Information Frictions and Take-up of Government Credit Programs*

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June 28, 2023

Abstract

Most governments in developing countries offer subsidized credit programs to the agricultural sector. We document that farmers often lack information on how these programs work, their eligibility criteria and loan terms offered. We study the impact of information frictions on credit take-up by exploiting plausibly exogenous variation in the construction of new mobile phone towers in rural areas of India without previous mobile phone coverage. Areas receiving coverage experience higher take-up of agricultural credit. The effects are concentrated in short-term credit to small land holders, which have been the target of a major Indian government credit program, the Kisan credit cards.

Keywords: Mobile phones, Shared Mobile Infrastructure Scheme (SMIS), Kisan credit cards, Kisan call centers.

JEL Classification: G21, Q16, E51

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

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1 Introduction

Farmers in developing countries often lack access to traditional financial services because of key market failures such as information asymmetries, lack of competition or property rights that are not enforceable (Karlan and Morduch, 2010; Karlan et al., 2016). In response, several governments have introduced programs offering subsidized credit for agriculture, with the hope that higher take up will facilitate adoption of modern technologies and help farmers absorb income shocks and smooth consumption. However, targeted individuals might be unaware of the existence of such programs, or lack information about eligibility criteria, application procedures or loan terms offered. This type of information frictions are particularly relevant for farmers in remote and unconnected areas, which are also more likely to be eligible for government credit programs.

In this paper, we study the impact of information frictions about credit programs available to farmers on credit take-up using data from India. To capture changes in potential access to information by farmers, we exploit variation in mobile phone coverage generated by the Shared Mobile Infrastructure Scheme (SMIS), which was launched by the Indian government in 2007 to finance the construction of about 7,000 mobile phone towers in previously unconnected areas. We match the geographical coverage brought by new towers with data on phone calls made by farmers to one of India's leading services for agricultural advice, the Kisan Call Centers (KCC), a free-of-charge service that answer farmers' calls on topics related to agriculture, including information on government credit programs. To study the impact of potential access to information on credit take-up by farmers we use detailed data collected via the Input Survey that accompanies the Indian Agricultural Census.

We start by using an event-study design to document the evolution of calls by farmers' calls around the construction of new mobile phone towers in previously uncovered areas. Using high-frequency (monthly) variation, we document that the construction of the first mobile phone tower in a given area is followed by a significant increase in the number of farmers' calls to call centers for agricultural advice. This is consistent with a large and under served demand for agricultural related information in rural India. In the majority of calls about agricultural credit, farmers ask questions regarding Kisan credit cards, a specific type of card offering short-term credit at rates subsidized by the government.

We then study the effect of expanding mobile phone coverage on credit take up using the construction of new cell-phone towers under SMIS as a natural experiment. To account for the potentially endogenous location of the new SMIS cell-phone towers, we propose an identification strategy that compares locations where new towers were proposed by the Department of Telecommunications and eventually constructed, with locations where they were also proposed but eventually not constructed because they were relocated to other areas. We show that these two types of location are balanced on initial observable char-

acteristics once we control for determinants of tower relocation such as terrain ruggedness and potential population covered, and that they experienced similar pre-existing trends in credit take up in the 5 years preceding the introduction of new towers.

The main finding is that areas with a larger increase in mobile phone coverage after the construction of SMIS towers experienced a larger increase in agricultural credit take up by farmers. In terms of magnitude, areas with a standard deviation larger increase in coverage – or about 40% of land covered by the mobile network – experienced a 6.8 percentage points larger increase in the share of farmers with agricultural credit after the introduction of SMIS towers. We find similar effects when studying the impact on credit per farmer. A dynamic version of our main specification shows absence of pre-trends and persistent effects after the introduction of new towers. We show that results are robust to using alternative measures of credit take up and correcting standard errors for spatial correlation using the methodology proposed in Conley (1999).

Then, we investigate whether the positive effects on take up of agricultural credit can be explained by higher participation in the government credit programs that farmers ask about when calling call centers for agricultural advice. We find that the effects are concentrated in short-terms loans and among small agricultural establishments, which is consistent with the characteristics of the loans offered via Kisan credit cards. In addition, when studying heterogeneity across lenders, we find that the effects are driven by loans originated by Primary Agricultural Credit Societies (PACS), the type of lender that specializes the most in the origination of Kisan credit cards among those in our sample. Finally, using micro data from the Socio-Economic and Caste Census of India, we document that areas where new towers were constructed had a higher share of agricultural household declaring to use Kisan Credit Cards in 2012, about five years after the beginning of the tower construction program.

Overall, these results suggest that the construction of SMIS towers relaxed information frictions about existing government programs of subsidized credit. A potential concern is that the arrival of mobile phone coverage might promote local economic opportunities more generally, increasing local income and thus credit demand by farmers to expand their operations. This would explain higher take up also in the absence of any relaxation of information frictions. To isolate the role of access to information, we exploit an institutional feature of Kisan call centers, namely that calls originated in a given state are answered by a local call center in the official language of that Indian state (Gupta et al., 2022).

This institutional feature allows us to compare areas that receive similar mobile phone coverage via new SMIS towers, but where the ability of farmers to access information via call centers vary depending on the local diffusion of state-official languages. We document two findings. First, after the construction of the first mobile phone tower, calls to Kisan call centers increase faster in areas where the majority of the local population speaks the

same languages as call centers' agronomists. Second, the effect of SMIS towers on credit take up by farmers is reduced by around half in cells with a standard deviation higher share of non-state language speakers. Because the share of local population speaking non-state languages is not randomly assigned, we show that results are robust to augment our estimating equation with interactions of tower construction with observable characteristics capturing local economic development, geographic isolation or caste composition. Taken together, these results are consistent with an information mechanism driving the effect of mobile phone coverage on credit take up.

Related Literature

Our paper is related to several strands of the literature. First, it relates to the literature documenting the importance of information frictions as a potential constraint for the uptake of government programs among households and firms (Currie, 2006). Custódio et al. (2022) studies how access to information about government support programs initiated during COVID-19 affect firms in Portugal. They find that treated firms receiving information were more likely to apply and that the effects were more prominent among smaller firms. Using survey data on firms in the US, Humphries et al. (2020) find that small business were less aware about the initiative on government-backed loans to support these firms in 2020. Finkelstein and Notowidigdo (2019) find that providing information about the nutrition assistance program in the US significantly increased participation by the eligible population. We contribute to this literature by providing evidence on the importance of information frictions in limiting take up of subsidized agricultural credit by farmers in a developing country.

Second, our paper relates to the literature on the effects of mobile phone technologies on financial development. Jack and Suri (2014) study the impact of lowering transaction costs to transfer money among individuals on risk sharing. They find that households using a mobile phone system that reduces transaction costs are better able to smooth consumption when facing negative income shocks. Karlan et al. (2016) show that reminders from banks sent via SMS help clients achieve their saving goals, which in turn can have positive effects on their income growth (Dupas and Robinson, 2013; Karlan et al., 2014; Aggarwal et al., 2023). 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). Our paper contributes to this literature by providing evidence on how the diffusion of mobile phones can allow farmers to learn about existing government credit programs and thus promote take up by farmers.[1]

Our paper is also related to the large literature using randomized controlled tri-

[1]Our work also complements the work analyzing the economic impacts of large infrastructure programs in developing countries including transportation infrastructure (Aggarwal 2018, Donaldson 2018, Asher and Novosad 2020; Agarwal et al. 2022), rural electrification (Dinkelman 2011, Burlig and Preonas 2016, Lee, Miguel, and Wolfram 2020), and telecommunication services (Jensen 2007, Aker 2010).

als to evaluate the impact of mobile phone-based agricultural extension programs on agricultural outcomes (see Aker, Ghosh, and Burrell (2016) and Fabregas, Kremer, and Schilbach (2019) for recent reviews of this literature). For example, Casaburi, Kremer, Mullainathan, and Ramrattan (2019) and Cole and Fernando (2020) randomize access to agricultural advice to farmers in Kenya and India, respectively, and find evidence that the use of this phone service has a significant impact on agricultural practices. Relative to this literature, this paper studies the impact of mobile phone coverage on access to information and take up of credit programs.

Finally, to provide evidence on the information mechanism we present heterogeneous effects based on variation in languages proposed in Gupta et al. (2022). Gupta et al. (2022) study the effects of language barriers on the adoption of modern agricultural technologies in India by exploiting variation in languages between farmers and agricultural advisors in areas across state borders. Relative to Gupta et al. (2022), this paper studies the effects of information frictions on credit take-up, and exploits the expansion of mobile phone network via SMIS towers to generate variation in access to information.

The rest of the paper is organized as follows. Section 2 introduces the data used in the analysis, and provides institutional background on the diffusion of mobile phones in India and on the two government programs – the Shared Mobile Infrastructure Scheme and the Kisan Call Centers for agricultural advice – that are central to our empirical analysis. Section 3 presents our identification strategy and the main empirical results. Section 4 discusses and provides evidence on potential mechanisms. Section 5 offers concluding remarks.

2 Institutional Background and Data

2.1 The Shared Mobile Infrastructure Scheme (SMIS)

The Indian government played an important role in the expansion of the mobile phone network in rural areas, where market demand was often not large enough to justify infrastructural investment by private telecommunication companies. In 2007, the government launched the Shared Mobile Infrastructure Scheme (SMIS), aimed at providing subsidies to telecom operators for the construction and maintenance of mobile towers in identified rural areas without existing mobile coverage. Under Phase-I of the program, a total of 7,871 sites across 500 districts were identified as potential locations for new towers. Villages or cluster of villages not covered by the mobile phone network and with a population of at least 2,000 were prioritized. Telecom operators receiving government subsidies were responsible for installing and maintaining the towers between 2007 and 2013. Of the 7,871 proposed towers under Phase-I, 7,353 were eventually constructed. 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.

We obtained data on the towers constructed under SMIS from the Center for Development of Telematics (C-DoT) - the consulting arm of the Department of Telecommunications of India. The C-DoT provided us with the geographical coordinates of the location of the 7,871 initially proposed towers, the geographical coordinates of the location of the 7,353 effectively constructed towers, and the operational date of each tower. The latter is the date in which the construction of the tower is completed and the tower becomes operational. For simplicity, in the remainder of the paper we refer to this date as the date of construction. From the 7,353 towers constructed under Phase I of the SMIS program we remove 350 towers for which the construction date is missing. This leaves us with 7,003 mobile towers used in our empirical analysis. Figure 1 shows a timeline of construction of these towers by month. As shown, the construction of towers effectively started in January of 2008 and ended in May of 2010, with most towers being introduced between the second half of 2008 and the first half of 2009.

To measure the diffusion of mobile phone coverage in India we use data provided by the Global System for Mobile Communication Association (GSMA), the association representing the interests of the mobile phone industry worldwide. The data is collected by GSMA directly from mobile operators and refers to the GSM network, which is the dominant standard in India with around 89 percent of the market share in 2012 (Telecom Regulatory Authority of India, 2012). The data licensed to us provide geo-located information on mobile phone coverage aggregated across all operators. Our analysis focuses on the 2G technology, the generation of mobile phones available in India during the period under study, which allows for phone calls and text messaging.[2]

Figure 2 reports the geographical diffusion of 2G GSM mobile phone coverage in India at five-year intervals between 1997 and 2012. While the country had virtually no mobile phone coverage until 1997, the mobile phone network began to expand rapidly shortly afterwards, covering 22 percent of the population in 2002, 61 percent in 2007 and 89 percent in 2012.[3] Data from the World Bank (2014) indicate that mobile phone subscriptions per 100 people in India went from 0.08 in 1997 to 68.4 in 2012. Following a standard pattern of diffusion (Buys, Dasgupta, Thomas, and Wheeler, 2009; Aker and Mbiti, 2010), the spatial roll-out of mobile phone coverage started in urban areas and only later reached rural ones.

