2002 to 2007, and the period 1997 to 2002. Table XI reports the results. As shown, areas where new towers were constructed in the 2007 to 2010 period 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 X are not driven by pre-existing trends across treatment and control cells in the 10 years preceding the mobile phone tower construction program.

V.E The Effect of Mobile Phone Coverage on Farmers' calls

The first stage results presented in Table X show that variation in construction of new mobile phone towers under SMIP explains the change in mobile phone coverage between 2007 and 2012. However, as discussed in Section IV, an exogenous change in mobile phone coverage can generate HYV adoption through different mechanisms. One potential mechanism is that, after receiving mobile phone coverage, farmers start using mobile phones to receive relevant information about new agricultural technologies, which favors adoption. However, adoption could also be driven by general equilibrium effects: mobile phone coverage can create economic opportunities in these areas, which then increase their demand for agricultural output. Farmers might then decide to switch to newer technologies to cater the increase in local demand.

In this section we present evidence consistent with the information mechanism. In particular, we study whether new tower construction explains changes in farmers' calls to Kisan Call Centers for agricultural advice. To this end, we estimate equation (3) using as outcome variable the change in the number of farmers' calls from originated in given cell as described in equation (5).

The results are reported in Table XII for our most demanding specification including district fixed effects. Column (1) report the correlation between change in mobile phone coverage and change in calls. Relative to the results presented in Table VII which use data from the whole country, here we focus on the sample of cells used in the identification strategy. The magnitude of the OLS estimates suggest that cells with a one standard deviation larger increase in mobile phone coverage experienced a 4.9 percent larger increase in farmers' mobile phone calls for agricultural advice to Kisan Call Centers. Column (2) reports our IV estimate. The estimated coefficient is 1.11, which indicates that cells with 1 percent larger increase in mobile phone coverage experienced an increase in farmers' calls of roughly the same magnitude (or 42 percent for 1 standard deviation difference coverage growth across cells).

Overall, the results reported in Table XII are consistent with mobile phone coverage affecting technology adoption via information diffusion. Our data contains detailed information on the content of farmers' calls. Thus, in columns (4) to (9), we apply our identification strategy to calls related to seed varieties and credit. We find positive and significant IV coefficients for both these outcomes. The magnitude of the point estimates indicates that cells with a one standard deviation larger increase in mobile phone coverage experienced a 19.8 percent larger increase in calls regarding seed varieties and around 1 percent larger increase in calls on loans and credit cards.

VI Concluding Remarks

Mobile phones have experienced a widespread and fast diffusion in both developed and developing countries in the last 20 years. The benefits – as well as the costs – of this diffusion are still to be understood, especially in rural areas of developing countries. In this paper we study the effect of mobile phone coverage on technology adoption and access to credit by Indian farmers. To this end, we exploit fine geographical variation: our data allows to observe, at 10-by-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 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 the majority of Indian farmers. In addition, our paper provides suggestive evidence on how diffusion of mobile phones in conjunction with services for agricultural advice can promote access to credit by 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 initial findings indicate that areas receiving mobile phone coverage experienced faster adoption of high-yielding varieties of seeds, and higher increase in access to credit by small farmers between 2007 and 2012.

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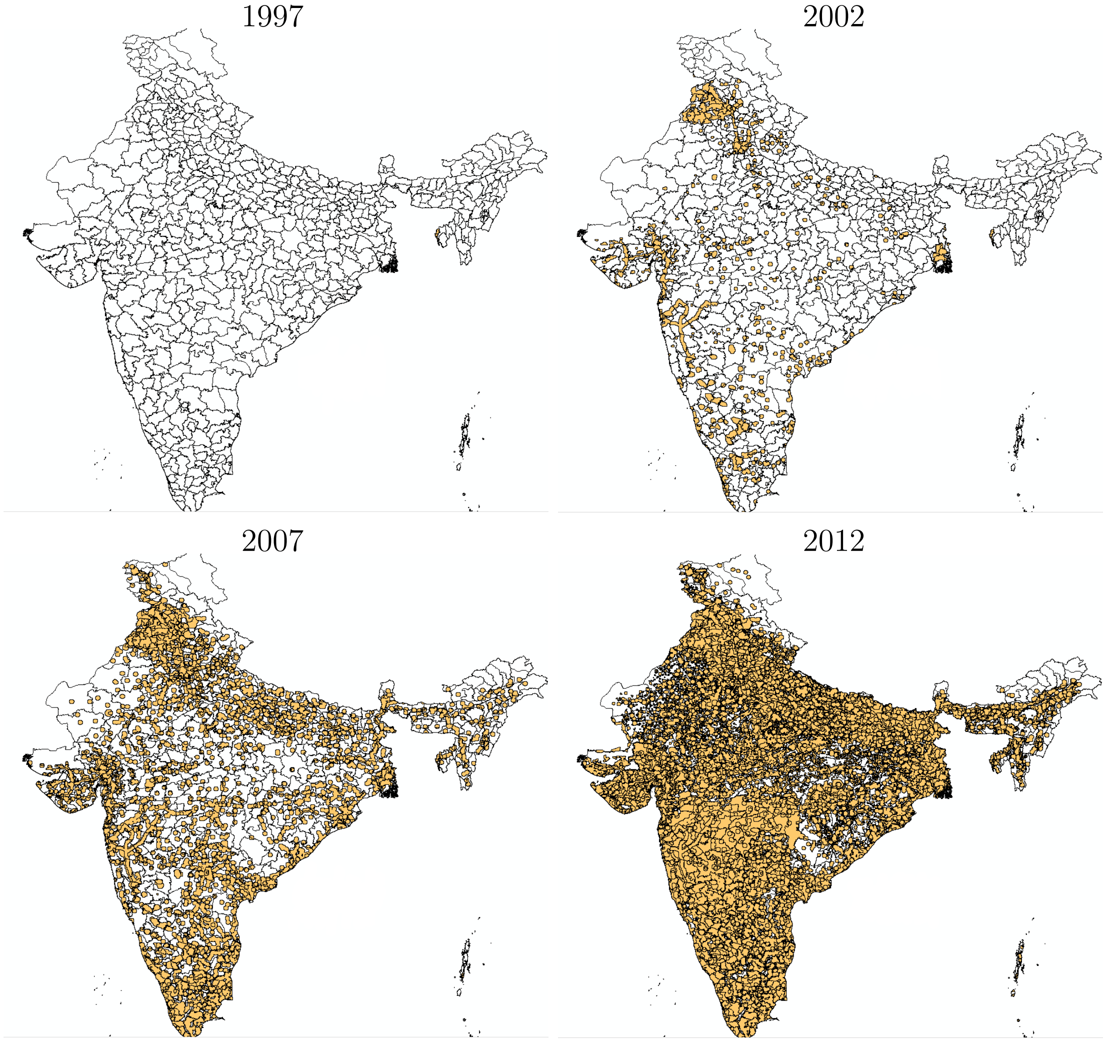
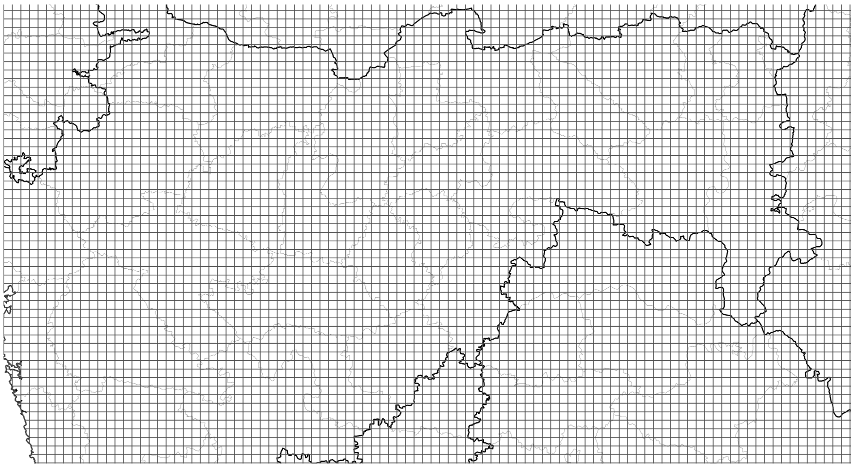
Figures and Tables

