Information Frictions and Take-up of Government Credit Programs*

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December 4, 2023

Abstract

Most governments in developing countries offer subsidized credit programs to the agricultural sector. However, 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 farms, which have been the target of a major government subsidized credit program, the Kisan credit cards.

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

JEL Classification: G21, Q16, E51

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* We received valuable comments from Shawn Cole, Nicola Gennaioli, Sergei Guriev, Sabrina Howell, Dean Karlan, Marco Manacorda, Pepita Miquel, Imran Rasul, Gabriella Santangelo, Chris Udry and seminar participants at Columbia University, NYU Stern, Bocconi University, Queen Mary University, University of Maryland, Northwestern University, Berkeley Haas, UBC, BGSE Summer Forum. 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 market failures such as information asymmetries, lack of competition among lenders or imperfect enforcement (Karlan and Morduch, 2010; Karlan et al., 2016). Using these market failures as a justification for policy, over the past decades several governments have intervened in rural credit markets – mostly via straightforward subsidization of agricultural credit – with the hope that larger take-up will facilitate adoption of modern technologies and help farmers absorb income shocks and smooth consumption (Besley, 1994). While these initiatives have indeed broadened the amount of credit available to farmers, evidence suggests that targeted individuals might be unaware of the existence of such programs, or lack information about eligibility criteria, application procedures or loan terms offered.[1] These 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 relaxing information frictions about credit programs available to farmers on credit take-up using data from India. To capture changes in potential access to information, we exploit variation in mobile phone coverage generated by the Shared Mobile Infrastructure Scheme (SMIS). This program was launched by the Indian government in 2007, and financed 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 and free-of charge services for agricultural advice, the Kisan Call Centers (KCC). 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.

The main identification challenge is the endogenous location of new mobile phone towers. To address this issue, we restrict our sample to areas that were part of the initial list of proposed tower locations drafted by the Department of Telecommunication. All proposed locations are in rural areas with no mobile phone coverage as of 2007, when the program was launched. Our identification strategy compares locations where phone towers were proposed and eventually constructed (treatment group), with locations where phone towers were also proposed but eventually not constructed (control group). Towers in the control group were canceled or relocated, either to increase the population covered or because of technical issues related to the slope of the terrain in the initially proposed site.

We show that treatment and control areas are balanced on initial observable charac-

[1]Using survey data from Kenya, Dupas et al. (2014) document that knowledge of loan options among farmers and small entrepreneurs is extremely limited in rural areas. Data from the National Sample Survey of 2013 shows low awareness by Indian farmers of government programs such as Minimum Support Prices (NSS 70th Round, 2013).

teristics once we control for determinants of tower relocation such as terrain ruggedness, potential population covered and the availability of a connection to the power grid. Consistently with our identification assumption, treated and control areas experience similar pre-existing trends in credit outcomes in the 5 years preceding the introduction of new towers. Using detailed geographical data on areas covered by mobile phone signal reported by private operators to the Global System for Mobile Communication Association (GSMA), we document that construction of SMIS towers strongly predicts differential mobile coverage in the years following the launch of the program.

Our first finding is that areas that received new phone towers via the SMIS program experienced faster increase in farmers' calls to Kisan call centers. Data at call-level from Kisan call centers contains information on the question asked by the farmer and the answer provided by the agronomist. We use text analysis to categorize calls based on the topic of each question. We document a significant increase in both total number of calls per farmer, and in the number of calls related to credit. In the majority of calls about agricultural credit, farmers ask questions regarding Kisan credit cards, a specific type of card offering short-term loans at rates subsidized by the government. Using the timestamp of each call, we also document the evolution of farmers' calls around the construction of the first mobile phone tower in an event study design. Overall, these findings are consistent with under served demand for agricultural related information in the areas targeted by the program.

We then study the effect of expanding mobile phone coverage on credit outcomes. Credit data is from the Agricultural Input Survey (AIS), and it is available at 5-year intervals between 2002 and 2017. As the SMIS mobile phone towers were constructed between 2008 and 2010, we consider the 2002 and 2007 waves of the AIS as the pre-period, and the 2012 and 2017 waves as the post period. 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 magnitudes, treated cells experienced a 1.1 percentage points larger increase in the share of farmers with agricultural credit after the construction 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. 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 are consistent with 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-term loans and among small and medium agricultural establishments (i.e. those with less than 10 hectares in size), which match the characteristics of the loans offered via Kisan credit cards. We also 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 households declaring to use Kisan Credit Cards in 2012, about five years after the beginning of the tower construction program.

These results are consistent with SMIS towers relaxing information frictions. However, a first potential concern with this interpretation is that the arrival of mobile phone coverage promotes local economic opportunities more generally (e.g., Jensen, 2007; Aker and Mbiti, 2010), increasing local income and thus farmers' demand for credit 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 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 varies 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 KCC increase faster in areas where the majority of the local population speak the same language as call centers' agronomists. Second, the effect of SMIS towers on credit take-up is muted in areas where more than 50% of the local population does not speak the official language of the state where they reside. Because the share of local population speaking non-state languages is not randomly assigned, we show that results are robust to augmenting 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 a reduction in information frictions driving the effect of mobile phone coverage on credit take-up.

Farmers speaking the same language of call center advisors gain potential access to different types of information. This includes information about government credit programs, which could *directly* affect take-up, and information about other agriculture-related issues, such as best farming practices or available technologies, which could *indirectly* affect credit take-up via a demand channel. Despite our analysis of farmers' calls shows that farmers indeed lack information about credit programs available to them, tracing a direct link between access to a specific type of information and credit take-up is empirically challenging outside of an experimental setting.

We provide suggestive evidence on the specific role of information about credit programs by testing whether the effects of treatment on credit take-up depend on KCC advisors familiarity with such programs, which we proxy with bank branch density around the KCC office answering farmers' calls in each Indian state. We find that treatment effects are stronger when there is a higher density of Primary Agricultural Credit Societies (PACS) – the primary issuer of agricultural credit to farmers in our sample – around the physical location of the KCC office of each state. Although only suggestive, this finding is consistent with the importance of access to direct information about credit programs in explaining the documented credit take-up.

In the final section of the paper, we discuss the magnitude of the response of credit take-up to the number of farmers' calls implied by our estimates. Assuming the effects are fully driven by an information mechanism, our estimates imply that the information obtained via one call spreads, on average, to 3.3 farmers within the same area. Although callers are actively seeking information when contacting Kisan call centers – and are therefore likely to act upon it – this magnitude can only be rationalized if information spreads from callers to non-callers. We discuss several aspects of our setting that might contribute to explain this level of diffusion. First, higher mobile phone coverage in treated areas can facilitate both the diffusion from callers to non-callers, as well as additional diffusion among non-callers that can now use mobile phones to communicate with each other. Second, survey evidence shows that callers to Kisan call centers are selected on several dimensions, including higher education (Gandhi and Johnson, 2017). More educated farmers are more likely to be part of the social network of other farmers (Varshney et al., 2022), and seeding information with individuals that are central to social networks has been shown to be a powerful mode of dissemination of information within a community (Banerjee et al., 2018).

Related Literature

Our paper is related to several strands of the literature. First, it relates to the literature on the role of information frictions in credit market participation in developing countries. Dupas et al. (2014) document limited knowledge of savings and loans options offered by local bank branches among a sample of households in rural Kenya. Using an information intervention that improves knowledge of loan application conditions and procedures, as well as providing a voucher that allows individuals to be eligible for a loan, they find limited effects of the intervention on starting a loan application and credit take-up. Survey responses indicate that fear of losing collateral and distrust in commercial banks are major factors in dissuading participants from taking up a loan. In another related work, De Mel et al. (2011) study the effect of information sessions about microfinance loan products on small-scale entrepreneurs in Sri Lanka, finding relatively large effects on take-up within a short time period after the intervention (three months). In the context of India and Indonesia, Cole et al. (2011) document how financial education programs have much more limited effects than a monetary subsidy on bank account openings. Compared to these studies, we focus on information frictions about a government credit program, in which the issuer is a trusted institution and the terms are especially favourable to farmers, offering subsidized rates without collateral for small agricultural loans.

Our focus on a government-sponsored credit program is shared by a recent body of work documenting the existence of information frictions on the uptake of government subsidized loans offered to households and firms in response to the Covid-19 emergency in industrialized countries (Custódio et al., 2022; Humphries et al., 2020). Compared to these studies, which focus on a rapidly changing environment characterized by a high degree of uncertainty and in which the timing of loan applications was particularly sensitive, we provide evidence on the role of information frictions on long-existing opportunities in rural credit markets in a developing country.