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

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

2.2 Data on outcome variables: Farmers' Calls and Agricultural Credit

Data on farmers' calls is from the Kisan Call Centers (KCC) initiative. KCC are a set of call centers introduced by the Indian Ministry of Agriculture in the mid-2000s to offer general agricultural advice to Indian farmers. Farmers can contact these call centers free of charge via landline or mobile phones. Calls are answered by trained agronomists, who address farmers' questions with advise that is specific to the agro-climatic characteristics of the area where the farmer is located. The Ministry opened 21 of such call centers, which answer calls from all Indian states. Figure 3 reports the number of calls received by KCC per year between 2006 and 2017. As shown, KCC received less than 1,000 calls per year in the first years after its introduction and reached about 3 million calls per year in the mid-2010s.

Calls to KCC can be categorized in different topics depending on the inquiry of the farmers. The main topics include: agricultural practices (advice on pesticides, seeds, fertilizers, irrigation), weather (request for weather forecasts), prices, and credit. We classify as calls about credit those where farmers ask how to obtain a loan to buy a specific input (e.g. a tractor, an irrigation system, a buffalo), as well as calls where farmers inquire about how they can obtain credit. In the majority (67%) of calls about credit, farmers ask questions regarding Kisan credit cards.

Kisan credit cards were introduced in 1998 by the Reserve Bank of India as a mechanism to provide access to credit to small farmers. They offer short-term credit at subsidized interest rates (7 to 9 percent per year). Loans are usually taken during the planting season and repaid after harvesting. In case of a bad harvest, farmers have the option to roll over the debt. Kisan credit cards have become a key source of short-term credit for farmers, and constitute up to 40 percent of agricultural credit in India (Bista et al., 2012). Access to information about this specific type of credit card is a potential determinant of access to credit, especially for small farmers. An analysis of the content of farmers' questions recorded in the calls data indicates there is still a significant informational gap on this topic. In particular, farmers make inquires that range from general information on what Kisan credit cards are, to how to file an application, to which bank to approach to obtain one, and to general features of the cards including the interest rate and maturity.

Data on agricultural credit is sourced from the Agricultural Input Survey (AIS), which is conducted at five-year intervals by the Ministry of Agriculture in coincidence with the Agricultural Census of India. Our empirical analysis focuses on the last four waves of the AIS: 2002, 2007, 2012 and 2017.[4] In the survey, all operational holdings from a randomly selected 7 percent sample of all villages in a sub-district are interviewed about their use of agricultural inputs, including information on seeds, herbicides, pesticides, irrigation and

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

credit.

The survey reports information on both number of agricultural holdings with credit and the amount of existing credit to agricultural holdings in a given district of India. In addition, the data allows us to distinguish credit by type of lender that originated it, maturity and size of the borrowers in hectares. There are four types of lenders covered in the data: Commercial Banks, Primary Agricultural Credit Societies (PACS), Land Development Bank (PLDB) and Regional Rural Banks (RRB).

Finally, we obtain data on household ownership of Kisan credit cards from the Socioeconomic and Caste Census (SECC). The SECC surveyed every household and individual in the country between 2011 and 2012, and records the number of households in each village that had a Kisan credit card with a credit limit of more than Rs. 50,000. We use the information available in version 2.0 of the Socioeconomic High-resolution Rural-Urban Geographic Data set (SHRUG) to map Indian villages to our cells (Asher et al., 2021). This allows us to directly measure the uptake of Kisan credit cards by Indian farmers.

2.3 Matching Datasets at Cell-level

The unit of observation in our empirical analysis are areas of 10×10 km, which we refer to as cells. We use a grid of 10×10 km cells to match information from the dataset presented above, which come at different levels of geographical aggregation. In what follows we explain how we map each dataset into cells. First, GSMA coverage data comes in geo-referenced polygons, which range in precision 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. We superimpose the grid of 10×10 km cells on the coverage polygons and compute the share of the area in each cell covered by the GSMA signal.

Credit data from the AIS is at the district-lender level. There are 524 districts in India and four types of lenders covered in the data: Commercial Banks, Primary Agricultural Credit Societies (PACS), Land Development Bank (PLDB) and Regional Rural Banks (RRB). To map district-lender information to the cell level, we undertake the following steps. First, we allocate agricultural credit originated by each lender in a given district across the cells of that district proportionally to the share of branches that each lender has in each cell within that district.[5] This neutral assignment rule implies that $Credit_{ilt} = Credit_{dlt} \times \frac{Branches_{idlt}}{Branches_{dlt}}$, where $Credit_{ilt}$ is the agricultural credit from lender l in cell i located in district d and year t. Second, we compute the total amount of agricultural credit in a given cell by summing the credit originated by all lenders in cell i.

[5]Data on the physical address of each bank branch in India is sourced from the RBI for commercial banks and RRB, while from the Village Census of India for PACS. Location of PLDB branches is not available in the RBI. These banks are thus excluded from our empirical analysis. We think this is unlikely to affect our main results as PLDBs are the lender type with the smallest fraction of agricultural credit recorded in AIS (8.5% of total agricultural credit in India).

Calls to Kisan Call Centers are geo-located at the subdistrict (or block) level and we assign them proportionally to all cells whose centroid is contained in the subdistrict. On average, there are 27 cells per subdistrict. Whenever information on the subdistrict from which the call is originated is missing, we use information on the district of the call and the crop for which the caller is seeking information to assign calls to a given cell. Summary statistics for all outcomes at the cell-level are reported in Table 1.

3 Empirics

3.1 Event-Study Evidence on Farmers' Access to Information

We start by documenting the evolution of farmers' calls to KCC when new SMIS mobile phone towers are introduced in areas without previous coverage using the following specification:

$$log(1 + Calls)_{it} = \alpha_i + \alpha_{st} + \sum_{k=-12}^{+36} \beta_k D_{it}^k + \varepsilon_{it} \quad (1)$$

The outcome variable in equation (1) is the natural logarithm of the total number of calls originated from cell i in month t. D_{it}^k is a dummy equal to 1 if month $t = k$ for cell i, and captures the time relative to the month of introduction of the first tower covering cell i, which we set at $k = 0$. We include the 12 months prior to the introduction of the first tower and the 36 months after. The specification has state-year and cell fixed effects, denoted by α_{st} and α_i, respectively. Standard errors are clustered at the district level. The objective of this exercise is to exploit the different timing of construction of mobile phone towers in different cells to document their impact on farmers' calls. Notice that we focus on cells that will eventually receive a mobile phone tower under the SMIS program described in section 2.

Figure 4 reports the estimated coefficients β_k along with their 95 percent confidence intervals. Three observations emerge. First, the coefficients are precisely estimated zeros in the months preceding the introduction of the first tower in a cell. Note that this is not a mechanical effect, as farmers always had the option to call KCC using landlines. Rather, the absence of pre-trends indicate that SMIS towers were not strategically placed in areas already experiencing increased demand for information. Second, within four months from the construction of the first tower we observe a significant increase in calls for agricultural advice. The magnitude of the estimated coefficients indicates, on average, a 5 to 10 percent increase in the number of calls to KCC in the first year post tower construction. Third, this differential effect continues to grow over the next 18 months, reaching a 40 to 50 percent increase in calls three years after the construction of the first tower in a cell.

3.2 Identification Strategy

Our identification strategy exploits variation in the construction of mobile phone towers under the Shared Mobile Infrastructure Scheme. In the initial phase of this program, the Department of Telecommunications identified 7,871 potential locations for new towers. All the locations in this initial list responded to certain specific criteria, including lack of existing mobile phone coverage and number of individuals potentially covered. For identification purposes, we exploit the fact that not all the locations in the initial list eventually received a tower. In some cases, towers were either relocated or not constructed. Thus, we compare cells where towers were initially proposed and eventually constructed with cells in the same administrative district where towers were initially proposed but eventually not constructed.

Figure 5 provides a visual example of how we classify cells into treatment and control group based on proposed and actual tower location.[6] Figure 6 shows the geographical distribution of treatment (in red) and control (in blue) cells for the state of Rajasthan – the largest Indian state by area –, while Figure A1 reports the geographical distribution across India as a whole. Our final regression sample consists of 8,451 unique cells, of which 6,292 (74%) in the treatment group and 2,159 (26%) in the control group.

The identification relies on the assumption that locations where a tower was proposed but eventually not constructed represent a good control group for those that eventually received a tower. The main challenge is that, although all proposed locations had to meet specific criteria, the decision to relocate or cancel a tower is not random. Based on conversations with the C-DoT officials responsible for the implementation of the program, towers were sometimes relocated (or canceled) when, upon visiting the actual site, technicians discovered logistical issues related to terrain characteristics or lack of an available connection to the electricity grid to power the tower, or realized that a relocation would increase the potential population covered. These three characteristics are observable in our data. Thus, our main identification assumption is that conditional on terrain ruggedness, availability of connection to the power grid and potential population covered, control cells are a good counterfactual for treated cells.

In Table 2 we provide evidence in support of this conditional exogeneity assumption, by formally testing for differences in baseline observable characteristics between treated and control cells. Each row in the table reports the estimated coefficient of an indicator variable, which is equal to 1 for cells where a new SMIS tower was proposed and eventually constructed, and 0 for cells where a new SMIS tower was proposed but eventually not constructed. All specifications include state fixed effects and condition on the baseline controls driving tower relocation, namely terrain ruggedness, connection to the power

[6] We compute coverage for each new tower based on its technical specifications, which corresponds to a 5 km coverage radius around its centroid (this estimate is from tender document No. 30-148/2006-USF provided to us by C-DoT officials responsible for the Phase I implementation of SMIS).

grid and potential population covered. As shown, treatment and control cells are balanced along a large set of observable characteristics including: share of employment in agriculture, share of irrigated land, crop suitability, share of scheduled castes, and night lights growth. The only exception is average distance to the nearest town, which is shorter for the treatment group, although small in terms of magnitude. Treatment and control cells also appear to be largely comparable in terms of available facilities, including presence of a school, hospital or bank branch, as well as availability of landline phone connections.

Consistent with the results of these balance tests, in the empirical analysis below we show that all our estimates are stable when including the observable cell characteristics reported in Table 2. As additional support of the identification assumption, in section 3.4.1, we document with event-study graphs that there are no pre-existing trends in the main measures of credit take up between treated and control cells in the period before the introduction of SMIS towers.

3.3 First Stage

The first stage regression estimates the effect of tower construction on mobile phone coverage in the sample of cells initially selected for SMIS. By construction, all such cells have zero mobile phone coverage in the baseline year 2007. We expect the treated cells – which received a tower – to experience a larger increase in mobile coverage after the program. However, notice that this effect is not mechanical: the outcome variable in the first stage is the actual mobile coverage reported by Indian telecommunication companies to GSMA, and not the predicted increase in coverage constructed using SMIS tower location. This is important because the tower construction program we use for identification is not the only driver of changes in mobile phone coverage in India during this period.

Our first-stage regression is as follows:

$$Coverage_{ist} = \alpha_i + \alpha_{st} + \gamma \mathbb{1}\left(\text{Tower}\right)_{is} \times Post_t + \delta_t X_{is} + u_{ist} \tag{2}$$

The outcome variable $Coverage$ is the share of land covered by the mobile phone network in cell i, state s and year t. $\mathbb{1}\left(\text{Tower}\right)$ is a dummy equal to 1 for cells where towers were proposed and eventually constructed, and 0 if towers were proposed but not constructed, while $Post$ is a dummy capturing the period after the introduction of SMIS. We estimate the first stage regression on the same cell-year panel for which we observe the main credit outcomes. The outcomes are reported at 5-year intervals in the Agricultural Input Surveys of 2002, 2007, 2012 and 2017. Thus, the $Post$ dummy is equal to 0 for the years 2002 and 2007, and 1 for the years 2012 and 2017.

The coefficient of interest is γ, which captures the effect of tower construction under the SMIS program on mobile coverage in a given cell. X_{is} is a vector of initial cell-level controls, which includes terrain ruggedness, connection to the power grid and potential

population covered as well as all the cell characteristics reported in Table 2. Baseline characteristics are interacted with year fixed effects. We include in all specifications state fixed effects interacted with year fixed effects to capture state specific trends (α_{st}). To take into account geographical correlation of the error term across cells we cluster standard errors at the district level.