Figure I: Evolution of Mobile Phone Coverage in India: 1998 to 2012



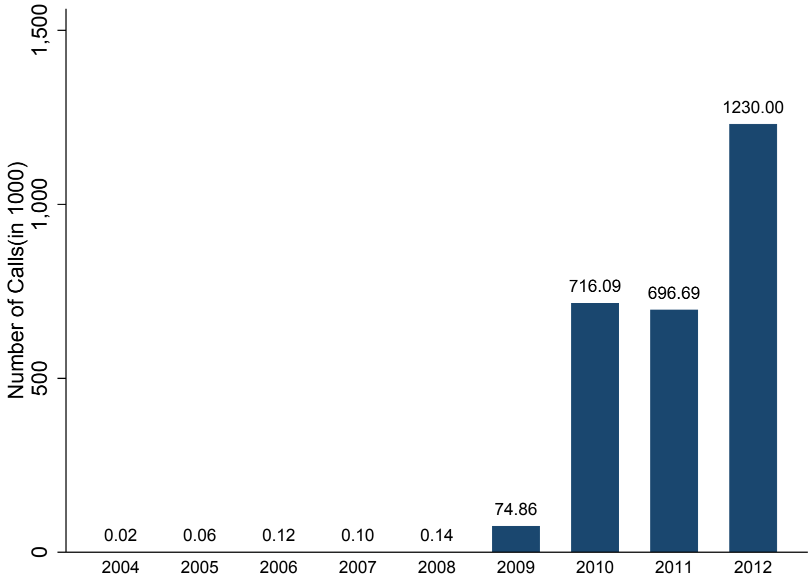
Notes: Source: GSMA

Figure II: Unit of observation: A Grid of India



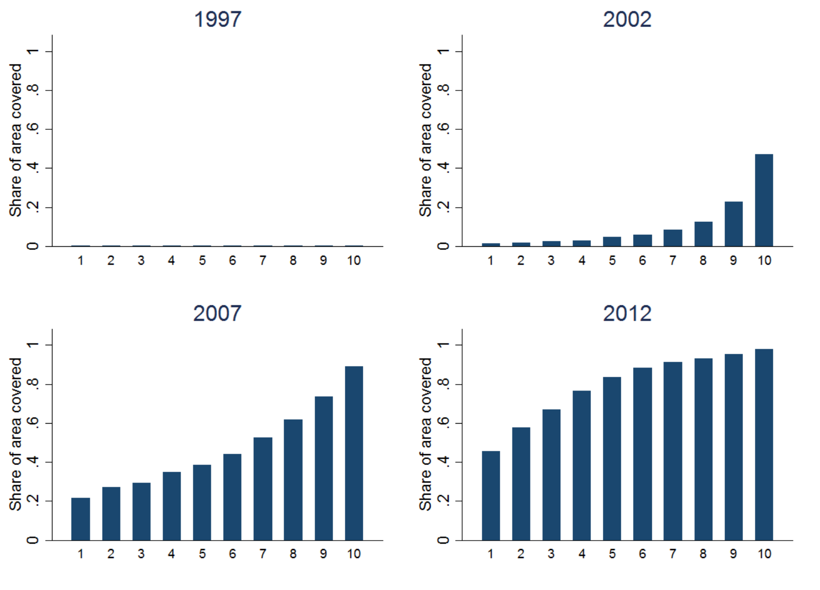
Notes: Source: Authors' calculations

Figure III: Total Number of Calls to Kisan Call Centers: 2004-2012



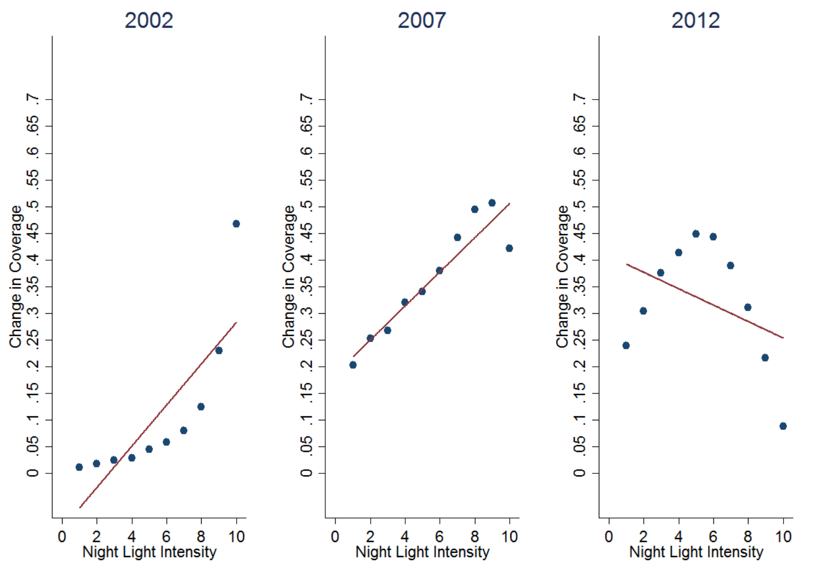
Notes: Source: Kisan Call Center, Ministry of Agriculture