Our paper also 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.

Our analysis is also linked to the large literature using randomized controlled trials 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. While this literature has mostly focused on real effects of extension programs on agricultural practices, we focus on how the diffusion of mobile phone coverage affect take-up of credit programs available to farmers.

Finally, it is worth noting that this paper is part of a broader research agenda that studies the role of information frictions in the process of development using the experience of India and of the KCC in particular. Our first study in this agenda, Gupta et al. (2022), documents the importance of language barriers between farmers and KCC advisors for the adoption of modern agricultural technologies – such as high-yielding varieties of seeds – by exploiting variation in languages in areas across state borders. Relative to Gupta et al. (2022), this paper focuses on the impact of a large infrastructure program

– the construction of mobile phone towers in previously unconnected areas of India – to study how access to information affects loan take-up in rural credit markets. In this sense, our paper is also related to the literature analyzing the economic impacts of large infrastructure programs in developing countries. In the context of India, for example, Agarwal et al. (2022) documents that Indian villages gaining access to the road network via a large infrastructure program experience an increase in loan take-up.[2]

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 presents robustness tests, and section 6 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 phone 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

[2]The literature has also documented the economic effects of transportation infrastructure (Aggarwal 2018, Donaldson 2018, Asher and Novosad 2020), rural electrification (Dinkelman 2011, Burlig and Preonas 2016, Lee, Miguel, and Wolfram 2020), and telecommunication services (Jensen 2007, Aker 2010).

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.[3]

Figure 2 reports the geographical diffusion of 2G GSM mobile phone coverage in India at five-year intervals between 2002 and 2017. India had virtually no mobile phone coverage as of the end of the 1990s. The mobile phone network began to expand rapidly afterwards, covering 22 percent of the population in 2002, 61 percent in 2007, and reaching 90 percent by 2012.[4] Data from the World Bank (2017) indicate that mobile phone subscriptions per 100 people in India went from 1.2 in 2002 to 86.3 in 2017. 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.

2.2 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 advice that is specific to the agro-climatic characteristics of the area where the farmer is located. The Ministry opened 21 of such call centers,

[3] 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).

[4] 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.

which answer calls from all Indian states. Panel (a) of Figure 3 reports the number of calls received by KCC per year between 2007 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 by the end of the sample period.

We categorize calls to KCC into ten categories based on the text of the question asked by the farmer. Panel (b) of Figure 3 reports the decomposition of calls by category between 2007 and 2017. The two main categories are represented by calls in which farmers ask advise on how to deal with pests affecting their crops, and calls in which farmers ask information on weather forecasts. Other categories include questions about seeds, fertilizers, irrigation, market prices and agricultural practices. Calls about credit range between 1.4 and 5 percent of total calls depending on the year, with an average of about 2.9%. 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), general calls on how to obtain credit, and calls in which farmers ask information about government programs favoring credit access. In the majority of the latter type of calls, farmers ask questions regarding how to obtain 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.[5] 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 credit.

The survey reports information on both number of agricultural holdings with credit

[5] 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.

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.[6] 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.

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.

[6]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 percent of total agricultural credit in India).

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 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 4 provides a visual example of how we classify cells into treatment and control group based on proposed and actual tower location.[7] Figure 5 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 percent) in the treatment group and 2,159 (26 percent) 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

[7] 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).

cells are a good counterfactual for treated cells.

In Table 2 we provide evidence in support of this conditional exogeneity assumption. In particular, we test whether initial cell-level characteristics predict the construction of a tower in a given cell, conditional on the cell being included in the list of potential tower locations from the Ministry of Telecommunication. We regress the binary treatment indicator on all cell-level initial characteristics in a single regression, which also includes state fixed effects and controls for main determinants of tower relocation, namely terrain ruggedness, connection to the power grid and potential population covered. As shown, treatment and control cells are uncorrelated with observable characteristics including level and pre-trends in local income as proxied by nightlights, crop suitability, share of scheduled castes, and initial presence of different types of lenders as well as total number of bank branches. Of the 18 variables studied in Table 2, two are correlated with treatment status: distance to nearest town, which is shorter for the treatment group although small in terms of magnitude, and presence of an education facility, which is lower in the treatment group.

In the empirical analysis we show that 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.

3.2 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:

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

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 sub-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 22.9 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, 21.4 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 70.73 in column (2). We can safely reject that the first stage is weak.

Finally, because mobile coverage is reported by operators at yearly level, we can also estimate the effect of tower construction on mobile phone coverage by year. The results are reported in Figure 6. Recall that the Ministry of Telecommunication targeted areas without pre-existing coverage. Thus, mobile coverage is zero for all cells in our sample until the beginning of the SMIS program in 2008. Between 2008 and 2012, treated cells experience a faster growth in coverage relative to control cells, with the difference between the two groups increasing up to about 20 percentage points of the cell area by 2012, and then remaining relatively constant between 2012 and 2017.

3.3 Farmers' calls to Kisan Call Centers

We start by studying the effect of mobile phone coverage on number of calls to Kisan Call Centers. We present three specifications: an OLS regression showing the correlation between mobile phone coverage and calls per farmer, a reduced form regression, and a two stage least square specification of the form:

$$\left(\frac{\#\text{ calls to KCC}}{\#\text{ farmers}}\right)_{ist} = \alpha_i + \alpha_{st} + \beta\,\widehat{Coverage}_{ist} + \lambda_t X_{is} + \varepsilon_{ist} \tag{2}$$

where $\widehat{Coverage}_{ist}$ is the mobile phone coverage in cell i and state s predicted by the construction of SMIS towers in the first stage. Standard errors are clustered at the sub-district level.

We focus on two versions of the outcome variable: one using total number of calls to Kisan call centers, and second using only number of calls in which the farmer asks questions about credit programs. Both variables are expressed in per 1000 farmers. We estimate this specification focusing on the years 2002, 2007, 2012 and 2017, the same years for which credit outcomes are observable in the Agricultural Input Survey.

The results are reported in Table 4. Columns (1) and (2) show that higher mobile phone coverage is correlated with more calls per farmers. The reduced form estimates in columns (3) and (4) show that cells where SMIS towers were constructed experience larger increase in calls per farmer relative to counterfactual cells where towers were proposed but not constructed. The IV coefficients reported in columns (5) and (6) show that cells with one standard deviation higher increase in mobile coverage experienced about 15 more calls per 1,000 farmers after the introduction of the SMIS program, and about 1.4 more calls about credit per 1,000 farmers.

Because data on calls is observable at high frequency, we can study the evolution of farmers' calls to Kisan call centers around the construction of SMIS mobile phone towers in an event study using the following specification:

$$\left(\frac{\#\text{ calls to KCC}}{\#\text{ farmers}}\right)_{ist} = \alpha_i + \alpha_{st} + \sum_{k=-12}^{+36} \beta_k D_{it}^k + \varepsilon_{it} \tag{3}$$

The outcome variable in equation (3) is the total number of calls originated from cell i in month t divided by number of farmers. 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 48 months after. The specification has state-year and cell fixed effects, denoted by α_{st} and α_i, respectively. 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 7 reports the estimated coefficients β_k along with their 95 percent confidence intervals. We find relatively small and not statistically significant effects in the twelve months preceding the introduction of the first tower in a cell. This is not a mechanical effect, as farmers always had the option to call KCC using landlines. Still, the number of calls in the early year of our sample, which include the months around adoption of the first towers in treated cell, is limited. Within three months from the construction of the first tower we observe a significant – though modest – relative increase in calls for agricultural advice. The magnitude of the effect implies an increase of 4 to 5 additional calls to Kisan call centers per 1,000 farmers per year within 48 months from the construction of the first tower in treated cells.