Table 3 reports the first-stage results. The estimated coefficient in column (1) indicates that cells covered by new SMIS towers have a 22 percentage points larger increase in the share of land covered by mobile phone signal after the introduction of SMIS relative to the control group. In column (2) we include all the observable socio-economic cell characteristics reported in Table 2. Consistent with the fact that treatment status is not strongly correlated with initial characteristics, the magnitude of the point estimate is stable when including these additional controls. According to the specification in column (2), cells covered by new SMIS towers have, on average, 20 percentage points larger share of land covered by mobile phones in the post SMIS period. Below the regressions we also report the Kleibergen and Paap (2006) first stage F-statistics for the validity of the instrument, which is equal to 44.6 in column (2). We can safely reject that the first stage is weak.

3.4 Second stage results on Credit take-up

3.4.1 Main effects on Credit Take up by farmers

Table 4 reports the results on the effect of mobile phone coverage on credit outcomes. We focus on two main outcomes: share of farmers with credit, and monetary value of credit (in Rupees) per farmer. Both outcomes are sourced from the Agricultural Input Survey. For each outcome, we present three specifications: an OLS regression, a reduced form regression in which we estimate equation 2 replacing $Coverage$ with credit outcomes, and a 2SLS specification of the form:

$$Credit_{ist} = \alpha_i + \alpha_{st} + \beta \widehat{Coverage}_{ist} + \lambda_t X_{is} + \varepsilon_{ist} \tag{3}$$

Where $\widehat{Coverage}_{ist}$ is the predicted coverage from the first stage regression. We start by documenting the effects of coverage on credit outcomes calculated using total agricultural credit, i.e. including loans of all maturities, borrowers of all sizes, and lenders of all types. In the next section we will present heterogeneous effects along these dimensions.

Panel A of Table 4 reports the results when the outcome variable is the share of farmers with credit. Data on coverage is normalized so that the reported coefficients capture the effect on the outcomes for 1 standard deviation change in mobile coverage (43 percent of a cell area).

The coefficients obtained using a simple OLS specification show that changes in coverage are correlated with positive increases in the share of farmers with credit (columns

1 and 2). Columns (3) and (4) report reduced form estimates of the effect of treatment, showing that among the cells selected for the SMIS program, those that effectively received a tower experienced a 1.5 percentage point higher increase in the share of farmers with credit in the post period relatively to cells that did not receive a tower. Finally, columns (5) and (6) report the 2SLS estimated coefficients. The coefficient in column (5) indicates that cells with a standard deviation larger increase in coverage experienced a 6.8 percentage points larger increase in the share of farmers with credit after the introduction of SMIS. Column (6) shows that this effect remains stable and precisely estimated when introducing all cell level baseline characteristics interacted with year fixed effects.

Next, in Panel B of Table 4 we focus on credit per farmer, finding results consistent with the positive effect on credit take-up. In particular, column (6) shows that cells with a standard deviation larger increase in mobile coverage experienced a 1,370 Rupees larger increase in credit per farmer, which correspond to about 30% of a standard deviation in the outcome variable.

In both Panel A and B, 2SLS estimates are two to three times larger in magnitude than the OLS. This is consistent with measurement error in coverage leading to substantially attenuated estimates. As emphasized in section 2.1, the data licensed to us provide geo-located information on mobile phone coverage aggregated across all operators. The quality of submissions is likely to vary considerably across operators and the data provide no information on the strength of the signal. Both sources of measurement error are likely to be particularly relevant when focusing on very fine geographies such as our grid cells of 10 X 10 km. A second potential source of downward bias in the OLS coefficients is due to unobserved heterogeneity, whereby cells on a steeper gradient in terms of credit take-up experienced lower increase in coverage. Simply based on observable characteristics, though, this seems not very plausible, as the OLS estimates are largely insensitive to the inclusion of additional controls. A third plausible explanation for the difference between the OLS and the 2SLS estimates rests on the set of cells affected by our instrument (i.e., the compliers). In our context, the compliers are cells that experienced an increase in coverage due to the construction of a SMIS tower and would otherwise not have been covered by private telecommunication companies. If the absence of private infrastructural investment is indicative of these areas' backwardness, and if information returns are greater in cells furthest from the technological frontier, then it is not surprising that the effects of coverage on the complier population are stronger than in the population at large, leading to larger 2SLS estimates than OLS estimates.

Finally, in Figure 7 we report an event-study analysis in which we interact the treatment dummy with year fixed effects and plot the estimated βs from the regression below:

$$Credit_{ist} = \alpha_i + \alpha_{st} + \sum_{\substack{t=2002 \\ t \neq 2007}}^{2017} \beta_t \mathbb{1}\left(\text{Tower}\right)_{is} \times year_t + \delta_t X_{is} + \varepsilon_{ist}. \tag{4}$$

where

$$t = 2002, 2007, 2012, 2017$$

As shown, we find no evidence of differential pre-existing trends in share of farmers with credit or credit per cultivator between treatment and control cells in the five years 2002 to 2007. After the introduction of SMIS towers, the reduced form effects are stable at 1.5 percentage points for the share of farmers with credit, and between 200 and 300 Rupees for credit per farmer.

Overall, the results reported in Table 4 indicate a positive and significant effect of mobile phone coverage on credit take up by farmers. Coupled with the evidence on calls presented in section 3.1, these results suggest that improved potential access to information about credit programs facilitate take of agricultural credit. Two important open questions remain. First, are the positive effect on take up of agricultural credit driven by higher participation in the subsidized government programs available to farmers? Second, are the effects driven by access to information or by other changes to the local economy brought about by access to mobile phones? We try to address these questions in the following sections.

3.4.2 Heterogeneous Effects by maturity, type of lender and farm size

First, we investigate whether the effects documented in the previous section are consistent with an expansion in the take up of government credit programs. We start in Table A1 by splitting credit per farmer into three categories of loans depending on their maturity: short term, medium term, and long term loans. The main finding is that the effects documented in Table 4 are uniquely driven by a relative increase in short term agricultural credit. This is consistent with take up of Kisan credit cards playing an important role. Recall that in 67% of calls about credit in our data farmers ask questions about Kisan credit cards, a major program for credit to farmers which offers loans at subsidized rates for agricultural purposes that have to be repaid within 12 months. Thus, any borrowing via Kisan credit cards' would be classified as a short term loan.

Next, in Table A2, we split our credit outcomes into three categories depending on the type of lender that originated the loan. We focus in particular on three categories of lenders: Commercial Banks, Primary Agricultural Credit Societies (PACS), and Regional Rural Banks (RRB). In our sample, PACS constitute on average 58% of credit to agriculture between 2002 and 2017, followed by Commercial Banks (29%), and RRB (13%), as shown in Figure A2. The results in Table A2 show that the effects documented in Table 4 are largely driven by an increase in credit originated by PACS, followed by positive but non-statistically significant effects for Commercial Banks, while we find no effect of coverage on credit originated by RRB. These results are consistent with data reported by the National Bank for Agricultural and Rural Development (NABARD), which show how

PACS distribute about 32% of agricultural credit to farmers in the form of Kisan credit cards.

Finally, in Table A3 we split borrowers by farm size. Size categories reported by the Agricultural Input Survey include: very small farms (below 1 hectare), small farms (1 to 2 ha), small-medium farms (2 to 4 ha), medium farms (4 to 10 ha) and large farms (10 and above ha). According to the Agricultural Input Survey of 2007, and as reported in Figure A3, very small farms constitute the vast majority (63.7 percent) of agricultural holdings in India, followed by small farms (18.7 percent). Even in terms of area farmed, as of 2007 very small farms constitute around 20.7 percent of agricultural land, small farms constitute 20.4 percent. We find that the effect of mobile phone coverage on credit outcomes are larger for small farms, monotonically decreasing in farm size, and statistically significant for all size categories except large farms. These heterogeneous effects are consistent with the information mechanism described above, as small farmers are the primary beneficiaries of the subsidized credit programs implemented via Kisan Credit Cards.

3.4.3 Take up of Kisan Credit Cards

We investigate further the take up of Kisan Credit Cards among farmers in the cells in our sample using micro data from the Socio-Economic and Caste Census of India (SECC). SECC was carried out by the Ministry of Rural Development between 2011 and 2012 to get a comprehensive picture of the socio-economic status of Indian households. Importantly for our purposes it contains information on whether the main source of income of a household is agriculture, and on the household has a Kisan credit card with a credit limit of 50,000 Rupees or more.[7] We match SECC data with cells in our sample using the SHRUG2.0 dataset created by the Data Development Lab.

Because data on Kisan credit cards from the SECC is only available for the unique wave of the Census carried out in 2011-12, we do not observe take up of these credit cards in the pre-period. Thus, we estimate a cross-sectional regression at the cell level for 2011-12 where the outcome variable is the share of agricultural households with a Kisan credit card with limit above 50,000 Rupees. We focus on the same sample of cells used in our previous analysis, namely cells that were initially selected to receive a SMIS tower. The results are reported in Table 5. In column (1) we estimate a reduced form regression of access to Kisan credit cards on a dummy capturing the construction of a SMIS tower, while in column (2) we estimate a 2SLS regression of access to Kisan credit cards on mobile coverage instrumented with the construction of a SMIS tower. We find positive and significant effects for both specifications. The coefficient in column (2) in

[7]According to a survey by NABARD on 714 farmers across 5 Indian states, this threshold is about one-third of the average value of loans via Kisan credit cards observed in the survey (166,320 Rs). The minimum take up in the survey ranged from 5,000 Rs in Bihar to 25,000 Rs in Karnataka, while the maximum loans observed in the survey ranged from 82,600 in Assam to 2,500,000 Rs in Punjab (Mani, 2016, p. 43).

particular indicates that cells with a standard deviation higher coverage in 2012 had a 5.7 percentage points larger share of agricultural households with a Kisan credit card. The magnitude of this effect is consistent with the 2SLS results reported in Panel A of Table 4.

Of course, the identification assumptions behind the results presented in Table 5 are stronger than the ones behind equation (3). In particular, the cross-sectional specifications estimated here do not allow us to control for time invariant unobservable characteristics using cell-fixed effects, nor to test for pre-existing trends in the outcome variable. Still, we think this is important additional evidence that the expansion of agricultural credit in treated areas of our sample was driven by take-up of Kisan credit cards, the government program about which farmers ask the majority of credit related questions to call centers for agricultural advise once new towers become available.

4 Discussion of Mechanisms

The results presented in the previous section document that the arrival of mobile towers was followed by an increase in the number of calls to call centers for agricultural advice. The majority of farmers that contact call centers to inquire about credit programs ask questions regarding Kisan credit cards, a program of subsidized credit for small farmers. We then document that the expansion of mobile phone coverage brought by SMIS towers favored take up of credit by farmers, especially small farmers borrowing short term. Areas receiving towers in our sample also have a larger share of agricultural households holding a Kisan credit card as of 2011-12, four years after the launch of SMIS.

These results are consistent with SMIS tower relaxing information frictions about existing government programs of subsidized credit. However, our estimates on the effect of mobile coverage could subsume different mechanisms linking mobile phone coverage with credit take up. For example, the arrival of mobile phone coverage might promote local economic opportunities more generally, increasing local income and thus credit demand by farmers to expand their operations. In this section we provide additional evidence that is consistent with the documented effects being driven by an information channel.

4.1 Isolating access to information via call centers using language differences

To make progress in the direction of isolating the role of information, we follow Gupta et al. (2022) and exploit an institutional feature of Kisan call centers, namely that calls originated in a given state are answered by a local call center in the official language of that Indian state. This effectively creates a language barrier to access the service for individuals that do not speak the official language of the state in which they reside, because their mother tongue is either an official language of India but not the one of

the state in which they reside, or one of the about one hundred additional non-official languages spoken in India.[8] This implies that, even among areas that receive similar mobile phone coverage via new SMIS towers, the ability of farmers to access information might vary by local language.

Figure 8 shows an illustrative example of such barriers using data from the state of Odisha. The red outlined area in the southern part of the state is inhabited by a majority of local population speaking Kui, a Dravidian language that is not an official language of India. While this area has a similar diffusion of agriculture as the rest of the Odisha (panel b) and has experienced an expansion in mobile phone coverage similar to the rest of state (panel c), phone calls by farmers to KCC from this area have been significantly lower (panel d).