Figure IV: Mobile Phone Coverage by Night Light Intensity



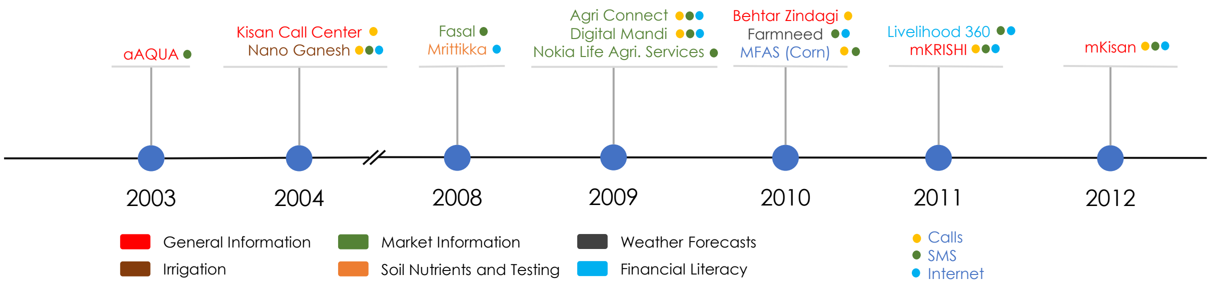
Notes: The average share of land with mobile phone coverage in each decile is calculated for the 4 years in which the Agricultural Input Survey was conducted: 1997, 2002, 2007 and 2012. Night Light Intensity data refers to 1996.

Figure V: Change in Mobile Phone Coverage by Night Light Intensity



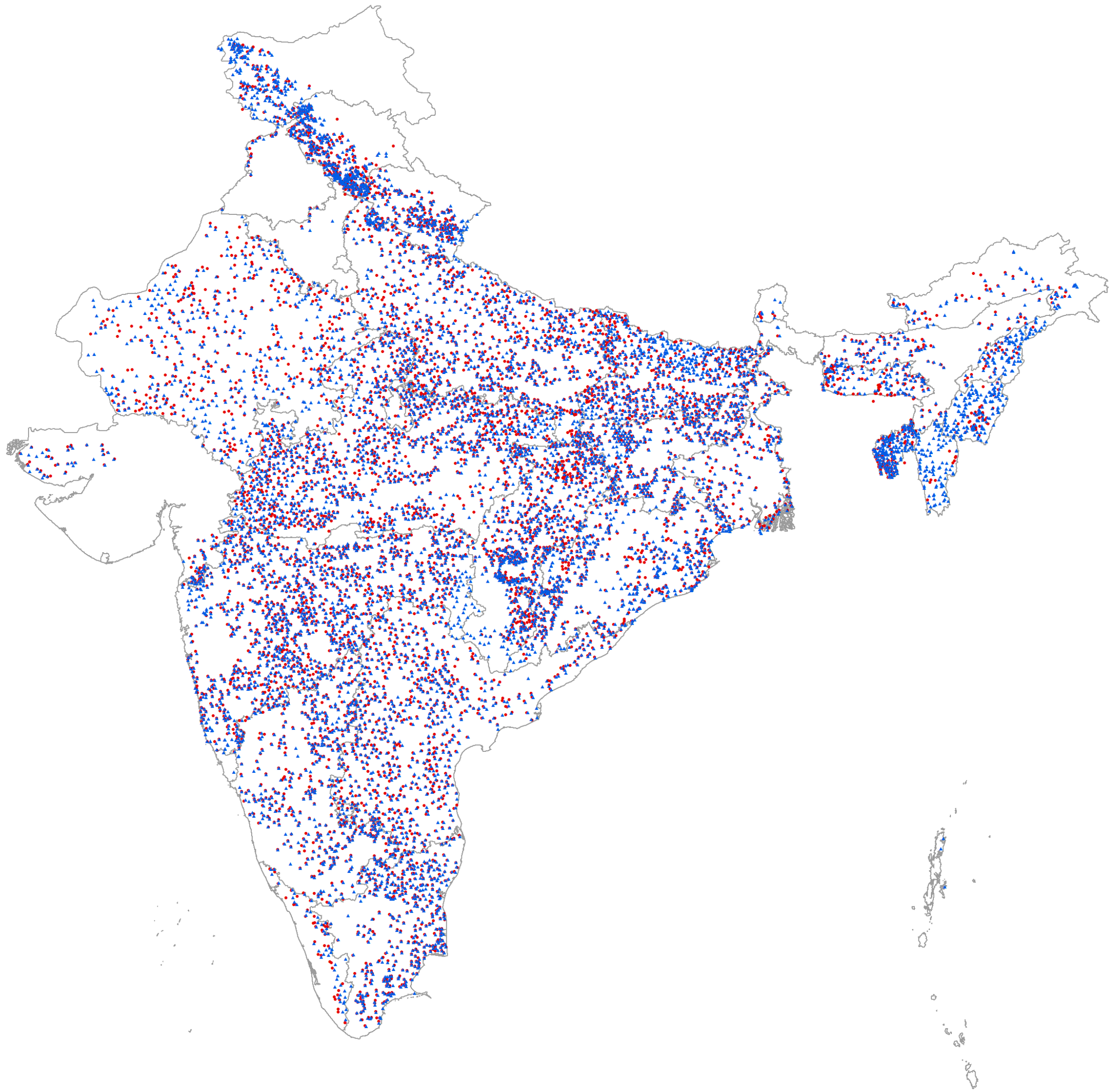
Notes: Changes in mobile phone coverage are sourced from GSMA and are calculated between waves of the Agricultural Input Survey. Night Light Intensity data refers to 1996.

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



Notes: Source: GSMA mAgri Deployment Tracker

Figure VII: Geographic location of Constructed versus Proposed Towers under SMIP



Notes: Location of eventually constructed towers are represented with red circles. Location of SMIP proposed towers under USOF Phase I are represented with blue triangles.