3.4 Credit take-up

3.4.1 Main effects on credit take-up by farmers

Table 5 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, and are observed in years 2002, 2007, 2012 and 2017. As in the previous section, for each outcome, we present three specifications: an OLS regression, a reduced form regression in which we estimate equation (1) replacing *Coverage* with credit outcomes, and a 2SLS specification of the form:

$$Credit_{ist} = \alpha_i + \alpha_{st} + \beta\,\widehat{Coverage}_{ist} + \lambda_t X_{is} + \varepsilon_{ist} \tag{4}$$

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 5 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 a one 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 an increase 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 1.1 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 one standard deviation larger increase in coverage experienced a 5.5 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 5 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 1,100 Rupees larger increase in credit per farmer, which correspond to about 30 percent 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 the returns to information are larger 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 8 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:

$$Credit_{ist} = \alpha_i + \alpha_{st} + \sum_{\substack{t=2002 \\ t\neq 2007}}^{2017} \beta_t \, \mathbb{1}\left(\text{Tower}\right)_{is} \times year_t + \delta_t X_{is} + \varepsilon_{ist}. \tag{5}$$

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 1.1 percentage points for the share of farmers with credit, and around 200 Rupees for credit per farmer.

Overall, the results reported in Table 5 and Figure 8 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 3.3, these results suggest that improved potential access to information about credit programs facilitate take of agricultural credit. Several 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? Third, what does the magnitude of the estimated coefficients imply in terms of the relationship between farmers' calls and credit take up? The rest of the paper attempts to address these questions.

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 5 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. Kisan credit cards offer loans at subsidized rates for agricultural purposes that have to be repaid within twelve months. Thus, any borrowing via Kisan credit cards is 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: Commercial Banks, Primary Agricultural Credit Societies (PACS), and Regional Rural Banks (RRB). In our sample, PACS constitute on average 58 percent of credit to agriculture between 2002 and 2017, followed by Commercial Banks (29 percent), and RRB (13 percent), as shown in Figure A2. Table A2 shows that the effects of mobile phone coverage on credit take up are largely driven by an increase in credit originated by PACS, while we find no effect of coverage on credit originated by Commercial Banks and RRBs. These results are consistent with data reported by the National Bank for Agricultural and Rural Development (NABARD), which show how PACS distribute about 32 percent 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, very small farms constitute the majority (63.7 percent) of agricultural holdings in India, followed by small farms (18.7 percent). In terms of area farmed, each size category represent a relatively similar share of total agricultural land, as can be seen in Figure A3. Although when splitting the sample by holding size we tend to lose statistical significance, the magnitude of the point estimates of the effect of mobile phone coverage on credit outcomes are larger for smaller farms, more precisely estimated for medium-size farmers, and monotonically decreasing in farm size. These heterogeneous effects are consistent with the information mechanism described above, as smaller 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 whether the household has a Kisan credit card with a credit limit of 50,000 Rupees or more.[8] 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 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 6. 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 (1) indicates that cells receiving a SMIS tower experienced a 1.1 percentage points large increase in the share of agricultural households with Kisan credit cards. The magnitude of this effect is consistent with the reduced form results reported in Panel A of Table 5.

Of course, the identification assumptions behind the results presented in Table 6 are stronger than the ones behind equation (4). 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 advice.

[8]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).

4 Discussion of Mechanisms

The results presented in the previous section are consistent with SMIS towers relaxing information frictions about existing government programs of subsidized credit. There are two challenges with this interpretation of the results. The first is that the arrival of mobile phone coverage in a given region can promote credit take up via mechanisms other than access to information through Kisan call centers. 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. A second challenge is that Kisan call centers offer information to farmers on many topics, and not just on how to access credit programs available to them. Thus, farmers gaining access to the service might take up credit in response to information that is not credit related. In this section, we discuss these two challenges and provide additional evidence to address them.

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 another official language of India that is not the one of the state in which they reside, or one of the about one hundred additional non-official languages spoken in the country.[9] 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 9 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

[9] 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.

sample. In Figure 10 we estimate equation (3) separately for cells in which the majority of the local population speaks the official language of the state and for those in which the majority speaks either a non-state official language of India or a non-official language.[10] 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.

Next, we re-estimate our main reduced form results of Table 5 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:

$$\begin{aligned} Credit_{ist} &= \alpha_i + \alpha_{st} + \beta_1 \mathbb{1}\left(\text{Tower}\right)_{is} \times Post_t \\ &+ \beta_2 \mathbb{1}\left(\text{Tower}\right)_{is} \times Post_t \times \text{Non-state language share}_{is} + \delta_t X_{is} + \eta_{ist} \quad (6) \end{aligned}$$

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 7. 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 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 10 and Table 7 are consistent with an information mechanism driving the effect of mobile phone coverage on credit take-up. Still, differential access to information can 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

[10] 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.

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.

The results presented in previous sections 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. This indicates the existence of an informational gap. 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.

As additional suggestive evidence on the role of information about credit programs, we test whether the effects of treatment on credit take-up depend on KCC agronomists' familiarity with credit programs available to farmers. As a proxy for agronomists' familiarity with credit programs we use the bank branch density around the KCC office answering farmers' calls in each Indian state. For each KCC office, we compute bank branch density by dividing the number of branches in the sub-district where the office is located by the population of that sub-district. Then, we test whether the effect of treatment on credit take-up depends on bank branch density around the KCC office of each state.

There are two key potential issues with this approach. First, our approach relies on the hypothesis that KCC advisors have a better knowledge of government credit programs for farmers when there is more bank activity in the area where they work, but this hypothesis is untestable with our data. However, we can at least study whether the effects depend on the type of banks that are located around the KCC office. In the areas where new SMIS towers were built, Primary Agricultural Credit Societies (PACS) tend to be the primary lender of farmers. Thus, we explore whether the effects on credit take-up depend on the density of commercial banks vs PACS vs RRBs branches in the area around the KCC office of each state.

A second potential issue with our approach is that bank branch density in the area surrounding the KCC office might be correlated with bank branch density in the areas from which farmers' calls. Thus, any heterogeneous effect might just capture the level of financial development of a given state, above and beyond the degree of knowledge of KCC advisors. To attenuate this concern, we control in all regressions for bank branches in the cells in our sample – those from which calls are originated – interacted with Treat $\times$ Post.

The results are reported in Table 8. Column (1) reports our baseline specification. Columns (2) to (4) report heterogeneous effects by bank density in the area around the

KCC office of each state. As shown, the positive effect of treatment on credit take-up is higher in states where there is a higher density of bank branches around KCC offices. These heterogeneous effects are larger and precisely estimated when we test for heterogeneity in the density of PACS branches around KCC offices. Taken together, these findings point towards the importance of access to information about credit programs in explaining the documented credit take-up.

4.3 Discussion of magnitudes

It is important to discuss the magnitude of the response of credit take-up to the number of farmers' calls implied by the estimates presented in Tables 4 and 5. For this quantification, we focus on the reduced form estimates, which are easily interpretable as the impact of being treated via the construction of a SMIS tower on calls per farmer and credit per farmer.

Column (3) of Table 4 shows that treated cells experience 3.3 more calls per thousand farmers – or 0.33 more calls per 100 farmers – than control cells after the introduction of the SMIS program. Column (4) of Table 5 shows that treated cells experience a 1.1pp larger increase in the share of farmers with credit in the same period. The combination of these two estimates implies an increase of 3.3 farmers with access to credit per call to Kisan call centers.

How much of this effect can be attributed specifically to calls about credit? Given the fact that access to Kisan call centers provides access to different types of information at the same time, it is challenging to provide an exact answer to this question. The estimates in column (3) and (4) of Table 4 indicate that about 10% of the additional calls to Kisan call centers generated by SMIS towers construction are calls in which farmers ask information about credit. Under the assumption that all calls have a similar impact on credit take up, independently from the type of question asked, this implies that about 10% of the effect of calls on credit take up can be attributed specifically to calls about credit. To the extent that calls about credit are more informative for access to credit than calls about other topics such as weather forecast or pesticides (a plausible assumption), we think of this 10% as a lower bound of the *direct* effect of access to information about credit programs on credit take up.

As discussed in section 4, access to information about topics other than credit can *indirectly* foster take up via a demand channel. For example, a farmer that learns about new seeds or better agricultural practices via Kisan call centers might now demand more credit to adopt such technologies, even if that farmer is perfectly informed about the subsidized credit programs available to her. Disentangling the exact magnitude of the direct vs indirect effects of access to information via Kisan Call centers would require an experimental setting in which only information on credit is provided, holding constant all other types of information. Still, we think that the evidence presented in Table 8 – along with the stylized facts that farmers ask about credit programs and take up the type of loans they ask about – indicates that both effects are at play.