This example is illustrative of a strong statistical trend that we observe across all our sample. In Figure 9 we estimate equation (1) separately for cells where the majority of the local population speaks the official language of the state of the cells vs cells where the majority speaks either a non-state official language of India or a non-official language.[9] The figure shows that, after the construction of the first mobile phone tower, calls to KCC increase in both groups. However, the increase is more pronounced in areas where the majority of the local population speaks the same languages as KCC agronomists. Within 3 years from the construction of the first tower, calls in these cells increase by around 30 percentage points more than in those where the majority of the local population speaks a non-official language.

Next, we re-estimate our main reduced form results of Table 4 by including an interaction that captures the differential effect of SMIS towers across cells with a different initial share of state official language speakers as follows:

$$\begin{aligned} Credit_{ist} &= \alpha_i + \alpha_{st} + \beta_1 \mathbb{1}\left(\text{Tower}\right)_{is} \times Post_t \\ &+ \beta_2 \mathbb{1}\left(\text{Tower}\right)_{is} \times Post_t \times \text{Non-state language share}_{is} + \delta_t X_{is} + \eta_{ist} \quad (5) \end{aligned}$$

where the initial cell-level controls X_{is} interacted with time fixed effects also include the share of non-state language speakers. The results are reported in Table 6. As shown, we find negative and statistically significant estimates for β_2 in all specifications, indicating that the speed of credit take up after the introduction of SMIS towers depends on the

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

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

language barriers between farmers and call center advisors. We normalize the share of non-state language speakers by one standard deviation of that variable in our sample (0.24, as can be see in the summary statistics Table 1). Thus, the magnitude of the estimated coefficients β_2 implies that the effect of SMIS towers on credit take up by farmers is reduced by around half in cells with a standard deviation higher share of non-state language speakers.

Taken together, the results in Figure 9 and Table 6 are consistent with an information mechanism driving the effect of mobile phone coverage on credit take up. Still, differential access to information can still drive credit take up via channels other than the diffusion of information about credit programs. We discuss this point in the next section.

4.2 Indirect effects via access to other types of information

Isolating which specific type of information explains the increase in credit take-up documented in the data is particularly challenging. In an ideal experimental setting, the researcher could control the specific information provided to each farmer and then study their individual borrowing response. In our setting, farmers speaking the same language of call center advisers gain potential access to different types of information, which include information about credit programs but also information about agricultural technologies such as high yielding variety seeds, fertilizers and irrigation techniques, as documented in previous work (Gupta et al., 2022). Access to information about agricultural technologies can indirectly foster credit demand to adopt them.

Although we cannot rule out that this indirect channel explains part of the documented effects on credit take up, two results support the importance of access to information about credit programs. First, we observe that farmers indeed use Kisan call centers to ask information about credit programs available to them, including how to access them, eligibility criteria and loan contract terms. Second, the results presented in section 3.4.2 indicate that credit take up is largely driven by the categories of farmers and the type of loans targeted by government credit programs such as Kisan credit cards. In addition, the effects are concentrated on the type of lender (PACS) that specializes the most in the origination of Kisan credit cards, while one would expect a more uniform increase in origination across lenders if the effects were driven by a local increase in credit demand. We also document in section 3.4.3 that, indeed, households in cells receiving SMIS towers are more likely to have a Kisan credit card in the post SMIS period. Taken together, these findings point towards the importance of access to information about credit programs in explaining the documented credit take up.

4.3 Robustness Tests

In this section we present a set of robustness tests for the key results of the paper. We start with a discussion of standard errors. A well documented concern in studies whose identification strategy relies on geographical variation is that spatial correlation in the data can lead to incorrect computation of the standard errors. To partially address this concern, in all the specifications in the paper we cluster standard errors at the district level, i.e. allowing errors to be correlated across cells located within the same administrative district units. However, a more comprehensive way to address spatial correlation is to implement the correction of standard errors proposed in Conley (1999). This method adjust standard errors by allowing to be correlated based on spatial proximity. The results are reported in Table A4. Accounting for spatially correlated standard errors between 50 km and 500 km does not significantly affect the results. Compared to the baseline specification that clusters the standard errors at the district level, both reduced form and 2SLS estimates typically become slightly more precise and the coefficients of interest remain statistically significant at conventional levels.

The main credit take up outcomes – share of farmers with credit and credit per farmer – are constructed using in the denominator the baseline number of farmers in each cells as observed in the 2001 Indian Census. We use this specification to ensure the documented effects are driven by variation in the numerator rather than changes in the number of farmers over time in each cell. In Table A5 we show that the main results documented in Table 4 are robust to allowing the number of farmers in each cell to vary over time. For this test, we use the number of farmers observed in the 2001 Census for the 2002 and 2007 waves, and the number of farmers observed in the 2011 Census for the 2012 and 2017 waves.

Finally, our empirical model interprets the differential impact of mobile phone coverage in areas with different diffusion of state languages as the effect of language barriers between farmers and call center agricultural advisors. A potential concern with this interpretation is that the share of local population speaking non-state official languages is not randomly assigned across geographical areas. In particular, areas with a greater share of non-state language speakers might also be more specialized in agriculture, more geographically isolated or characterized by lower levels of economic development. In this case, one would load on the interaction term between non-state language speakers and mobile phone coverage also variation driven by other local conditions. In Table A6 we augment our model by including interactions of SMIS towers with measures of agricultural intensity (share of population employed in agriculture), geographical isolation (distance from closest city), local economic development (night lights intensity), and the share of population that belongs to a scheduled caste. As shown, the main results of Table 4 are robust to the inclusion of these additional interaction terms.

5 Concluding Remarks

In this paper, we provide evidence on the effects of the expansion of mobile phone coverage on take-up of agricultural credit in rural areas of India by exploiting variation generated by the construction of new towers in previously unconnected areas. Our results indicate that – when coupled with the availability of free-of-charge call centers for agricultural advice – mobile phone coverage helps alleviate information frictions about government credit programs and facilitate take-up of subsidized credit products designed specifically for small farmers.

It is important to emphasize that our analysis focuses on documenting the impact of information frictions on credit take-up, and not on the effects of credit take-up on farmers' income, consumption, investments or profits. The latter set of outcomes has been the object of a large literature in development economics, which has found mixed evidence on the impact of access to credit on real outcomes. For example, Banerjee et al. (2015) use data from six randomized evaluations of microcredit products across different countries and finds positive effects of microcredit on investment but no significant effects on income or consumption of low-income households. When it comes to agricultural credit, existing evidence has shown that certain forms of loans to farmers, such as the short-term credit contracts studied in this paper, can help farmers smooth consumption, with positive effects on income and wages (Fink et al., 2014). We think that this is an important avenue for future research.

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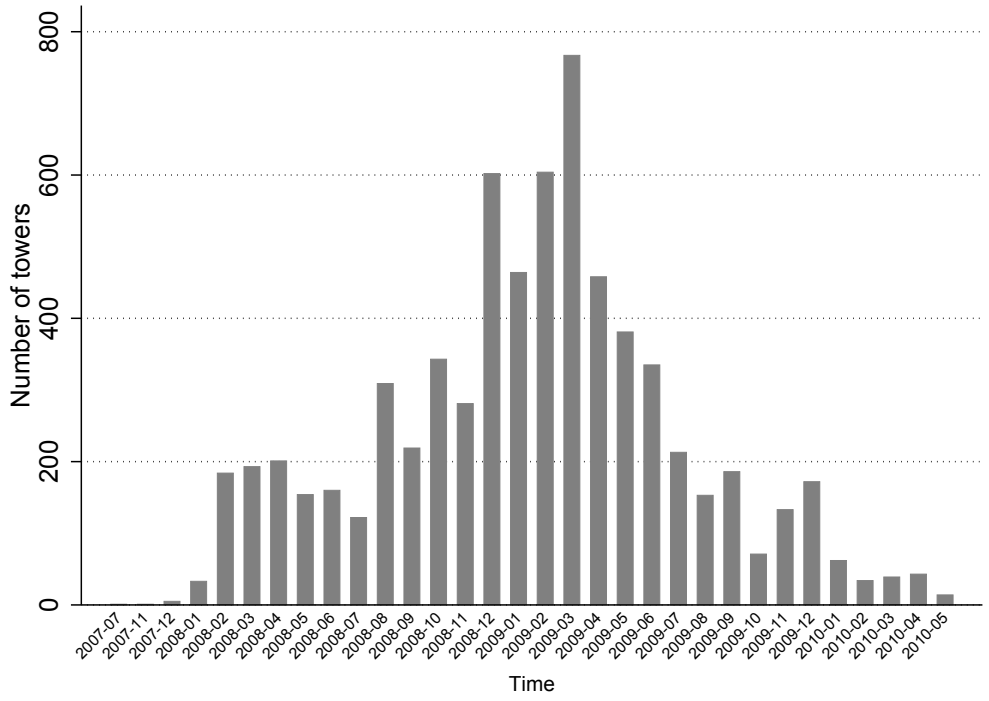
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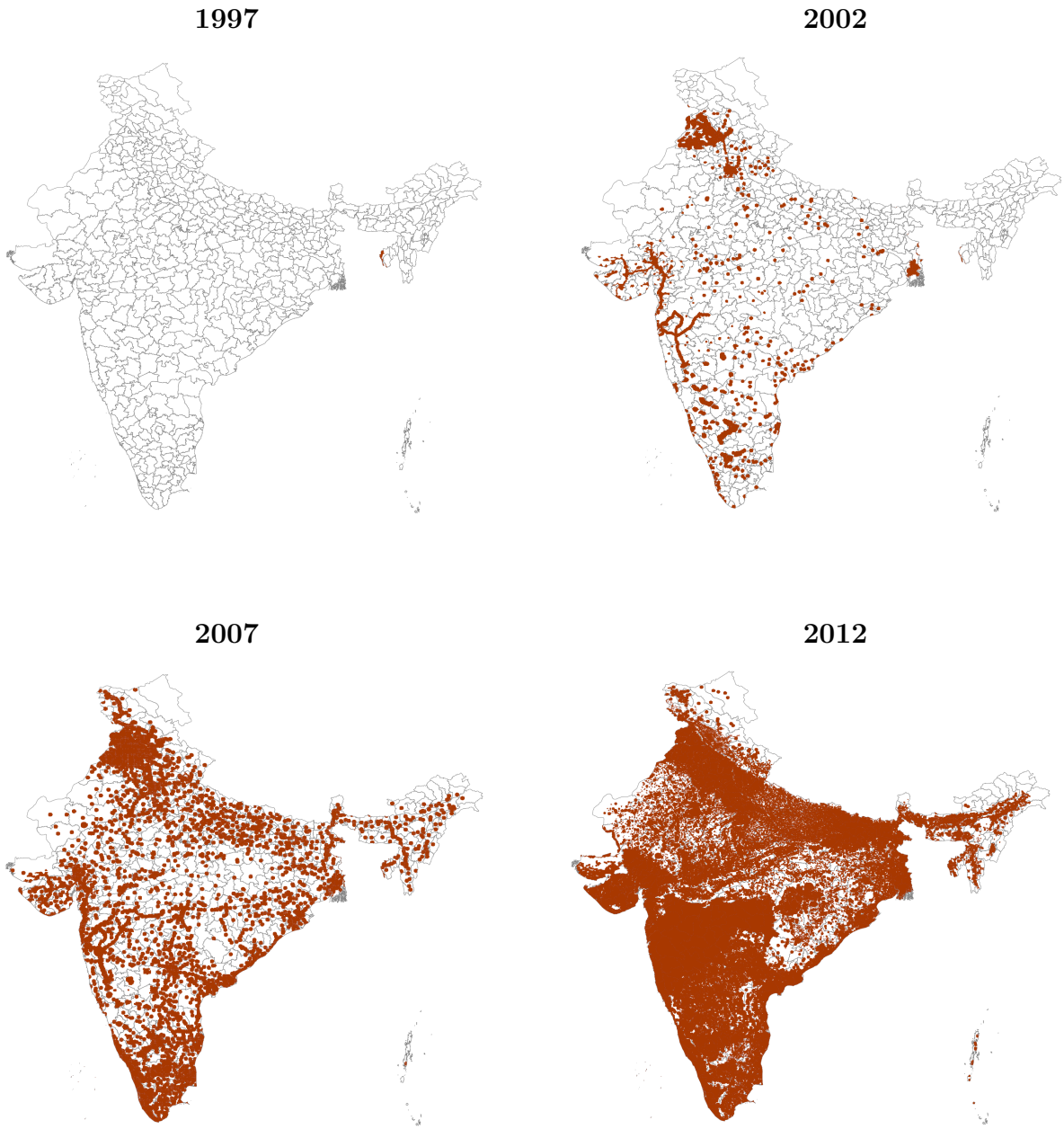
Figures