Figure VIII: Proposed vs Actual Covered Areas
Mahasrashtra (MH) State

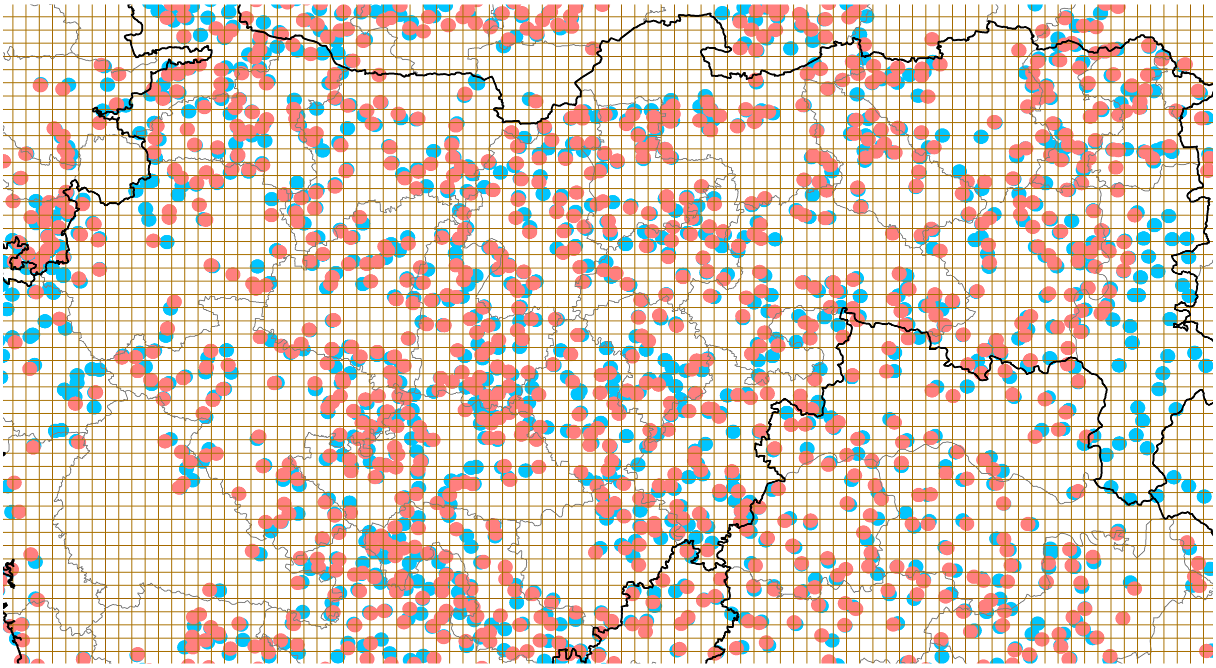
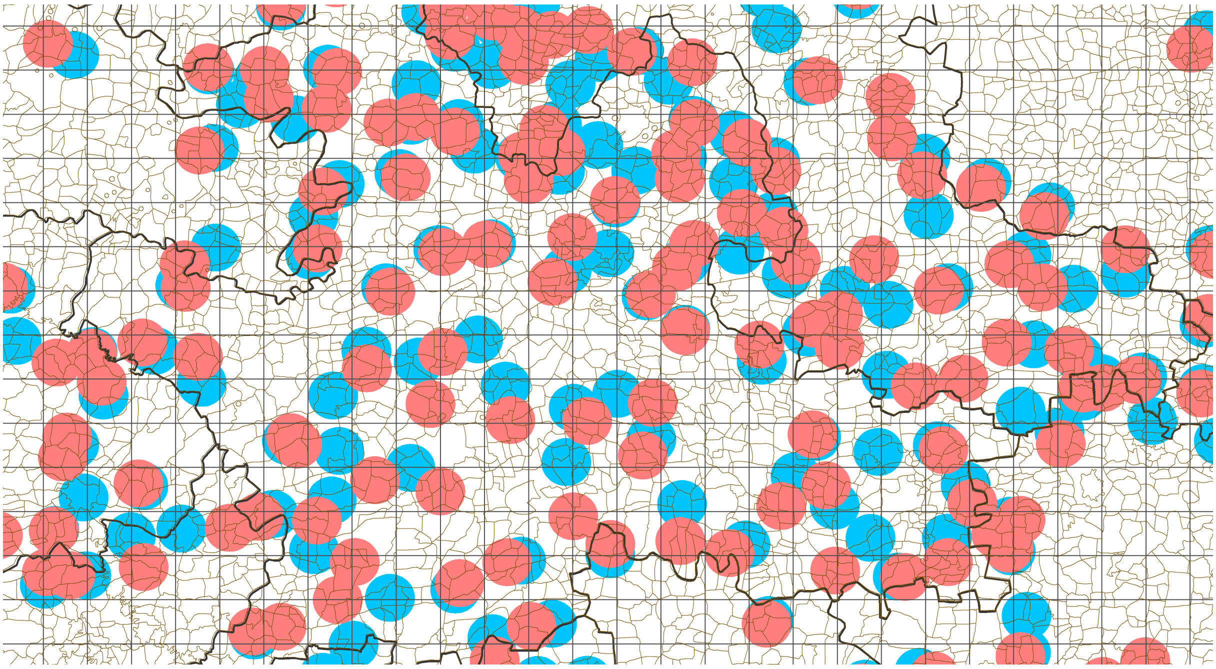


Figure IX: Proposed vs Actual Covered Areas
Solapur, MH District



Notes:
1. Area in red represents the area covered by towers eventually constructed. Area in blue represents the area covered by towers initially proposed. Areas are constructed by assuming a 5-km radius of coverage around the tower geo-coordinates.