Next, it is necessary to discuss the plausibility of the magnitude of the effect of calls on credit take up. The heterogeneous effects by language documented in section 4.1 suggest that access to information via Kisan call centers is a key determinant of the effect of SMIS tower construction on credit take up. Assuming the effects are fully driven by an information mechanism, our estimates imply that the information obtained via one call spreads, on average, to 3.3 farmers within the same area. This magnitude can only be rationalized if information spreads from callers of Kisan call centers to non-callers.

There are several aspects of our setting that are important to consider in assessing the plausibility of this level of diffusion. The first is that higher availability of mobile phone coverage in treated areas can facilitate both the diffusion from callers to non-callers, as well as additional diffusion among non-callers that can now use mobile phones to communicate with each other.

A second important aspect to consider is that farmers calling Kisan call centers are selected in terms of their personal characteristics and their role in local communities. A survey of callers to Kisan call centers implemented in 2017 by the Indian Centre for Management in Agriculture (Gandhi and Johnson, 2017) indicates that callers tend to be – on average – relatively educated farmers, the majority of them having completed secondary education.[11] Existing evidence in the literature shows that more educated farmers are also more likely to be part of the social network of other farmers. Varshney et al. (2022) uses data on 478 mustard farmers in the state of Rajasthan to document the characteristics of the social network of each farmer. They document how farmers with higher education are more likely to be mentioned among the three farmers with whom respondents declare to interact the most.[12] Existing studies have also shown that seeding information with a selected group of individuals that are central in the local network can be a powerful tool to disseminate information within a community (Conley and Udry, 2010; Beaman et al., 2021; Banerjee et al., 2018).

5 Robustness Tests

Standard errors correction. 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.

[11] Table 2.8, page 19 in Gandhi and Johnson (2017) shows that 72.12% of surveyed callers had completed higher secondary education.

[12] Among all farmers surveyed, the share of components of their social network having secondary education or above is 32%, higher than the share of farmers with middle school (21%), primary school (21%) or those that have not completed primary education (26%). See Table 3 in Varshney et al. (2022).

To partially address this concern, in all the specifications in the paper we cluster standard errors at the sub-district level, i.e. allowing errors to be correlated across cells located within the same administrative sub-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 sub-district level, both reduced form and 2SLS estimates typically become slightly more precise and the coefficients of interest remain statistically significant at conventional levels.

Alternative definition of outcomes. 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 5 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.

Endogeneity of language differences. 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 5 are robust to the inclusion of these additional interaction terms.

Measurement error. A potential concern with the construction of the measure of credit take-up at cell-level using the assignment rule described in section 2.3 is that it may generate measurement error that is non-classical and thus a source of bias for our estimates.

There are several results in the paper suggesting that non-classical measurement error is unlikely to be a source of bias. First, it could be that cells receiving a tower were on different growth trajectories because they have a higher share of banks specialized in agricultural lending. However, this would imply a positive association between tower construction and credit outcomes in the period *before* the tower construction, which we do not find in our pre-trends analysis. Second, our estimates could be biased if cells that were more banked were also more likely to receive SMIS towers. However, as shown in Table 2, tower construction is not correlated with the presence of bank branches or agricultural credit societies at baseline, and estimates are stable when including these controls interacted with year fixed effects.

Finally, it could still be that unobservable cell characteristics that explain differential credit take-up after 2007 are also correlated with tower placement. To be able to explain the findings, such type of measurement error would need to vary across regions speaking different languages, types of banks, loan maturities, and time in the same way as the effect of mobile phone towers on access to information about credit programs. Although we cannot rule out the role of unobservables, the heterogeneous effects described in the paper suggest this is unlikely to be the driving force of our results. Notice also that measurement issues are not present when we study the effect of tower construction on the share of households with Kisan credit cards, as this outcome is directly observed at the cell-level by aggregating village-level information from SECC. The fact that we find similar effects using this alternative measure reassures us that measurement error is unlikely to be a significant source of bias.

6 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 find 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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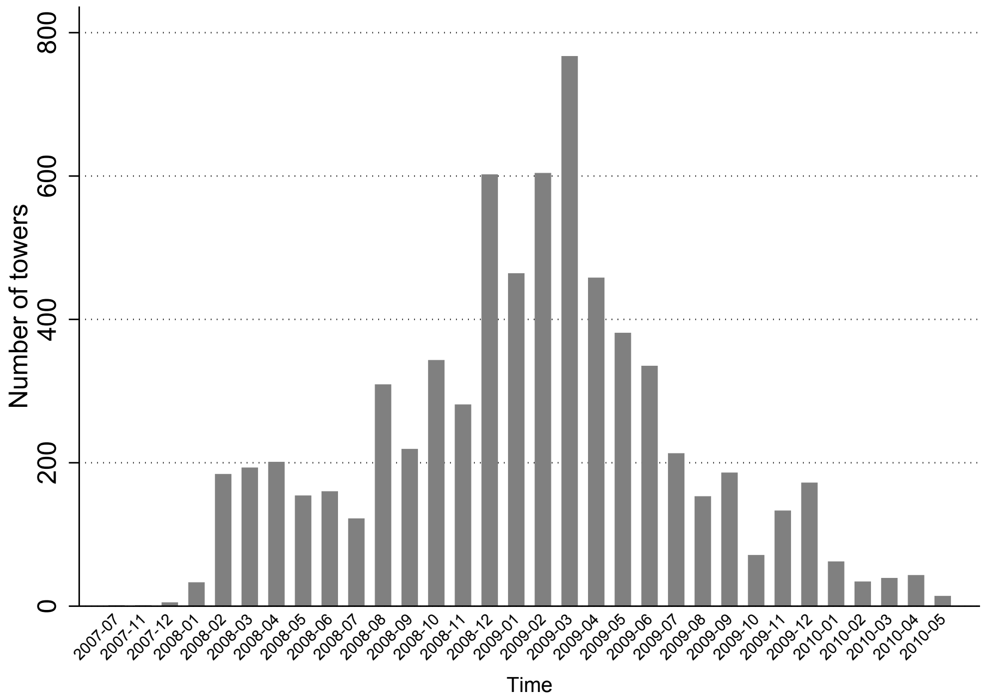
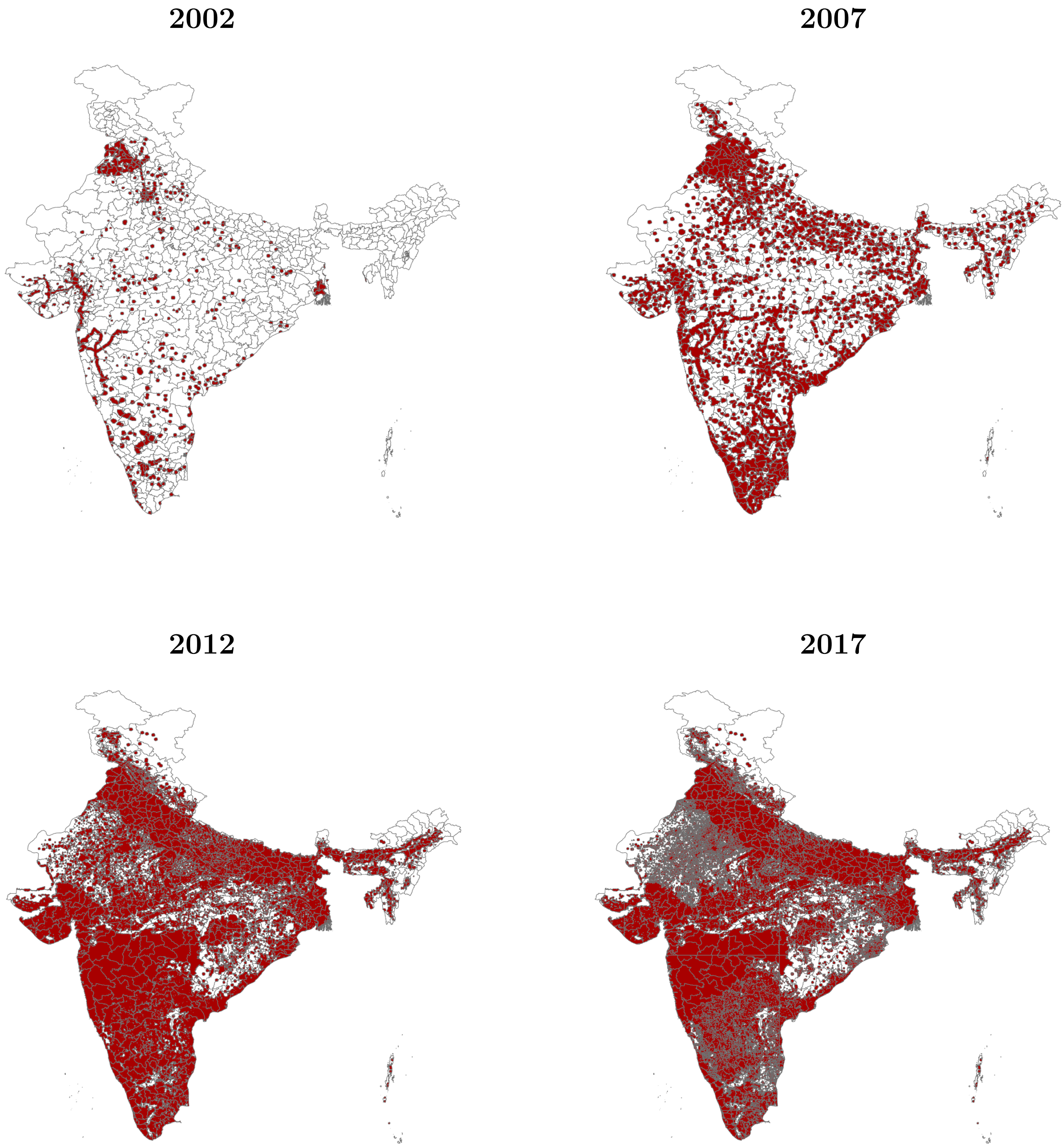
Figures