Figure 1: Timeline of tower construction under SMIP Phase I



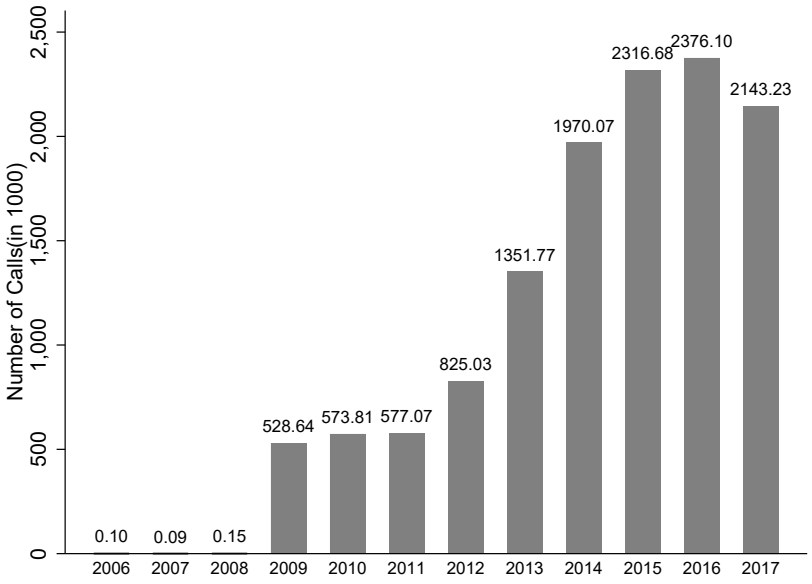
Notes: Source: Department of Telecommunications, India

FIGURE 2: MOBILE PHONE COVERAGE EVOLUTION, INDIA 1997-2012



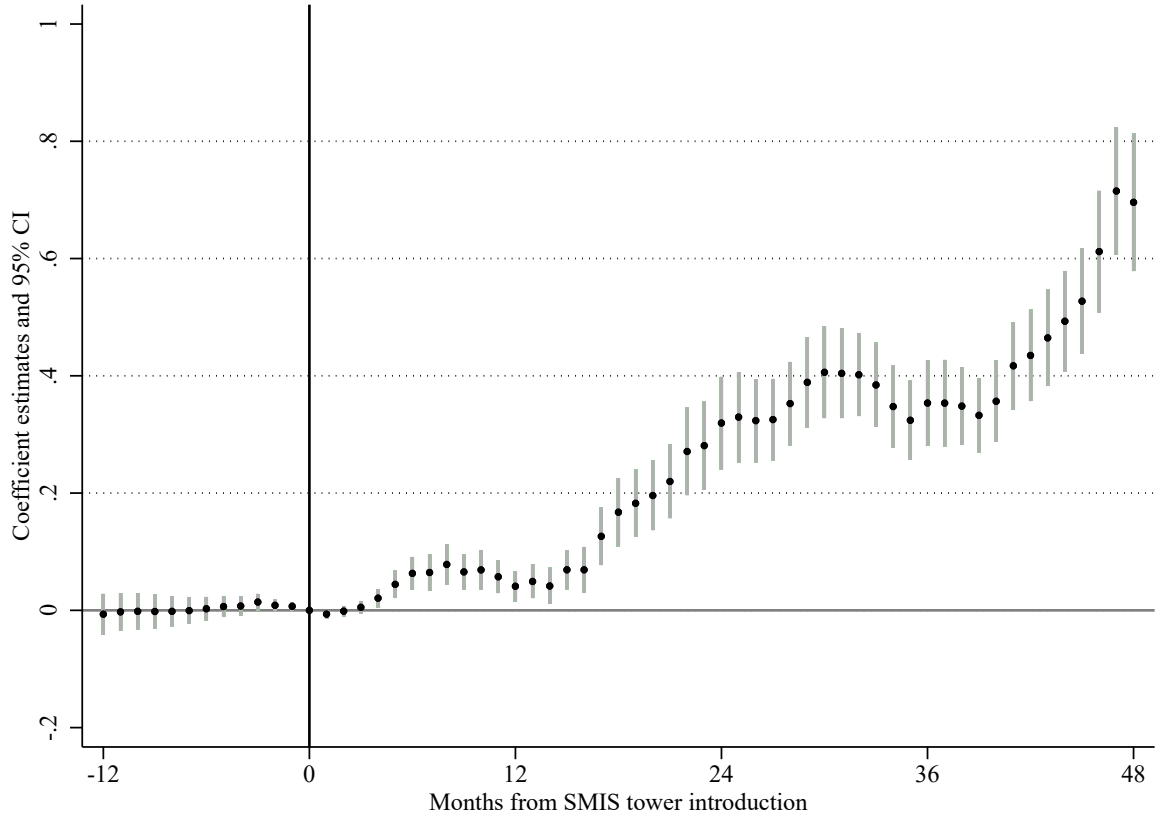
Notes: The figure reports geo-referenced data on mobile phone coverage for all of India at five-year intervals between 1997 and 2012. Source: GSMA.

Figure 3: Total Number of Calls to Kisan Call Centers: 2006-2017



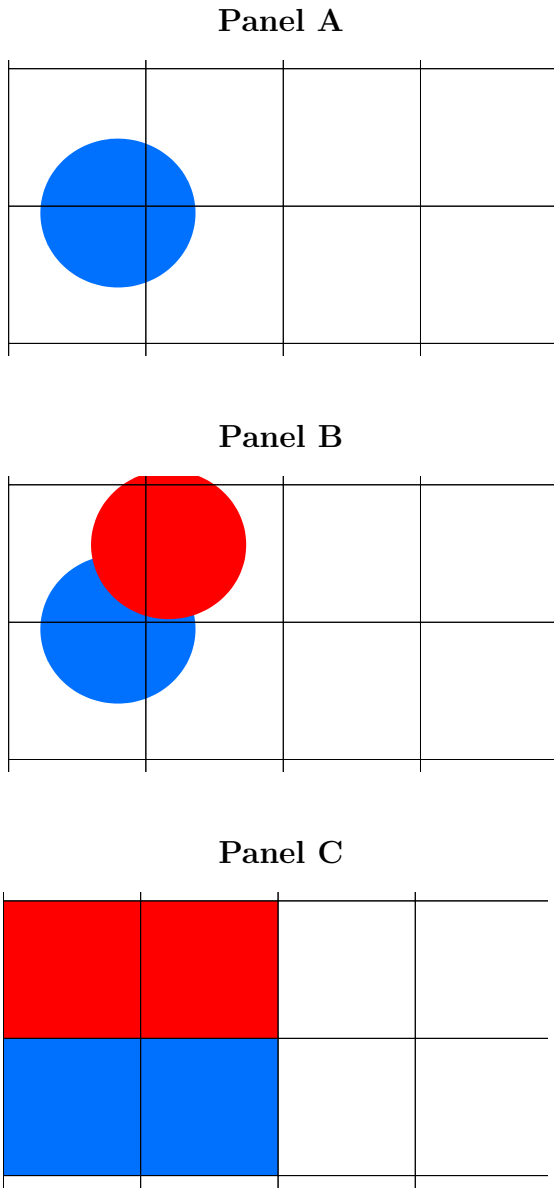
Notes: Source: Kisan Call Center, Ministry of Agriculture

Figure 4: Event Study- Kisan Call Centers



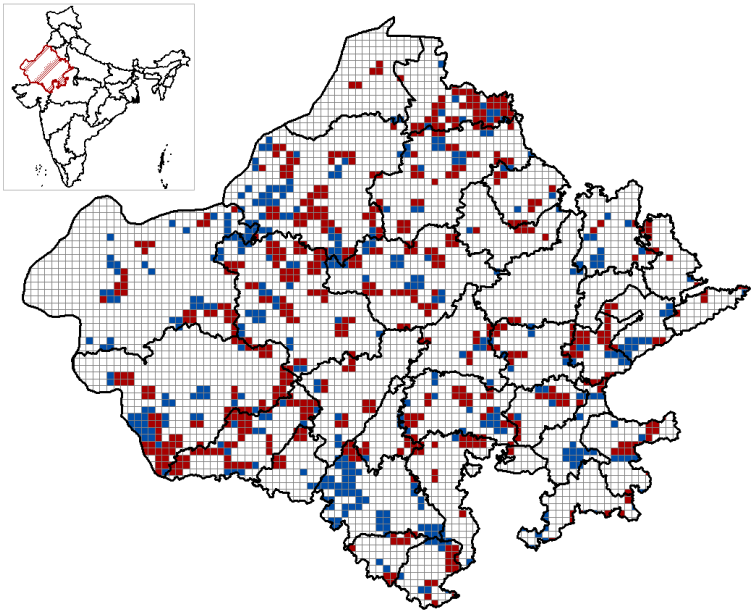
Notes: This figure presents the effect of tower construction on the number of calls made to Kisan Call Centers.

FIGURE 5: AN EXAMPLE OF CLASSIFICATION OF CELLS INTO TREATMENT AND CONTROL GROUPS



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

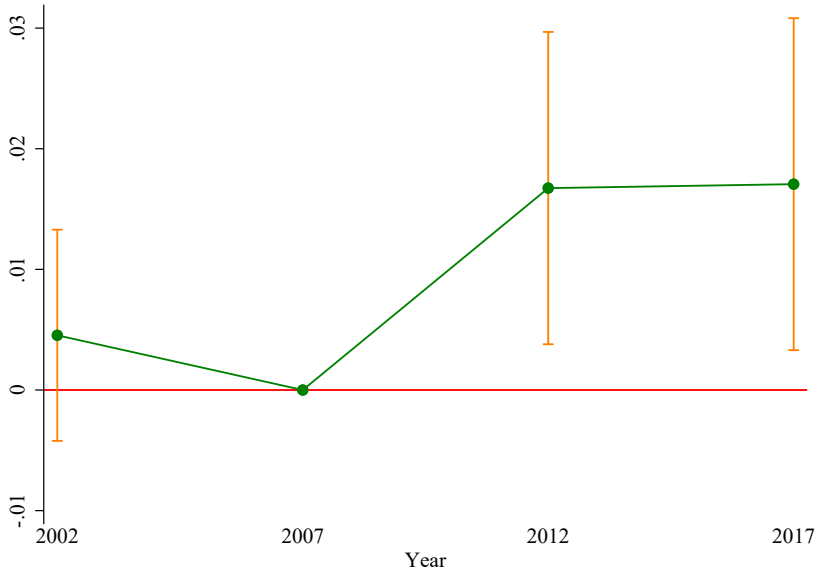
Figure 6: Treatment and Control Cells
(Rajasthan State)