Table I: Summary Statistics

	Mean	Median	Std. Deviation	N
All Cells (OLS):				
2007-2012:				
Δ HYV Share	0.024	0.007	0.06	26539
Δ Mobile Coverage	0.283	0.096	0.437	26539
Δ Pesticide Share	0.001	0	0.092	26059
Δ Certified Seeds Share	0.096	0.059	0.115	21745
Δ Log(Calls)	1.688	1.624	1.295	26539
Δ (Calls/Population)	1.735	0.759	3.302	24610
2002-2007:				
Δ HYV Share	0.013	0.005	0.048	26539
Δ Mobile Coverage	0.32	0.01	0.413	26539
Δ Pesticide Share	0.024	0.003	0.076	26294
Δ Certified Seeds Share	-0.017	-0.008	0.03	22455
1997-2002:				
Δ HYV Share	0.025	0.009	0.085	26539
Δ Mobile Coverage	0.095	0	0.267	26539
Δ Pesticide Share	0.052	0.015	0.109	26462
Δ Certified Seeds Share	-0.032	-0.003	0.081	21340
Cells used for identification:				
2007-2012:				
Δ HYV Share	0.035	0.015	0.069	6582
Δ Mobile Coverage	0.62	0.757	0.38	6582
Δ Pesticide Share	0.019	0.004	0.094	6396
Δ Certified Seeds Share	0.068	0.049	0.076	4937
Δ Log(Calls)	1.522	1.498	1.045	6582
Δ (Calls/Population)	1.4	0.73	5.633	6582
District level outcomes:				
2007-2012:				
Δ Mobile Coverage	0.235	0.249	0.232	419
Δ Holdings Under $\text{Credit}_{\text{Total}}$	0.123	0.08	0.246	367
Δ Holdings Under $\text{Credit}_{\text{VerySmall}}$	0.118	0.071	0.27	353
Δ Holdings Under $\text{Credit}_{\text{Small}}$	0.126	0.099	0.255	358
Δ Holdings Under $\text{Credit}_{\text{SmallMedium}}$	0.124	0.099	0.238	358
Δ Holdings Under $\text{Credit}_{\text{Medium}}$	0.123	0.122	0.262	346
Δ Holdings Under $\text{Credit}_{\text{Large}}$	0.037	0.032	0.322	284
Δ $\text{Log(Amount)}_{\text{Short-term}}$	0.424	0.45	1.418	337
Δ $\text{Log(Amount)}_{\text{Medium-term}}$	0.458	0.347	1.905	286
Δ $\text{Log(Amount)}_{\text{Long-term}}$	-0.031	-0.156	2.197	241

Table II: Categories based on reason for the call made to KCC

Query Type	Freq.	Percent
Pesticides	678,015	48.8
Yield	175,522	12.6
Fertilizers	144,572	10.4
Weather	72,822	5.2
Field Preparation	62,902	4.5
Market Information	50,043	3.6
Credit	26,527	1.9
Other reasons	178,855	12.9
Total	1,389,258	100.0

Notes: The table shows the queries made by farmers in their calls to Kisan Call Center (KCC). Queries data based on 'reason for calls' and 'the response of the representative'. The sample is from KCC data between 2006-2011.

Table III: Crop distribution for calls made to KCC

Crop	Freq.	Percent
Rice	149,040	19.9
Wheat	90,081	12.0
Cotton	80,316	10.7
Chilli	43,882	5.9
Brinjal	39,482	5.3
Tomato	33,899	4.5
Sugarcane	33,765	4.5
Okra	28,849	3.9
Onion	27,132	3.6
Groundnut	26,411	3.5
Soy	25,668	3.4
Rape	24,610	3.3
Maize	21,513	2.9
Gram	20,146	2.7
Maize	20,105	2.7
Potato	19,504	2.6
Moong	18,615	2.5
Peas	16,146	2.2
Banana	14,825	2.0
Millet	14,378	1.9

Notes: The table shows the top 20 crops (by call volume) for which queries where made by farmers in their calls to Kisan Call Center (KCC). The sample is from KCC data between 2006-2011.

Table IV: Basic Correlations: HYV Adoption and Mobile Coverage

	All waves	2007-2012		2002-2007		1997-2002	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Δ Coverage	0.007**	0.021***	0.004***	-0.004	0.000	-0.005	0.002
	[0.003]	[0.005]	[0.001]	[0.003]	[0.001]	[0.006]	[0.002]
District fe			y		y		y
Observations	79,617	26,539	26,537	26,539	26,537	26,539	26,537
R-squared	0.009	0.023	0.837	0.001	0.808	0.000	0.835

Notes: Changes in dependent variables are calculated over the interval of five years (1997-2002, 2002-2007, 2007-2012). Column (1) pools together the data from all waves of Agricultural Input Survey. Δ Coverage is the change in the cell area covered under GSM mobile coverage calculated over the five years corresponding to the wave. Column (3), (5) and (6) includes the district-fixed effects. The unit of observation is a 10-by-10 km cell. Only cells with non-missing Δ HYV value in 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 V: Δ Share of Operational Holdings with Credit and Δ Coverage : 2007-2012

	(1) All	(2) Very Small	(3) Small	(4) Small-Medium	(5) Medium	(6) Large
Δ Coverage	0.120**	0.154***	0.107*	0.106*	0.081	-0.044
	[0.056]	[0.058]	[0.059]	[0.055]	[0.058]	[0.082]
Observations	345	332	336	334	316	250
R-squared	0.012	0.017	0.009	0.010	0.005	0.001

Notes: The dependent variable is the change in share of operational holdings with access to credit. Each column corresponds to different size of operational holdings. Size categories include: 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). Changes in dependent variables are calculated over the interval of five years (2007-2012). Δ Coverage is the change in the district area covered under GSM mobile coverage between 2007 and 2012. The unit of observation is a district. Standard errors clustered at district level are reported in brackets. Significance level: *** p<0.01, ** p<0.05, * p<0.1 .

Table VI: Δ Log(credit) and Δ Coverage : 2007-2012 By Size of holdings and loan maturity

	(1) All	(2) Very Small	(3) Small	(4) Small-Medium	(5) Medium	(6) Large
A. Total						
Δ Coverage	0.431	1.046***	0.417	-0.199	0.096	-0.095
	[0.302]	[0.358]	[0.350]	[0.361]	[0.300]	[0.427]
Observations	346	322	334	330	294	210
R-squared	0.006	0.029	0.005	0.001	0.000	0.000
B. Short-maturity						
Δ Coverage	0.948***	1.597***	0.869**	0.002	0.168	0.233
	[0.353]	[0.387]	[0.388]	[0.337]	[0.338]	[0.447]
Observations	337	314	327	318	290	204
R-squared	0.023	0.060	0.018	0.000	0.001	0.001
C. Long-maturity						
Δ Coverage	-0.493	0.351	0.590	-0.136	-0.632	-0.945
	[0.491]	[0.624]	[0.584]	[0.513]	[0.573]	[0.893]
Observations	304	220	262	254	235	142
R-squared	0.004	0.001	0.005	0.000	0.006	0.010

Notes: The dependent variable is the change in log of credit amount taken by agricultural holdings. Each column corresponds to different size of operational holdings. Size categories include: 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). Changes in dependent variables are calculated over the interval of five years (2007-2012). Panel A aggregates all loan maturity; Panel B is for short-term credit with maturity less than 18 months; Panel C considers long-term maturity loans with maturity greater than 18 months. Δ Coverage is the change in the district area covered under GSM mobile coverage between 2007 and 2012. The unit of observation is a district. Standard errors clustered at district level are reported in brackets. Significance level: *** p<0.01, ** p<0.05, * p<0.1 .