Figure 1: Timeline of tower construction under SMIS Phase I



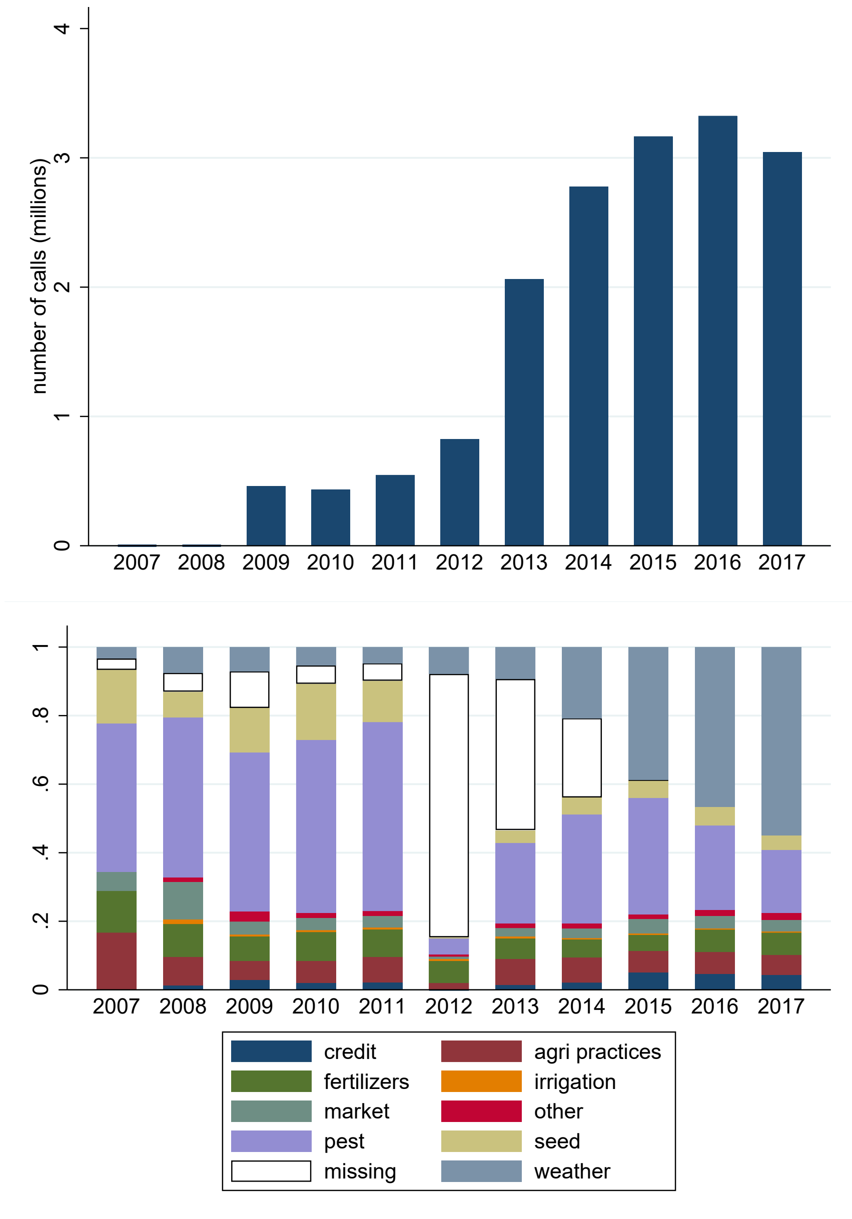
Notes: Source: Department of Telecommunications, India

Figure 2: Mobile Phone Coverage Evolution, India 2002-2017



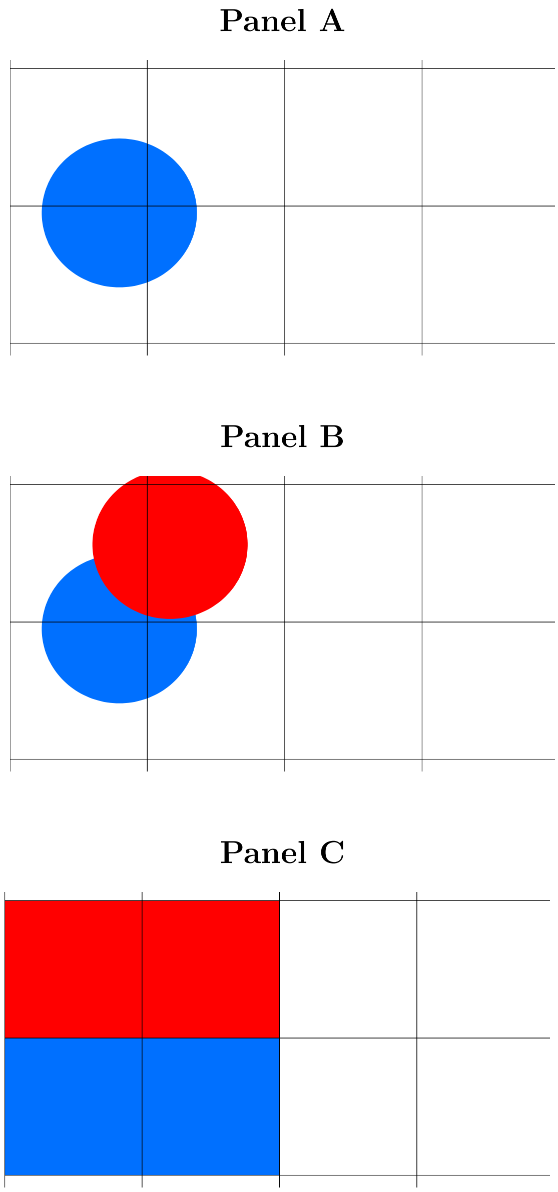
Notes: The figure reports geo-referenced data on mobile phone coverage for all of India at five-year intervals between 2002 and 2017. Source: GSMA.