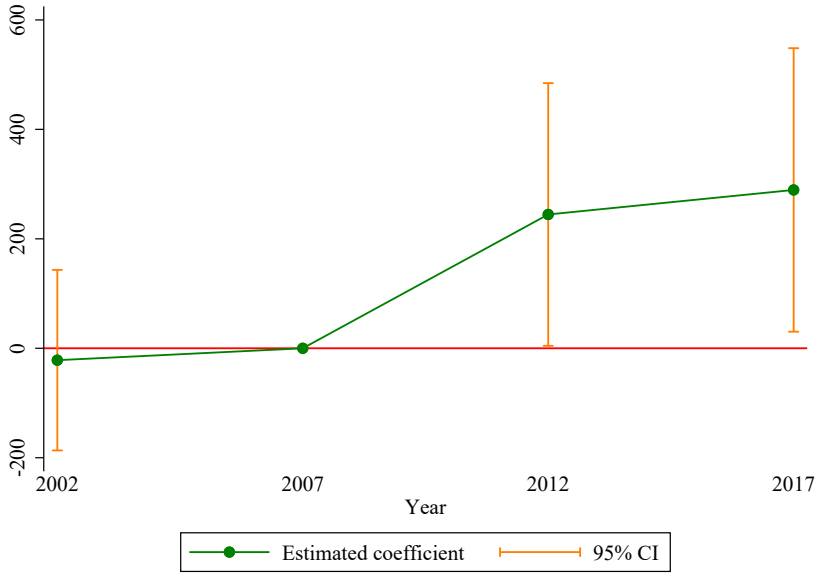
Notes: Treatment (red) and control (blue) cells for the state of Rajasthan. District boundaries are labeled in black. Treatment cells are those that are both proposed *and* covered by mobile tower under SMIS Phase I. Control cells are those that are proposed *and not* covered by mobile tower under SMIS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

Figure 7: Event Study- Reduced Form Effects

(a) Share of farmers with credit



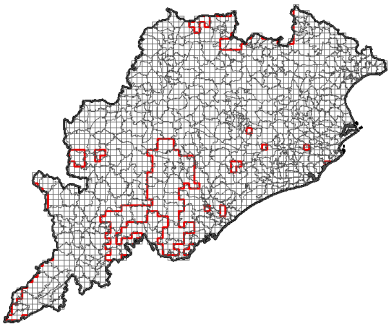
(b) Credit per farmer



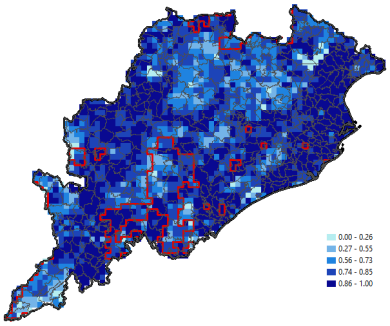
Notes: This figure presents the Reduced Form estimates of the SMIS tower construction program on the share of farmers with credit (panel a) and credit per farmer (panel b). We normalize the coefficients in 2007 to 0. We use data from the Agricultural Input Survey and the 2001 Population Census to compute the outcome variables. We divide the number of farmers with credit (from the AIS data) by the number of farmers found in a cell (from the 2001 Population Census) to obtain the share of farmers with credit. We divide the agricultural credit in a cell (in 2007 rupees; from the AIS data) by the number of farmers found in a cell (from the 2001 Population Census) to obtain the credit per farmer in rupees. The dependent variable in panel b is winsorized at the 5% level.

FIGURE 8: COVERAGE AND FARMERS CALLS BY LANGUAGE IN THE STATE OF ODISHA

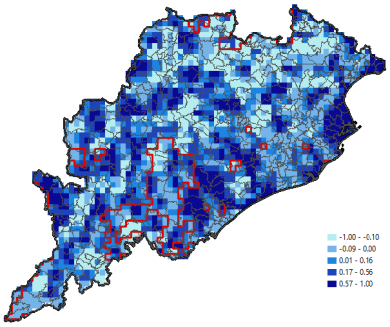
(a) Non-official language speakers



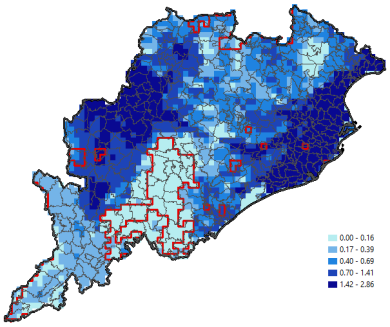
(b) Share of farmed land



(c) Change in mobile coverage

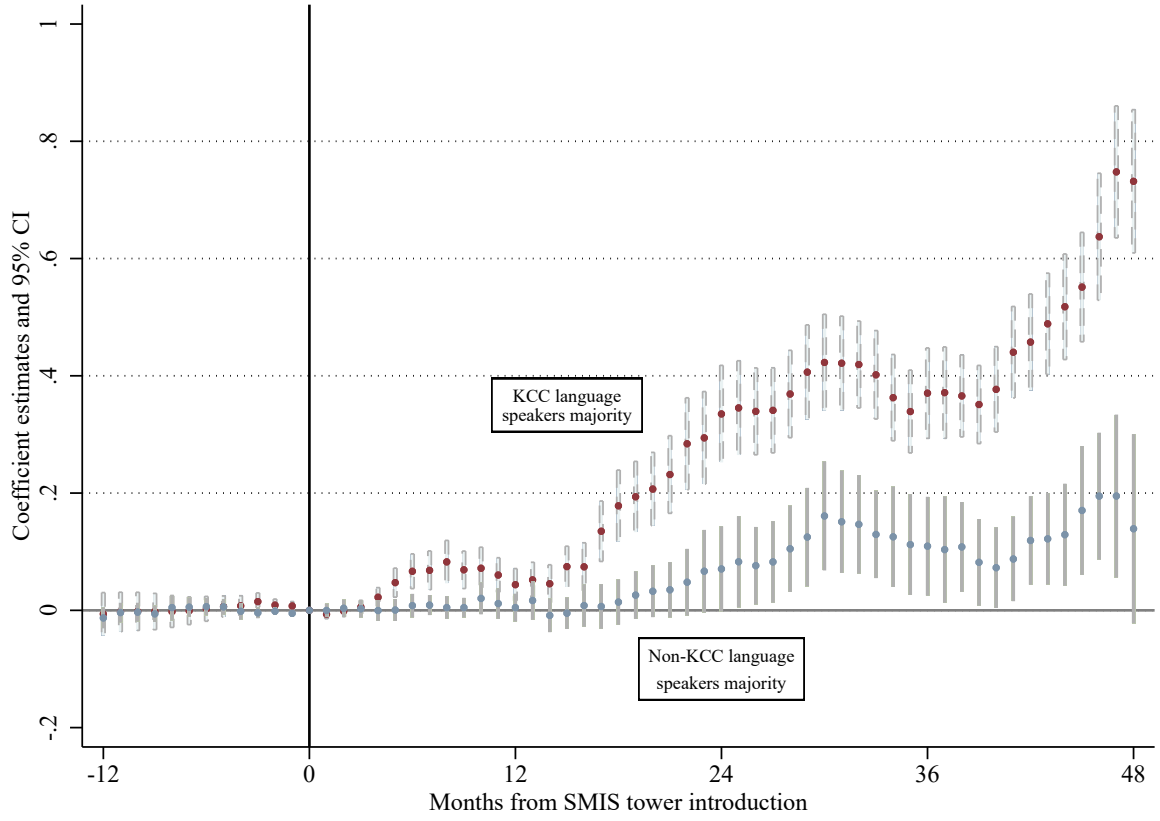


(d) Change in calls to KCC



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

Figure 9: Event Study- Kisan Call Centers by Language Speakers



Notes: This figure presents the effect of tower construction on the number of calls made to Kisan Call Centers, separately for cells where there is a KCC language majority or not.

Tables

Table 1: Summary Statistics

	N	Mean	Median	Standard Deviation
Coverage share	29,283	0.361	0.000	0.431
Share of non-state language speakers	29,024	0.126	0.013	0.241
Share of ag households with KCC	8,592	0.107	0.049	0.149
Share of farmers with credit				
Aggregate	29,283	0.146	0.032	0.215
By Farm Size				
Very Small (<1 ha)	29,283	0.062	0.007	0.112
Small (1-2 ha)	29,283	0.039	0.005	0.064
Semi Medium (2-4 ha)	29,283	0.027	0.003	0.045
Medium (4-6 ha)	29,283	0.015	0.001	0.030
Large (>10 ha)	29,283	0.003	0.000	0.012
By Lender Type				
CB	29,283	0.021	0.000	0.081
PACS	29,283	0.118	0.011	0.187
RRB	29,283	0.007	0.000	0.049
Credit per farmer				
Aggregate	29,283	2,783.7	454.6	4,238.8
By Farm Size				
Very Small (<1 ha)	29,283	743.9	51.4	1,281.7
Small (1-2 ha)	29,283	700.8	75.7	1,141.5
Semi Medium (2-4 ha)	29,283	629.5	52.3	1,042.4
Medium (4-6 ha)	29,283	432.7	17.2	762.3
Large (>10 ha)	29,283	79.9	0.0	163.2
By Lender Type				
CB	29,283	356.0	0.0	1,042.2
PACS	29,283	1,968.6	107.1	3,111.3
RRB	29,283	0.6	0.0	2.5
By Credit Maturity				
Short-term	29,283	2,489.6	364.4	3,787.0
Medium-term	29,283	102.1	0.0	290.8
Long-term	29,283	48.2	0.0	139.3

Notes: This table reports the number of observations, mean, median and standard deviation for the outcomes used in the paper and the explanatory variable. The unit of observation is a 10×10 km cell and the sample includes all cells that were promised towers under the SMIP program. Coverage share is calculated using the GSMA coverage data. The share of non-state language speakers is computed using the census. The share of agricultural households with Kisan Credit Cards is computed using the Socio Economic and Caste Census (SECC), which was obtained from SHRUG. Share of farmers with credit and credit per farmer are obtained from the Agricultural Input Survey and we utilize 4 rounds- spanning 2002 to 2017.

Table 2: Balance Table

Dependent Variable	**Coefficient (St. Err)**
Agri workers/Working Pop.	0.005
	(0.007)
Distance to nearest town (kms)	-6.684*
	(3.575)
Percent of area irrigated	-0.010
	(0.011)
Crop Suitability	-1.377
	(70.868)
Population share of scheduled castes	0.008
	(0.006)
Night lights growth (2001-06)	0.018
	(0.033)
Night lights growth (1996-06)	-0.020
	(0.050)
Avaibility of ...	
... Drinking water facility	-0.001
	(0.001)
... Education Facility	-0.003
	(0.007)
... Recreation facility	-0.001
	(0.005)
... Medical Facility	0.007
	(0.011)
... Telephone Office	0.004
	(0.013)
... Credit Society Facility	0.027
	(0.018)
... Banking Facility	0.001
	(0.004)

Notes: This table reports the coefficients and standard errors from the test on the balance of observable characteristics, run on the sample of cells included in the SMIS program. We regress each of the dependent variables on a binary treatment indicator on a cross-sectional dataset, with state fixed effects and standard errors clustered at the district level.