Table VII: Baseline Correlations: Farmers' Calls and Mobile Coverage

	Δ log(Calls)		Δ (Calls/Population)	
	(1)	(2)	(3)	(4)
A. All Calls				
Δ Coverage	0.378***	0.071***	0.094**	0.086***
	[0.075]	[0.016]	[0.037]	[0.013]
District fe		y		y
Observations	26,539	26,537	26,467	26,465
R-squared	0.016	0.870	0.002	0.553
B. Calls on Yields				
Δ Coverage	0.133***	0.036***	0.018*	0.016***
	[0.046]	[0.008]	[0.010]	[0.004]
District fe		y		y
Observations	26,539	26,537	26,467	26,465
R-squared	0.005	0.901	0.001	0.430
C. Calls on Credit				
Δ Coverage	0.010***	0.003***	0.001***	0.0003***
	[0.002]	[0.001]	[0.000]	[0.000]
District fe		y		y
Observations	26,539	26,537	26,467	26,465
R-squared	0.014	0.779	0.026	0.644

Notes: Changes in dependent variables are calculated over the 2007-2012. Calls data is from Kisan Call Center (KCC). Panel A includes all calls for which crop information is available; Panel B includes only calls on crop-yields; Panel C includes only calls seeking information on credit. Column (2) and (4) includes district-fixed effects. The unit of observation is a 10-by-10 km cell. Only cells with non-missing Δ HYV value in 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 VIII: SMIP coverage(0/1) 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 (0/1)	0.811	0.696	0.115***	0.026		
	(0.017)	(0.024)	(0.021)			
Literacy Rate	0.430	0.403	0.027**	0.008	0.007*	0.595
	(0.007)	(0.014)	(0.011)		(0.003)	
Share of agri. Workers	0.399	0.405	-0.005	0.000	0.007*	0.498
	(0.007)	(0.008)	(0.007)		(0.004)	
Agri. Land/Cultivable Area	0.627	0.606	0.021	0.000	-0.152	0.076
	(0.056)	(0.034)	(0.046)		(0.184)	
Percentage Irrigated	0.300	0.369	-0.069**	0.009	0.000	0.697
	(0.021)	(0.035)	(0.031)		(0.009)	
Night Lights (2001)	1.562	1.023	0.539***	0.015	-0.079	0.493
	(0.115)	(0.108)	(0.104)		(0.064)	
Education Facility (0/1)	0.872	0.851	0.021**	0.002	0.004	0.472
	(0.009)	(0.011)	(0.011)		(0.006)	
Medical Facility (0/1)	0.351	0.325	0.026*	0.002	-0.004	0.425
	(0.014)	(0.017)	(0.015)		(0.010)	
Post Office (0/1)	0.266	0.255	0.011	0.000	-0.006	0.481
	(0.016)	(0.017)	(0.016)		(0.007)	
Telephone Office (0/1)	0.017	0.015	0.002	0.000	-0.006**	0.362
	(0.004)	(0.003)	(0.003)		(0.002)	
Dist. to nearest town(kms)	34.213	49.852	-15.639***	0.049	-3.761**	0.569
	(1.879)	(3.377)	(2.950)		(1.748)	
Drinking Water Facility (0/1)	0.991	0.993	-0.001	0.000	-0.002	0.096
	(0.001)	(0.001)	(0.001)		(0.002)	
Banking Facility (0/1)	0.061	0.054	0.007	0.001	-0.005	0.183
	(0.004)	(0.005)	(0.004)		(0.004)	
Credit Society Facility (0/1)	0.128	0.099	0.029***	0.004	0.000	0.423
	(0.011)	(0.010)	(0.009)		(0.005)	
HYV Share (2001)	0.195	0.121	0.073***	0.033	0.012***	0.822
	(0.013)	(0.012)	(0.011)		(0.004)	
Δ HYV (2006)	0.019	0.014	0.005	0.002	0.000	0.854
	(0.004)	(0.003)	(0.003)		(0.001)	
Income per capita	70.854	63.371	7.483	0.000	-5.821	0.282
	(7.558)	(14.065)	(12.148)		(8.984)	
Expense per capita	63.911	58.433	5.478	0.000	-6.912	0.277
	(6.903)	(13.568)	(11.641)		(7.681)	

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 (Column 3 & 4). The treatment instrument we use 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 that are inhabited. 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 cell population and probability of having power supply. Standard errors clustered at district level are reported in brackets. Significance level: *** p<0.01, ** p<0.05, * p<0.1 .

Table IX: First Stage

Dependent Variable:	ΔCoverage$_{2007-2012}$			
	(1)	(2)	(3)	(4)
Treatment SMIP(0/1)	0.276***	0.167***	0.138***	0.081***
	[0.019]	[0.015]	[0.014]	[0.013]
Population (1000's)		0.012***	0.009***	0.010***
		[0.001]	[0.001]	[0.001]
Power Supply		0.384***	0.247***	0.126***
		[0.029]	[0.031]	[0.026]
Share pop. in agri.			-0.127	-0.189***
			[0.098]	[0.068]
Literacy Rate			0.351***	0.468***
			[0.066]	[0.058]
Distance to nearest Town(kms)			-0.003***	-0.002***
			[0.000]	[0.000]
Land irrigated/Agri land			-0.028	0.098***
			[0.026]	[0.023]
Credit Society Facility			0.164***	0.035
			[0.032]	[0.024]
Banking Facility			0.017	-0.015
			[0.037]	[0.035]
Income per Capita			0.000**	0.000
			[0.000]	[0.000]
District fe				y
Observations	6,582	6,582	6,582	6,562
F-stat	203	312.8	165.1	50.66
R-squared	0.105	0.378	0.443	0.595

Notes: This table reports first stage results. The dependent variable is change in area under GSMA mobile coverage from 2007 to 2012, based on the data provided by telecom companies to GSMA. Cell-level controls are created by aggregating village-level demographics and amenities information from 2001 Census data by assigning villages to the cell in which its centroids lie. The Treatment SMIP instrument we use 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 that are inhabited. Column (4) controls for district fixed effects. Standard errors clustered at district level are reported in brackets. Significance level: *** p<0.01, ** p<0.05, * p<0.1.