Figure 3: Total Number and Composition of Calls to Kisan Call Centers: 2007-2017



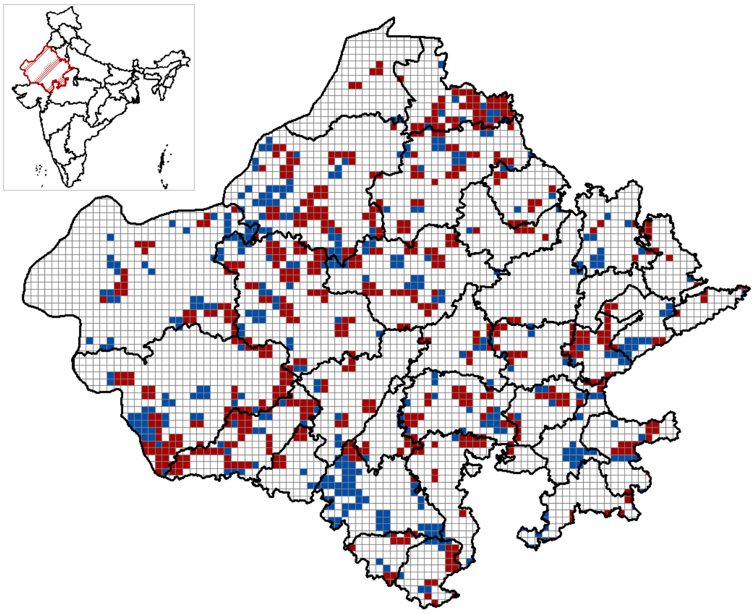
Notes: Source: Kisan Call Center, Ministry of Agriculture

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



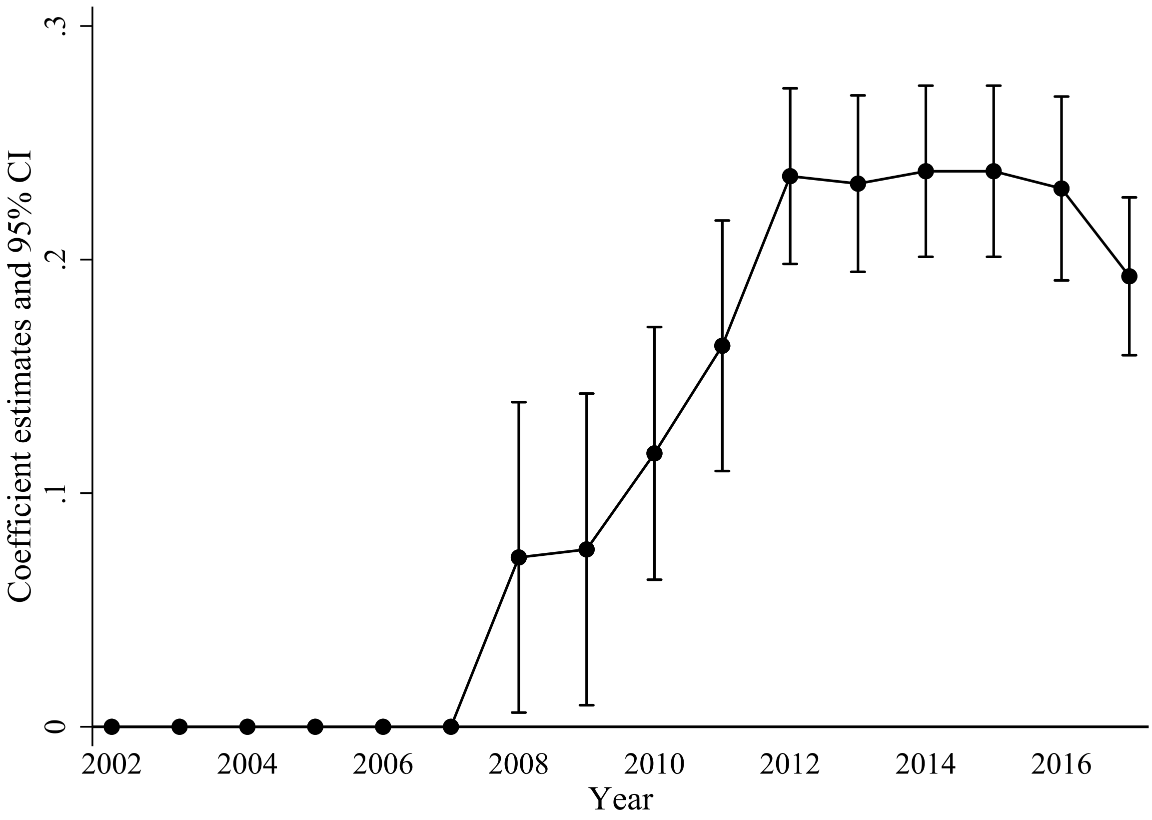
Notes: The figure provides an illustration of classification of cells into treatment(red) and control(blue) group. Panel A shows area covered by a *proposed* tower under SMIS. Panel B shows the area covered by an *actual* tower eventually constructed. Panel C shows the assignment of cells into treatment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

Figure 5: Treatment and Control Cells
Rajasthan State



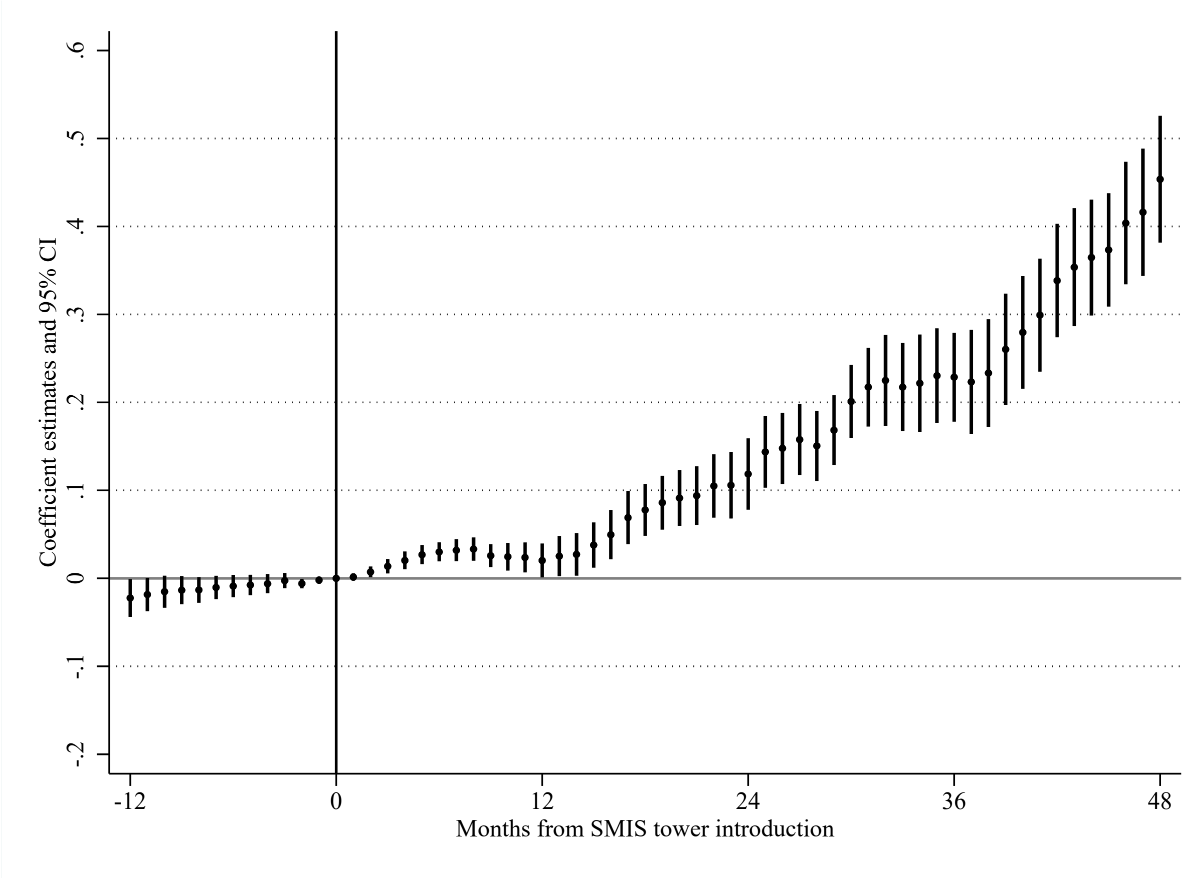
Notes: Treatment (red) and control (blue) cells for the state of Rajasthan. District boundaries are labeled in black. Treatment cells are those that are both proposed *and* covered by mobile tower under SMIS Phase I. Control cells are those that are proposed *and not* covered by mobile tower under SMIS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

Figure 6: The Effect of Tower Construction on Mobile Coverage, by year



Notes: This figure reports the estimated coefficients and 95 percent confidence intervals for the first-stage estimates of effects of SMIS tower construction program on the share of cell area under GSMA coverage across all years in the sample period.