Table 3: First Stage Results

Dependent Variable:	Coverage	
	(1)	(2)
Tower × Post	0.221***	0.203***
	(0.031)	(0.030)
N	29,283	29,283
F-Stat	50.423	44.589
Baseline Controls × Year FE	Yes	Yes
Other Controls × Year FE	No	Yes
Cell FE	Yes	Yes
State × Year FE	Yes	Yes

Notes: This table reports the effects of being treated under the SMIS program on cellphone tower coverage. Coverage refers to the standard deviation of coverage and is computed by dividing the share of coverage in a cell by the standard deviation of coverage in our sample. The unit of observation is a 10 × 10 km cell and the sample includes all cells that were initially selected to receive a tower under the SMIS program. Baseline controls include total population, power supply and ruggedness. Other controls include share of agricultural work, share of irrigated land, educational facilities, medical facilities, lending facilities, number of commercial banks, telephones per capita and distance to nearest town. All controls are at baseline from the 2001 Population & Village Census and are interacted with year fixed effects. Standard errors are clustered at the district level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table 4: Impact of Tower Construction on Credit

	OLS		RF		IV	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Share of farmers with credit						
Coverage	0.024***	0.021***			0.068***	0.072**
	(0.004)	(0.004)			(0.025)	(0.028)
Tower × Post			0.015***	0.015***		
			(0.005)	(0.005)		
Panel B: Credit per farmer						
Coverage	602.5***	497.5***			1,394.3***	1,369.5**
	(91.9)	(91.5)			(521.2)	(565.2)
Tower × Post			307.7***	277.5***		
			(107.1)	(103.5)		
N	29,283	29,283	29,283	29,283	29,283	29,283
Baseline Controls × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Other Controls × Year FE	No	Yes	No	Yes	No	Yes
Cell FE	Yes	Yes	Yes	Yes	Yes	Yes
State × Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table reports the effects of being included under the SMIS program on the share of farmers with credit (Panel A) and credit per farmer (Panel B). The data is computed using the Agricultural Input Survey (AIS) and the 2001 Population Census of India. We divide the number of farmers with credit (from the AIS data) by the number of farmers found in a cell (from the 2001 Population Census) to obtain the share of farmers with credit. We divide the agricultural credit in a cell (in 2007 rupees; from the AIS data) by the number of farmers found in a cell (from the 2001 Population Census) to obtain the credit per farmer in rupees. Tower is a binary indicator which equals 1 when a cell received a tower under the SMIS program. Post is a binary indicator which equals 1 after 2010. Coverage is the share of tower coverage in a cell divided by the standard deviation of coverage in our sample. The dependent variable in Panel B is winsorized at the 5% level. The unit of observation is a 10×10 km cell and the sample includes all cells that were initially selected to receive a tower under the SMIS program. Columns 1 and 2 report OLS results, columns 3 and 4 present Reduced Form results and columns 5 and 6 present IV results, where we instrument cellphone tower coverage using treatment status under the SMIS program. Baseline controls include total population, power supply and ruggedness. Other controls include share of agricultural work, share of irrigated land, educational facilities, medical facilities, lending facilities, number of commercial banks, telephones per capita and distance to nearest town. All controls are at baseline from the 2001 Population & Village Census and are interacted with year fixed effects. Standard errors are clustered at the district level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table 5: Effect on Kisan Credit Cards

Dependent Variable	Share of agricultural households with KCC	
	RF	IV
	(1)	(2)
Tower	0.012**	
	(0.005)	
Coverage		0.057**
		(0.024)
N	8,592	8,592
Baseline Controls	Yes	Yes
Other Controls	Yes	Yes
State FE	Yes	Yes

Notes: This table reports the effect of receiving a tower under the SMIS program on the share of agricultural households with a Kisan Credit Card (columns 1 and 2). The data is computed using the SHRUG2.0 dataset by the Data Development Lab. Tower is a binary indicator which equals 1 when a cell received a tower under the SMIS program. Coverage is the share of tower coverage in a cell divided by the standard deviation of coverage in our sample. The unit of observation is a 10×10 km cell and the sample includes all cells that were initially selected to receive a tower under the SMIS program. Column 1 presents Reduced Form results whilst column 2 presents IV results, where we instrument cellphone tower coverage using treatment status under the SMIS program. Baseline controls include total population, power supply and ruggedness. Other controls include share of agricultural work, share of irrigated land, educational facilities, medical facilities, lending facilities, number of commercial banks, telephones per capita and distance to nearest town. All controls are at baseline from the 2001 Population & Village Census. Standard errors are clustered at the district level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

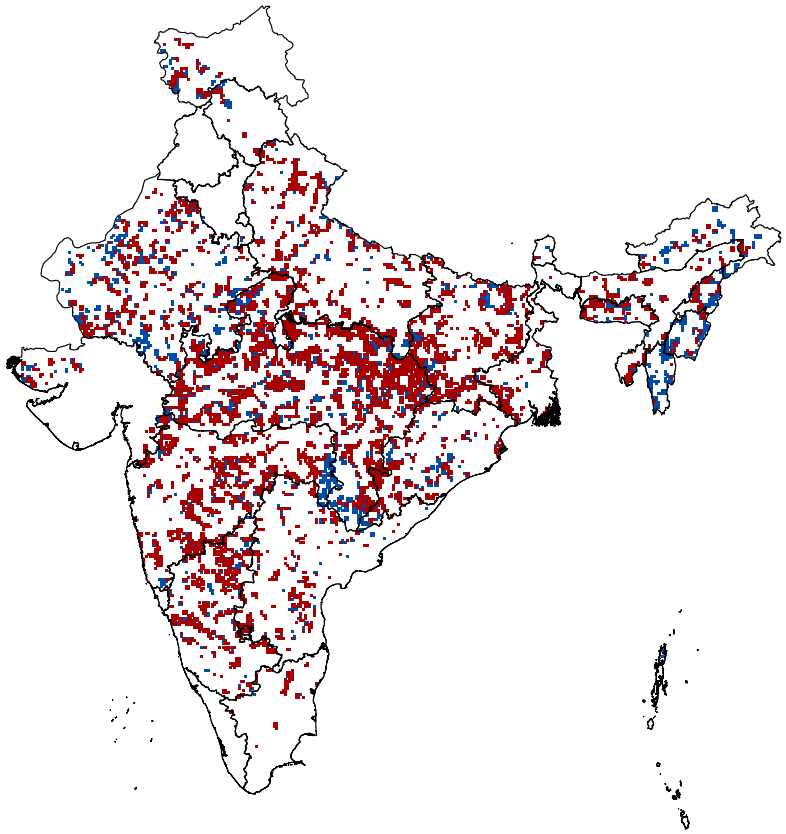
Table 6: Effect of Non-State Language Speakers

Dependent Variable	Share of farmers with credit		Credit per farmer	
	(1)	(2)	(3)	(4)
Tower × Post	0.018***	0.019***	381.4***	382.2***
	(0.006)	(0.006)	(127.9)	(124.3)
Tower × Post × Non-state language speakers	–0.006*	–0.007**	–159.3**	–188.8***
	(0.003)	(0.003)	(68.6)	(65.8)
N	29,024	29,024	29,024	29,024
Baseline Controls × Year FE	Yes	Yes	Yes	Yes
Other Controls × Year FE	No	Yes	No	Yes
Cell FE	Yes	Yes	Yes	Yes
State × Year FE	Yes	Yes	Yes	Yes

Notes: This table reports the reduced-form effects of how the share of non-state language speakers in a cell affects the credit take-up. The data is computed using the Agricultural Input Survey (AIS) and the 2001 Population Census of India. We divide the number of farmers with credit (from the AIS data) by the number of farmers found in a cell (from the 2001 Population Census) to obtain the share of farmers with credit. We divide the agricultural credit in a cell (in 2007 rupees; from the AIS data) by the number of farmers found in a cell (from the 2001 Population Census) to obtain the credit per farmer in rupees. Tower is a binary indicator which equals 1 when a cell received a tower under the SMIS program. Post is a binary indicator which equals 1 after 2010. The non-state language speakers are the share of individuals in a cell who do not speak any of the state's official languages divided by the standard deviation of the share of individuals who do not speak the state language. The unit of observation is a 10×10 km cell and the sample includes all cells that were initially selected to receive a tower under the SMIS program. Baseline controls include total population, power supply and ruggedness. Other controls include share of agricultural work, share of irrigated land, educational facilities, medical facilities, lending facilities, number of commercial banks, telephones per capita, distance to nearest town and the normalized non-state language speakers share. All controls are at baseline from the 2001 Population & Village Census and are interacted with year fixed effects. Standard errors are clustered at the district level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

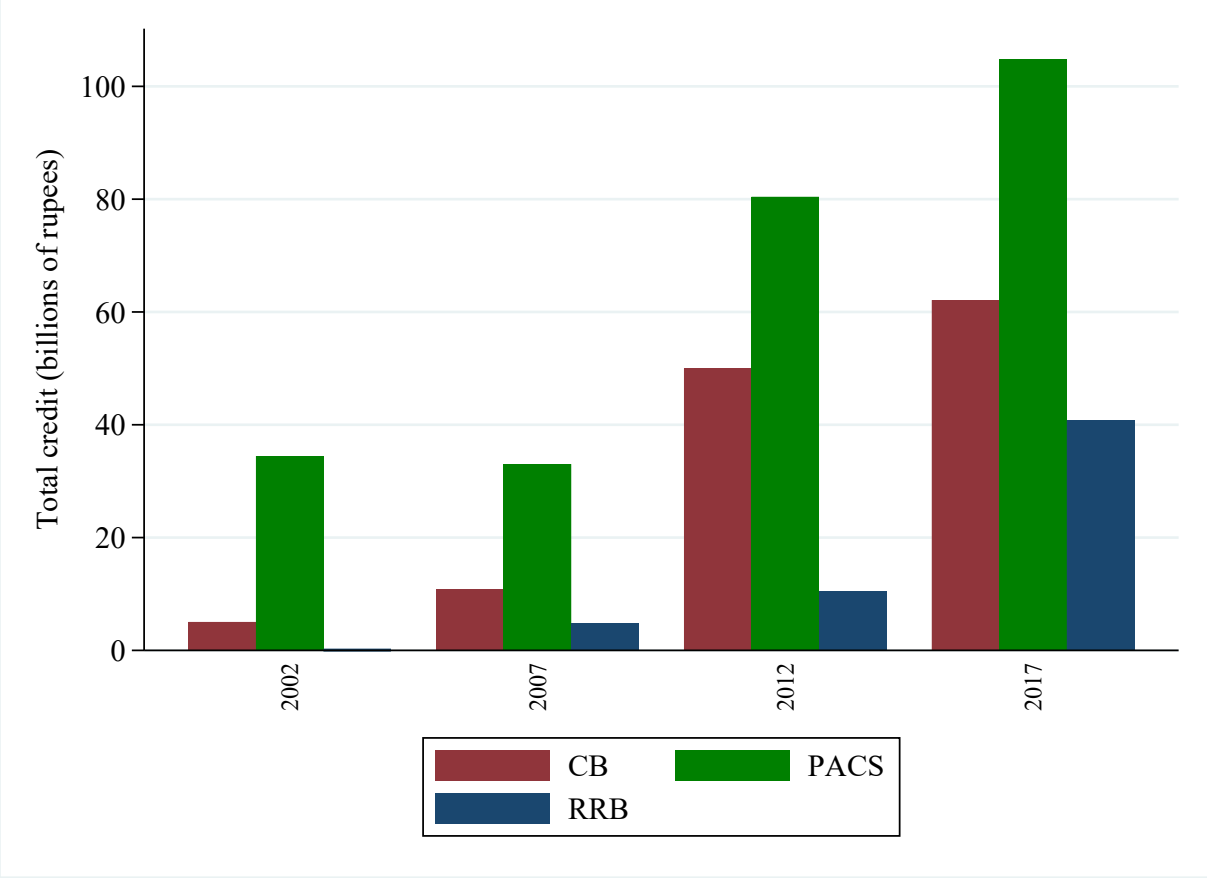
Appendix Figures

Figure A1: Treatment and Control cells under SMIP



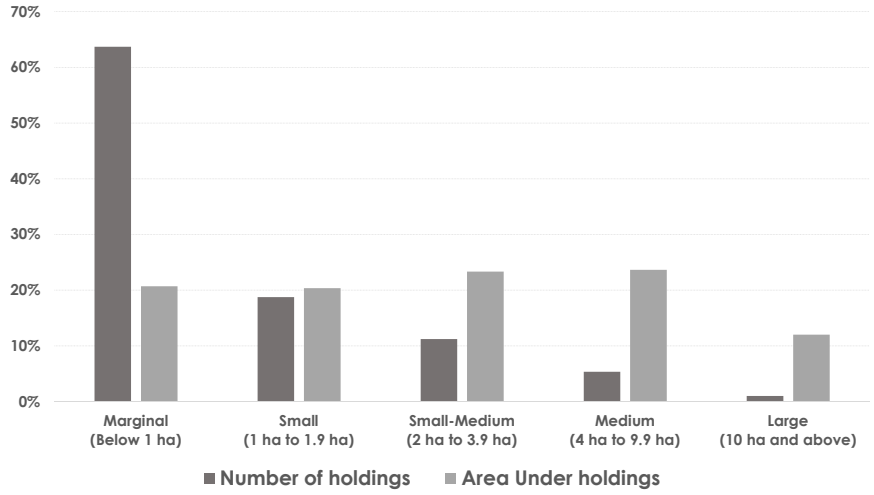
Notes: The figure shows the 6,562 identification cells distributed across treatment (red) and control (blue) cells for all of India. State borders are marked in black. Treatment cells are those that are both proposed *and* covered by mobile tower under SMIP Phase I. Control cells are those that are proposed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

Figure A2: AIS Lending



Notes: This figure shows AIS Lending by lender type in our sample of cells. CB refers to Commercial Banks, PACS refers to Primary Agricultural Credit Society and RRB refers to Regional Rural Banks.