Table X: Δ HYV and Δ Coverage: 2007-2012

	OLS			IV-2SLS			Reduced Form		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Δ Coverage	0.038***	0.035***	0.011***	0.104***	0.104***	0.043***			
	[0.007]	[0.007]	[0.003]	[0.032]	[0.035]	[0.015]			
Treatment SMIP(0/1)							0.017***	0.014***	0.003***
							[0.005]	[0.005]	[0.001]
Population (1000's)	-0.000**	-0.000	0.001***	-0.001**	-0.001**	0.000	0.000	0.000	0.001***
	[0.000]	[0.000]	[0.000]	[0.001]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Power Supply	0.023***	0.019***	0.007	-0.005	0.001	0.003	0.035***	0.027***	0.008
	[0.007]	[0.006]	[0.006]	[0.014]	[0.010]	[0.006]	[0.008]	[0.007]	[0.007]
Share pop. in agri.		0.018	0.006		0.025	0.011**		0.012	0.003
		[0.030]	[0.005]		[0.031]	[0.006]		[0.029]	[0.005]
Literacy Rate		0.014	0.004		-0.011	-0.012		0.025	0.008
		[0.028]	[0.010]		[0.027]	[0.011]		[0.028]	[0.010]
Distance to nearest Town(kms)		-0.000	-0.000*		0.000	0.000		-0.000	-0.000***
		[0.000]	[0.000]		[0.000]	[0.000]		[0.000]	[0.000]
Land irrigated/Agri land		-0.018	0.012**		-0.014	0.009*		-0.017	0.013**
		[0.011]	[0.005]		[0.011]	[0.005]		[0.011]	[0.005]
Credit Society Facility		-0.001	0.003		-0.013	0.002		0.004	0.004
		[0.015]	[0.003]		[0.016]	[0.003]		[0.015]	[0.003]
Banking Facility		0.004	-0.006*		0.004	-0.005		0.005	-0.006*
		[0.017]	[0.003]		[0.017]	[0.003]		[0.017]	[0.003]
Income per Capita		0.000	0.000		0.000	0.000		0.000	0.000
		[0.000]	[0.000]		[0.000]	[0.000]		[0.000]	[0.000]
District fe			y			y			y
Observations	6,582	6,582	6,562	6,582	6,582	6,562	6,582	6,582	6,562
R-squared	0.062	0.071	0.855	-0.027	-0.014	0.841	0.045	0.057	0.854

Notes: Changes in dependent variables are calculated over 2007-2012. Column(1)-(3) shows the estimates from OLS specification; Column (4)-(6) shows the second stage estimates using Treatment SMIP as the instrument; Column (7)-(9) shows the reduced form estimates. Δ Coverage is the change in the cell area covered under GSM mobile coverage calculated from 2007-2012. Column (3), (6) and (9) includes the district-fixed effects. The Treatment SMIP instrument 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 unit of observation is a 10-by-10 km cell. The sample includes all cells with zero cell phone coverage in 2006 that are inhabited. 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 XI: Δ HYV and Δ Coverage
Pre-Existing Trends

	(1) 2007-2012	(2) 2002-2007	(3) 1997-2002
Treatment SMIP(0/1)	0.003***	0.000	0.002
	[0.001]	[0.001]	[0.003]
Population (1000's)	0.000***	0.000	0.001***
	[0.000]	[0.000]	[0.000]
Power Supply	-0.002	0.002	0.003
	[0.003]	[0.002]	[0.005]
Share pop. in agri.	0.006	0.007	-0.001
	[0.005]	[0.005]	[0.009]
Literacy Rate	0.021**	0.002	-0.001
	[0.008]	[0.007]	[0.020]
Distance to nearest Town(kms)	-0.000*	-0.000*	-0.000*
	[0.000]	[0.000]	[0.000]
Land irrigated/Agri land	0.012*	0.007**	0.024*
	[0.007]	[0.003]	[0.013]
Credit Society Facility	0.004	0.004*	-0.003
	[0.003]	[0.002]	[0.002]
Banking Facility	-0.007**	0.001	-0.012**
	[0.003]	[0.003]	[0.005]
Income per Capita	0.000	-0.000	0.000
	[0.000]	[0.000]	[0.000]
District fe	y	y	y
Observations	5,223	5,223	5,223
R-squared	0.867	0.855	0.883

Notes: This table test for pre-existing trend 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. Changes in dependent variables are calculated over 2007-2012 (Column (1)); 2002-2007 (Column (2)) and 1997-2002 (Column (3)). The Treatment SMIP instrument 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 unit of observation is a 10-by-10 km cell. The sample includes all cells with zero cell phone coverage in 2006 that are inhabited. All columns controls for district fixed effects. Standard errors clustered at district level are reported in brackets. Standard errors clustered at district level are reported in brackets. Significance level: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

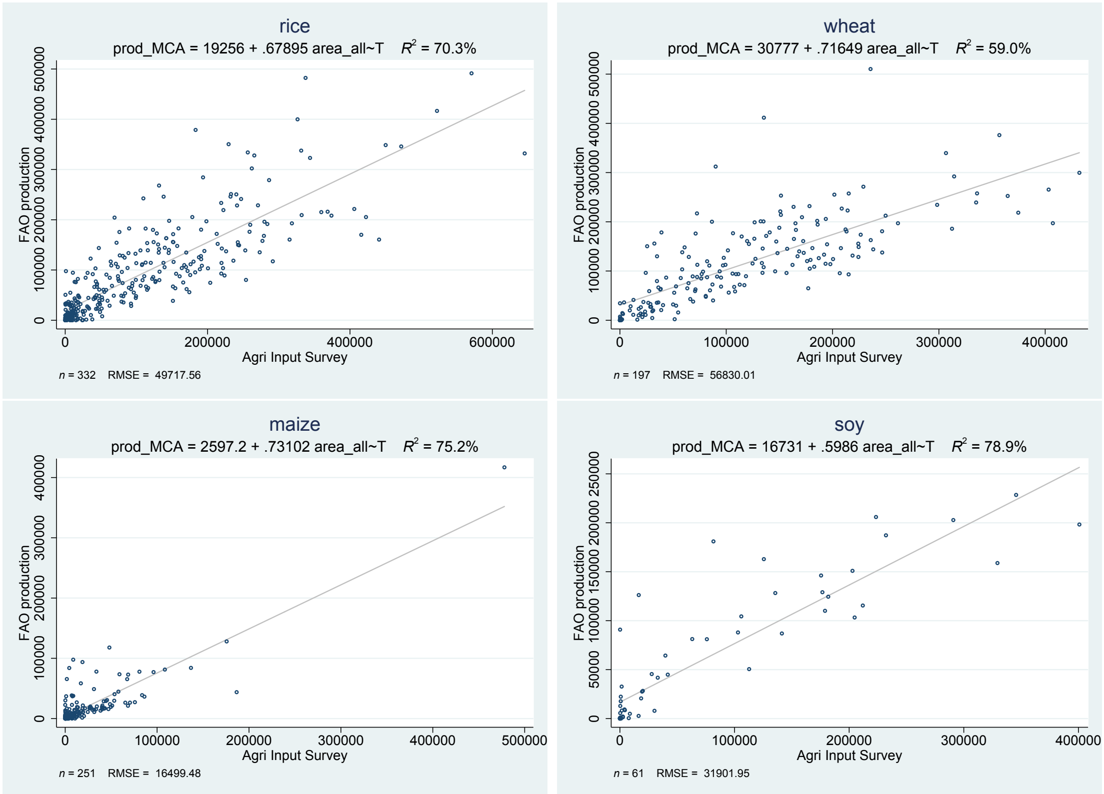
Table XII: Δ Calls and Δ Coverage: 2007-2012