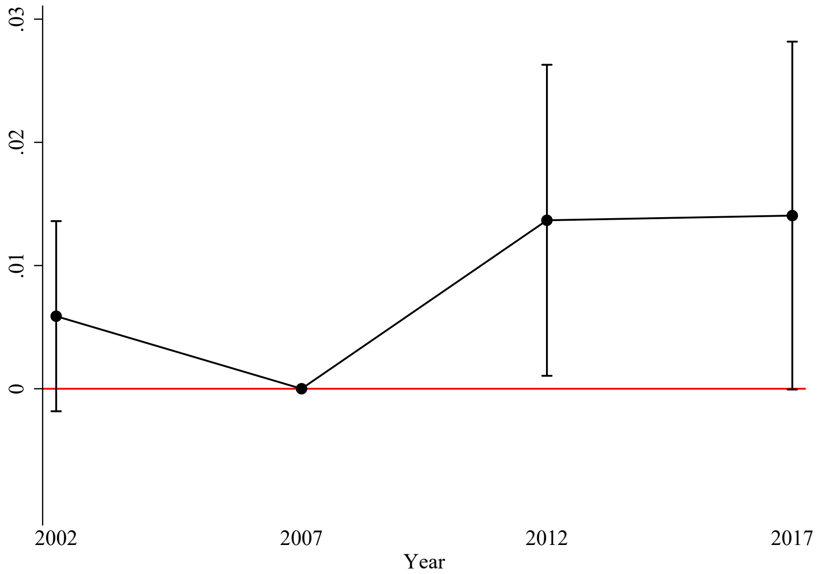
Figure 7: Calls per farmer around Tower Construction: Event Study



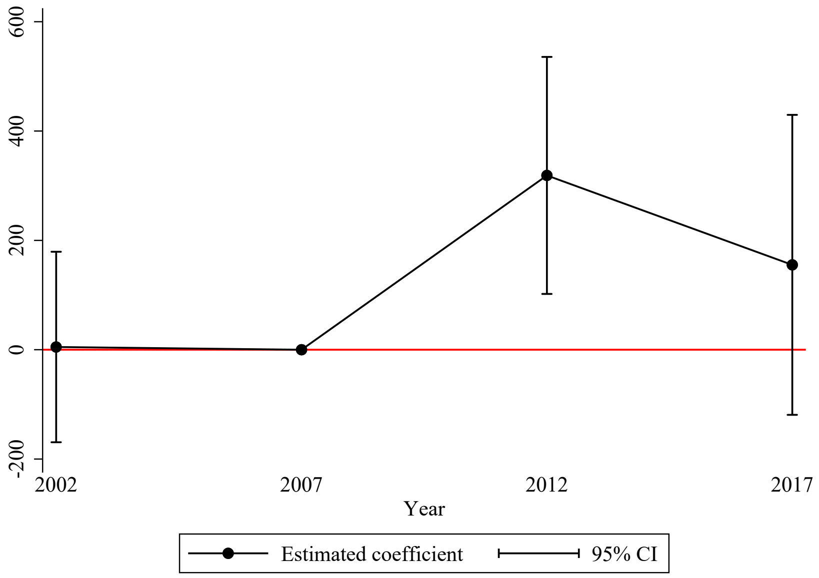
Notes: This figure reports the estimated coefficients and 95 percent confidence intervals on dummies capturing months relative to tower construction from equation (3).

Figure 8: Reduced Form Effects of Tower Construction on Credit Outcomes: Event Study

(a) Share of farmers with credit



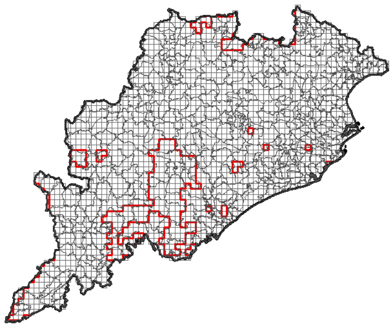
(b) Credit per farmer



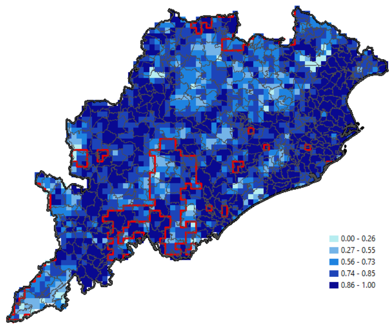
Notes: This figure presents the Reduced Form estimates of the SMIS tower construction program on the share of farmers with credit (panel a) and credit per farmer (panel b). We normalize the coefficients in 2007 to 0. We use data from the Agricultural Input Survey and the 2001 Population Census to compute 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 9: Coverage and Farmers Calls by Language in the State of Odisha

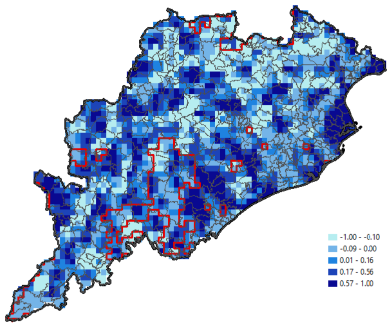
(a) Non-official language speakers



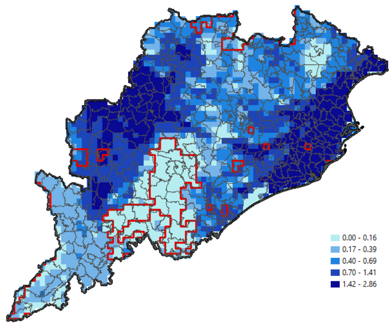
(b) Share of farmed land



(c) Change in mobile coverage

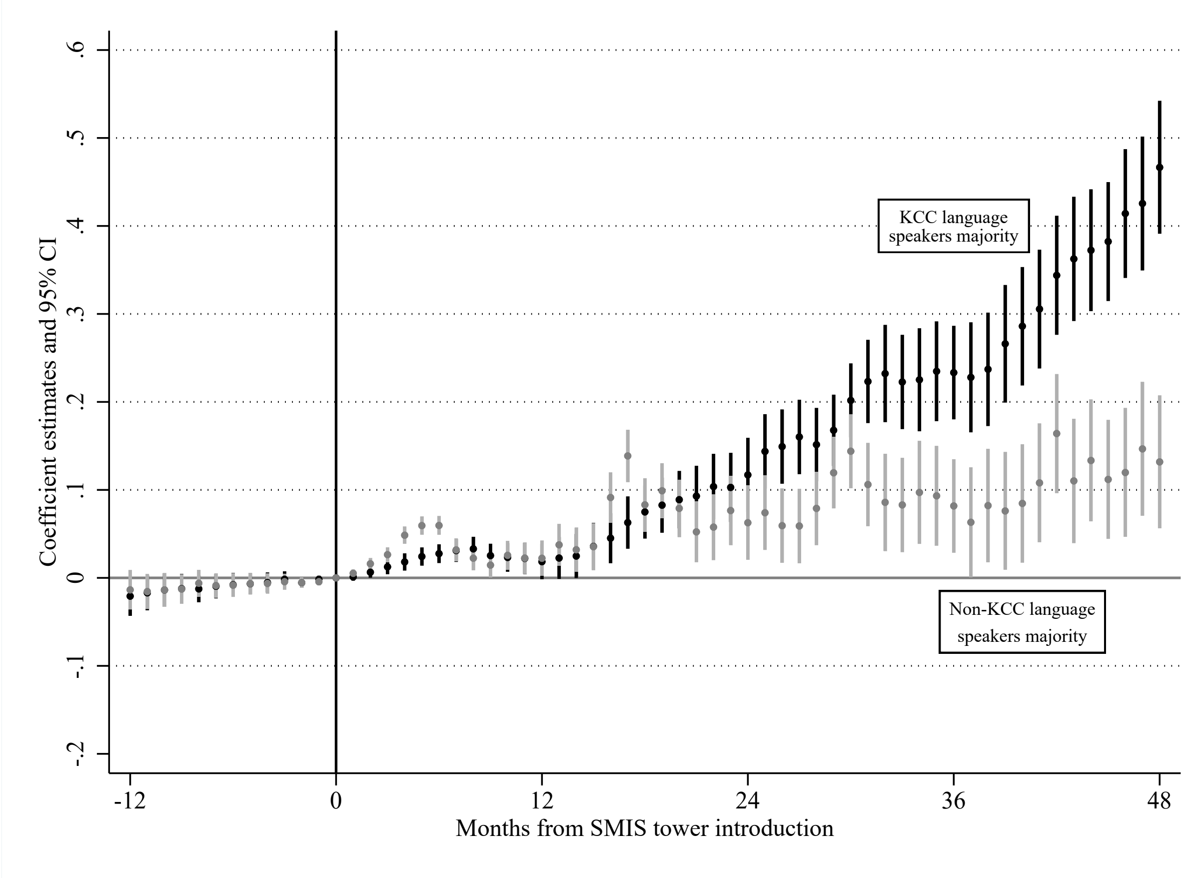


(d) Change in calls to KCC



Notes: Panel (a) shows 10 $\times$ 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 does not speak the official language of the state. 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 10: Calls per farmer around Tower Construction: Heterogeneity by Language



Notes: This figure reports the estimated coefficients and 95 percent confidence intervals on dummies capturing months relative to tower construction from equation (3), separately for cells where there is a KCC language majority or not.