Figure A3: Distribution of number of holdings and area under cultivation , by size of holdings



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

Appendix Tables

Table A1: Heterogeneity: By Maturity

Dependent Variable:	Credit per farmer		
	Short-term (1)	Medium-term (2)	Long-term (3)
Coverage	1,358.6**	–1.3	–16.5
	(549.1)	(43.3)	(19.6)
N	29,283	29,283	29,283
Baseline Controls × Year FE	Yes	Yes	Yes
Other Controls × Year FE	Yes	Yes	Yes
Cell FE	Yes	Yes	Yes
State × Year FE	Yes	Yes	Yes

Notes: This table reports the effects of being included under the SMIS program on the credit per farmer by credit maturity. The data is computed using the Agricultural Input Survey (AIS) and the 2001 Population Census of India. We divide the agricultural credit in a cell in each maturity category (in 2007 rupees; from the AIS data) by the number of farmers found in a cell (from the 2001 Population Census) to obtain the credit per farmer in rupees. Tower is a binary indicator which equals 1 when a cell received a tower under the SMIS program. Post is a binary indicator which equals 1 after 2010. Coverage is the share of tower coverage in a cell divided by the standard deviation of coverage in our sample. The dependent variable is winsorized at the 5% level. The unit of observation is a 10×10 km cell and the sample includes all cells that were initially selected to receive a tower under the SMIS program. Column 1 presents results for short-term credit, column 2 presents results for medium-term credit and column 3 presents results for long-term credit. Baseline controls include total population, power supply and ruggedness. Other controls include share of agricultural work, share of irrigated land, educational facilities, medical facilities, lending facilities, number of commercial banks, telephones per capita and distance to nearest town. All controls are at baseline from the 2001 Population & Village Census and are interacted with year fixed effects. Standard errors are clustered at the district level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table A2: Heterogeneity: By Lender

	Commercial Banks	PACS	RRB
	(1)	(2)	(3)
Panel A: Share of cultivators with credit			
Coverage	0.010	0.061**	0.001
	(0.009)	(0.027)	(0.005)
Panel B: Credit per cultivator			
Coverage	126.7	1,065.5**	0.2
	(103.5)	(460.2)	(0.3)
N	29,283	29,283	29,283
Baseline Controls × Year FE	Yes	Yes	Yes
Other Controls × Year FE	Yes	Yes	Yes
Cell FE	Yes	Yes	Yes
State × Year FE	Yes	Yes	Yes

Notes: This table reports the effects of being included under the SMIS program on the share of farmers with credit (Panel A) and credit per farmer (Panel B) by lender type. The data is computed using the Agricultural Input Survey (AIS) and the 2001 Population Census of India. We divide the number of farmers with credit in each lender category (from the AIS data) by the number of farmers found in a cell (from the 2001 Population Census) to obtain the share of farmers with credit. We divide the agricultural credit in a cell in each lender category (in 2007 rupees; from the AIS data) by the number of farmers found in a cell (from the 2001 Population Census) to obtain the credit per farmer in rupees. Tower is a binary indicator which equals 1 when a cell received a tower under the SMIS program. Post is a binary indicator which equals 1 after 2010. Coverage is the share of tower coverage in a cell divided by the standard deviation of coverage in our sample. The dependent variable in Panel B is winsorized at the 5% level. The unit of observation is a 10×10 km cell and the sample includes all cells that were initially selected to receive a tower under the SMIS program. Column 1 presents results for commercial banks, column 2 presents results for Primary Agricultural Credit Society (PACS) and column 3 presents results for Regional Rural Banks (RRB). Baseline controls include total population, power supply and ruggedness. Other controls include share of agricultural work, share of irrigated land, educational facilities, medical facilities, lending facilities, number of commercial banks, telephones per capita and distance to nearest town. All controls are at baseline from the 2001 Population & Village Census and are interacted with year fixed effects. Standard errors are clustered at the district level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table A3: Heterogeneity: By Holding Size

	Very Small	Small	Semi-Medium	Medium	Large
	(1)	(2)	(3)	(4)	(5)
Panel A: Share of farmers with credit					
Coverage	0.027*	0.019**	0.014**	0.008*	0.001
	(0.014)	(0.008)	(0.006)	(0.004)	(0.002)
Panel B: Credit per farmer					
Coverage	333.8**	351.8**	336.6**	242.9**	33.6
	(165.9)	(153.4)	(144.8)	(105.4)	(24.7)
N	29,283	29,283	29,283	29,283	29,283
Baseline Controls × Year FE	Yes	Yes	Yes	Yes	Yes
Other Controls × Year FE	Yes	Yes	Yes	Yes	Yes
Cell FE	Yes	Yes	Yes	Yes	Yes
State × Year FE	Yes	Yes	Yes	Yes	Yes

Notes: This table reports the effects of being included under the SMIS program on the share of farmers with credit (Panel A) and credit per farmer (Panel B) by farm size. The data is computed using the Agricultural Input Survey (AIS) and the 2001 Population Census of India. We divide the number of farmers with credit in each farm size category (from the AIS data) by the number of farmers found in a cell (from the 2001 Population Census) to obtain the share of farmers with credit. We divide the agricultural credit in a cell in each farm size category (in 2007 rupees; from the AIS data) by the number of farmers found in a cell (from the 2001 Population Census) to obtain the credit per farmer in rupees. Tower is a binary indicator which equals 1 when a cell received a tower under the SMIS program. Post is a binary indicator which equals 1 after 2010. Coverage is the share of tower coverage in a cell divided by the standard deviation of coverage in our sample. The dependent variable in Panel B is winsorized at the 5% level. The unit of observation is a 10×10 km cell and the sample includes all cells that were initially selected to receive a tower under the SMIS program. Column 1 presents results for Very Small holdings ($<$ 1 ha), column 2 presents results for Small holdings (1-2 ha), column 3 presents results for Semi-Medium holdings (2-4 ha), column 4 presents results for Medium holdings (4-10 ha) and column 4 presents results for large holdings ($>$ 10 ha). Baseline controls include total population, power supply and ruggedness. Other controls include share of agricultural work, share of irrigated land, educational facilities, medical facilities, lending facilities, number of commercial banks, telephones per capita and distance to nearest town. All controls are at baseline from the 2001 Population & Village Census and are interacted with year fixed effects. Standard errors are clustered at the district level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table A4: Robustness: Conley Standard Errors

	Share of farmers with credit (1)	Credit per farmer (2)
Panel A: IV Results		
Coverage	0.0723	1,369.5
Standard Errors (Baseline)	[0.0284]**	[565.2]**
Spatial Correlation, threshold:50 km	[0.0178]***	[350.3]***
Spatial Correlation, threshold:150 km	[0.0186]***	[364.8]***
Spatial Correlation, threshold:300 km	[0.0184]***	[362.1]***
Spatial Correlation, threshold:500 km	[0.0166]***	[352.7]***
Panel B: RF Results		
Tower × Post	0.0146	277.5
Standard Errors (Baseline)	[0.0052]***	[103.5]***
Spatial Correlation, threshold:50 km	[0.0036]***	[71.0]***
Spatial Correlation, threshold:150 km	[0.0038]***	[73.9]***
Spatial Correlation, threshold:300 km	[0.0037]***	[73.4]***
Spatial Correlation, threshold:500 km	[0.0034]***	[71.5]***
N	29,283	29,283
Baseline Controls × Year FE	Yes	Yes
Other Controls × Year FE	Yes	Yes
Cell FE	Yes	Yes
State × Year FE	Yes	Yes

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

Table A5: Robustness: Time varying farmers

	OLS	RF	IV
	(1)	(2)	(3)
Panel A: Share of farmers with credit			
Coverage	0.016***		0.064**
	(0.004)		(0.031)
Tower × Post		0.013**	
		(0.006)	
Panel B: Credit per farmer			
Coverage	411.6***		1,149.3**
	(93.6)		(571.8)
Tower × Post		227.5**	
		(104.7)	
N	29,299	29,299	29,299
Baseline Controls × Year FE	Yes	Yes	Yes
Other Controls × Year FE	Yes	Yes	Yes
Cell FE	Yes	Yes	Yes
State × Year FE	Yes	Yes	Yes

Notes: This table reports alternative estimates for the effects of being included under the SMIS program on share of farmers with credit and credit per farmer. The data is computed using the Agricultural Input Survey (AIS), the 2001 Population Census of India and the 2011 Population Census of India. We divide the number of farmers with credit in each lender category (from the AIS data) by the number of farmers found in a cell (we use the 2001 Population Census for 2002 and 2007, and the 2011 Population Census for 2012 and 2017) to obtain the share of farmers with credit. We divide the agricultural credit in a cell (in 2007 rupees; from the AIS data) by the number of farmers found in a cell (we use the 2001 Population Census for 2002 and 2007, and the 2011 Population Census for 2012 and 2017) to obtain the credit per farmer. Tower is a binary indicator which equals 1 when a cell received a tower under the SMIS program. Post is a binary indicator which equals 1 after 2010. Coverage is the share of tower coverage in a cell divided by the standard deviation of coverage in our sample. The dependent variable in panel B is winsorized at the 5% level. The unit of observation is a 10 × 10 km cell and the sample includes all cells that were initially selected to receive a tower under the SMIS program. Column 1 presents OLS results, column 2 presents Reduced Form results and column 3 presents IV results, where we instrument cellphone tower coverage using treatment status under the SMIS program. Baseline controls include total population, power supply and ruggedness. Other controls include share of agricultural work, share of irrigated land, educational facilities, medical facilities, lending facilities, number of commercial banks, telephones per capita and distance to nearest town. All controls are at baseline from the 2001 Population & Village Census and are interacted with year fixed effects. Standard errors are clustered at the district level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table A6: Robustness: Language Interaction

	Baseline	+Tower×Post ×Agriculture	+Tower×Post ×Distance	+Tower×Post ×Nightlights	+Tower×Post ×Scheduled Castes
	(1)	(2)	(3)	(4)	(5)
Panel A: Share of farmers with credit					
Tower × Post	0.019***	0.031*	0.025***	0.019**	0.028***
	(0.006)	(0.017)	(0.008)	(0.008)	(0.009)
Tower × Post × NS Speakers	–0.007**	–0.007*	–0.005	–0.006*	–0.009**
	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)
Panel B: Credit per farmer					
Tower × Post	382.5***	660.7*	660.2***	368.4**	418.1**
	(124.3)	(365.5)	(175.2)	(148.4)	(185.6)
Tower × Post × NS Speakers	–188.9***	–183.2***	–116.9*	–174.4**	–188.5**
	(65.6)	(65.6)	(66.0)	(68.0)	(73.1)
N	29,024	29,024	29,024	29,024	29,024
Baseline × Year FE	Yes	Yes	Yes	Yes	Yes
Other × Year FE	Yes	Yes	Yes	Yes	Yes
Cell FE	Yes	Yes	Yes	Yes	Yes
State × Year FE	Yes	Yes	Yes	Yes	Yes

Notes: This table reports alternative estimates for the effect of the SMIS program on credit outcomes as we add several covariates. Tower is a binary indicator which equals 1 when a cell received a tower under the SMIS program. Post is a binary indicator which equals 1 after 2010. NS Speakers is the share of non-state language speakers in a cell divided by the standard deviation of NS Speakers. The dependent variable in columns 6-10 is winsorized at the 5% level. The unit of observation is a 10 × 10 km cell and the sample includes all cells that were initially selected to receive a tower under the SMIS program. Column 1 presents baseline results with no additional covariates. Column 2 controls for share of agricultural work. Column 3 controls for median distance to the nearest town across all villages in the cell. Column 4 adds night lights activity in 2006. Column 5 adds the share of population that belongs to Scheduled Caste. Baseline controls include total population, power supply and ruggedness. Other controls include share of agricultural work, share of irrigated land, educational facilities, medical facilities, lending facilities, number of commercial banks, telephones per capita and distance to nearest town. All controls are at baseline from the 2001 Population & Village Census and are interacted with year fixed effects. Standard errors are clustered at the district level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.