	All calls			Calls on Yields			Calls on Credit		
	OLS	IV-2SLS	Reduced Form	OLS	IV-2SLS	Reduced Form	OLS	IV-2SLS	Reduced Form
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Δ Coverage	0.129***	1.113***		0.047**	0.520***		0.005***	0.022**	
	[0.033]	[0.294]		[0.019]	[0.200]		[0.001]	[0.009]	
Treatment SMIP(0/1)			0.090***			0.042***			0.002**
			[0.021]			[0.015]			[0.001]
Population (1000's)	0.016***	0.006	0.017***	0.006***	0.001	0.006***	0.000***	0.000	0.000***
	[0.002]	[0.004]	[0.002]	[0.001]	[0.002]	[0.001]	[0.000]	[0.000]	[0.000]
Power Supply	0.173***	0.042	0.182***	0.058	-0.005	0.060*	-0.001	-0.003	-0.001
	[0.059]	[0.062]	[0.058]	[0.037]	[0.036]	[0.036]	[0.001]	[0.002]	[0.001]
Share pop. in agri.	0.401**	0.571***	0.361**	0.194*	0.276***	0.178*	0.002	0.005	0.001
	[0.172]	[0.190]	[0.171]	[0.107]	[0.103]	[0.106]	[0.006]	[0.006]	[0.006]
Literacy Rate	0.111	-0.363*	0.158	0.086	-0.143	0.101*	0.012**	0.003	0.013***
	[0.116]	[0.196]	[0.115]	[0.052]	[0.136]	[0.055]	[0.005]	[0.006]	[0.005]
Distance to nearest Town(kms)	-0.001**	0.001**	-0.001***	-0.000**	0.001*	-0.000***	-0.000*	0.000	-0.000**
	[0.000]	[0.001]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Land irrigated/Agri land	0.261***	0.164**	0.273***	0.189***	0.142***	0.194***	0.011***	0.010***	0.012***
	[0.064]	[0.065]	[0.064]	[0.047]	[0.043]	[0.046]	[0.003]	[0.003]	[0.003]
Credit Society Facility	0.029	-0.007	0.032	0.008	-0.009	0.009	0.001	0.000	0.001
	[0.050]	[0.064]	[0.049]	[0.033]	[0.042]	[0.032]	[0.001]	[0.001]	[0.001]
Banking Facility	-0.091*	-0.070	-0.087*	-0.051	-0.040	-0.048	-0.002	-0.001	-0.002
	[0.052]	[0.070]	[0.050]	[0.032]	[0.042]	[0.031]	[0.002]	[0.002]	[0.002]
Income per Capita	-0.000	-0.000	-0.000	0.000	-0.000	0.000	0.000	0.000	0.000
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
District fe	y	y	y	y	y	y	y	y	y
Observations	6,562	6,562	6,562	6,562	6,562	6,562	6,562	6,562	6,562
R-squared	0.861	0.812	0.862	0.866	0.834	0.866	0.755	0.744	0.754

Notes: Changes in dependent variables are calculated over 2007-2012. Column (1)-(3) includes all calls for which crop information is available; Column (4)-(6) includes only calls on crop-yields; Column (7)-(9) includes only calls seeking information on credit. Δ Coverage is the change in the cell area covered under GSM mobile coverage calculated from 2007-2012. All columns includes the district-fixed effects. The Treatment SMIP instrument 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 unit of observation is a 10-by-10 km cell. The sample includes all cells with zero cell phone coverage in 2006 that are inhabited. Standard errors clustered at district level are reported in brackets. Standard errors clustered at district level are reported in brackets. Significance level: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Appendix

Table A1: Correlation between FAO and Agricultural Input Survey Data



Notes: Unit of observation is a district. Data reported for 4 largest crops by total production in India.

Table A2: Pre-Existing Trends: Δ Share of Operational Holdings with Credit and Δ Coverage

	(1) All	(2) Very Small	(3) Small	(4) Small-Medium	(5) Medium	(6) Large
2007-2012:						
Δ Coverage$_{2007-2012}$	0.109	0.178**	0.076	0.025	0.030	-0.027
	[0.068]	[0.073]	[0.071]	[0.067]	[0.071]	[0.092]
Observations	337	324	328	326	311	249
R-squared	0.135	0.174	0.077	0.047	0.115	0.187
2002-2007:						
Δ Coverage$_{2007-2012}$	-0.032	-0.059	-0.049	0.007	0.015	-0.045
	[0.041]	[0.043]	[0.055]	[0.055]	[0.055]	[0.080]
Observations	337	324	328	326	311	249
R-squared	0.164	0.212	0.122	0.072	0.129	0.124
1997-2002:						
Δ Coverage$_{2007-2012}$	0.024	0.035	0.030	-0.013	-0.045	-0.050
	[0.045]	[0.047]	[0.049]	[0.053]	[0.054]	[0.082]
Observations	337	324	328	326	311	249
R-squared	0.168	0.214	0.140	0.150	0.127	0.068

Notes: Standard errors clustered at district level are reported in brackets. Significance level: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Districts with non-missing Δ HYV considered. Controls Based on Village Coordinates.