Tables

Table 1: Summary Statistics

	N	Mean	Median	Standard Deviation
Coverage share	29,185	0.429	0.189	0.450
Share of non-state language speakers	28,930	0.096	0.007	0.205
Share of ag households with KCC	8,584	0.113	0.068	0.137
Share of farmers with credit				
Aggregate	29,185	0.158	0.073	0.208
By Lender Type				
CB	29,185	0.025	0.000	0.083
PACS	29,185	0.123	0.043	0.177
RRB	29,185	0.010	0.000	0.053
Credit per farmer				
Aggregate	29,185	2,946.7	1,036.3	4,104.7
By Lender Type				
CB	29,185	458.9	0.0	1,128.0
PACS	29,185	2,003.3	530.9	2,955.1
RRB	29,185	0.9	0.0	3.0
By Credit Maturity				
Short-term	29,185	2,619.3	914.6	3,640.8
Medium-term	29,185	122.5	0.0	308.5
Long-term	29,185	57.1	0.0	146.5

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 SMIS 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: Predictive power of pre-existing cell characteristics on treatment status

Dependent Variable:	1(Tower)
Agri workers/Working Pop.	0.033
	(0.082)
Distance to nearest town (kms)	-0.001**
	(0.000)
Percent Irrigated	-0.023
	(0.032)
Log (crop suitability)	-0.002
	(0.014)
Number of Telephone connections	-0.000
	(0.000)
Number of Credit Facilities	0.004
	(0.002)
Log Night Lights (2001)	0.016
	(0.014)
Night lights growth (1996-01)	-0.012
	(0.010)
Population share of ...	
...scheduled castes	0.012
	(0.094)
...individuals not speaking state's official language	-0.060
	(0.045)
Availability of ...	
...Drinking water facility	0.128
	(0.186)
...Education Facility	-0.130***
	(0.043)
...Recreation Facility	0.030
	(0.032)
...Medical Facility	0.028
	(0.029)
...Telephone Office	-0.000
	(0.011)
...Ag. Credit Society Facility	0.021
	(0.015)
...Commercial Bank Facility	0.011
	(0.016)
...Rural Banking Facility	-0.024
	(0.101)
Baseline Controls	Yes
State FE	Yes

Notes: This table tests whether initial characteristics predict the construction of a tower in a given cell conditional on the cell being included in the list of potential tower locations from the Ministry of Telecommunication. We regress the binary treatment indicator on all cell characteristics in a single regression. The regression includes state fixed effects and controls for determinants of tower relocation, namely total population, power supply and ruggedness. Standard errors are clustered at the sub-district level.

Table 3: First Stage

Dependent Variable:	Coverage	
	(1)	(2)
Tower × Post	0.229***	0.214***
	(0.0269)	(0.0255)
N	29,185	29,185
F-Stat	72.533	70.727
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 sub-district level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table 4: The effect of tower construction on calls per farmer in $\times 1000$.

Dependent Variable	# of calls per 1000 farmers					
	OLS		RF		IV	
	All Calls	Credit Calls	All Calls	Credit Calls	All Calls	Credit Calls
	(1)	(2)	(3)	(4)	(5)	(6)
Coverage	3.675***	0.403***			14.60**	1.449***
	(1.037)	(0.0896)			(6.412)	(0.522)
Tower × Post			3.308**	0.328***		
			(1.446)	(0.118)		
N	29,185	29,185	29,185	29,185	29,185	29,185
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 calls to the Kisan Call Centers per 1000 farmers. Odd columns report the effects on all calls and even columns report the effects on calls about credit programs. 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 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 sub-district level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table 5: The Effect of Tower Construction on Credit Take-up

	OLS		RF		IV	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Share of farmers with credit						
Coverage	0.019***	0.017***			0.056**	0.051**
	(0.004)	(0.004)			(0.024)	(0.026)
Tower × Post			0.013**	0.011**		
			(0.006)	(0.005)		
Panel B: Credit per farmer						
Coverage	518.5***	382.3***			1,297.1***	1,099.7**
	(74.9)	(76.0)			(487.2)	(503.4)
Tower × Post			297.6***	235.5**		
			(110.3)	(105.8)		
N	29,185	29,185	29,185	29,185	29,185	29,185
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 sub-district level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table 6: The Effect of Tower Construction on Kisan Credit Cards

Dependent Variable	Share of agricultural households with KCC	
	RF	IV
	(1)	(2)
Tower	0.011**	
	(0.005)	
Coverage		0.050**
		(0.020)
N	8,568	8,568
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 sub-district level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table 7: Heterogeneous Effects by Language

Dependent Variable	Share of farmers with credit		Credit per farmer	
	(1)	(2)	(3)	(4)
Tower × Post	0.015**	0.013**	346.0***	301.7***
	(0.006)	(0.006)	(120.2)	(115.3)
Tower × Post × 1(majority NS Speakers)	-0.027**	-0.029**	-697.1**	-805.5***
	(0.012)	(0.012)	(292.7)	(287.0)
N	28,930	28,930	28,930	28,930
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 sub-district level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

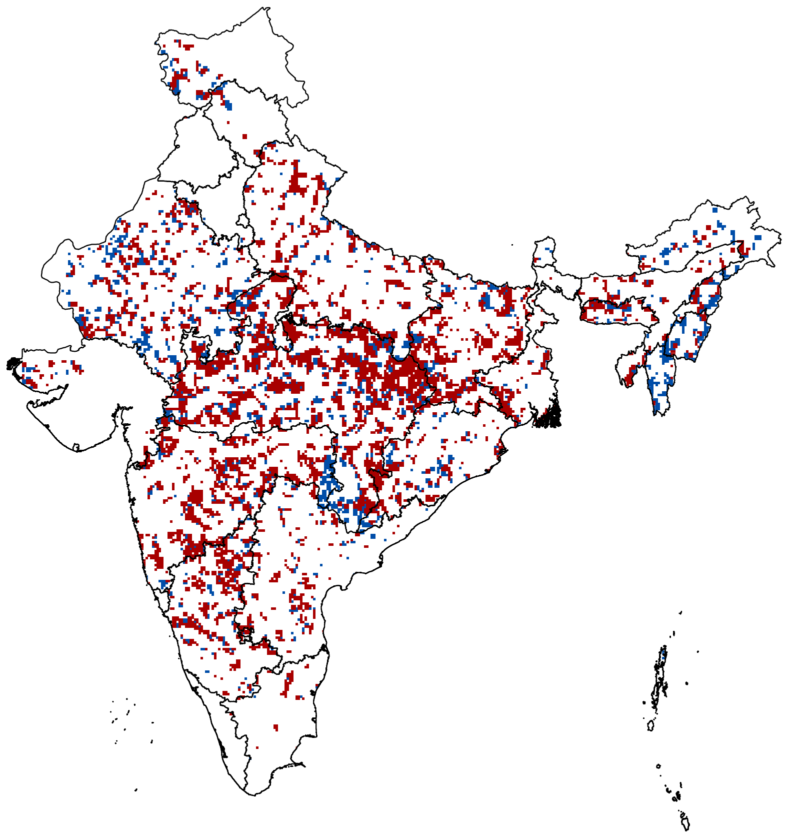
Table 8: Heterogeneity by Bank Branch Density around Kisan Call Centers' Locations

	(1)	(2)	(3)
Panel A			
	Share of farmers with credit		
Tower × Post	0.010	0.005	0.015***
	(0.006)	(0.007)	(0.005)
Tower × Post × Comm Banks	0.010		
	(0.007)		
Tower × Post × PACS		0.013**	
		(0.006)	
Tower × Post × RRB			–0.003
			(0.003)
Panel B			
	Credit per farmer		
Tower × Post	184.1	109.7	304.8***
	(125.4)	(133.7)	(108.8)
Tower × Post × Comm Banks	190.9		
	(121.5)		
Tower × Post × PACS		226.7**	
		(112.1)	
Tower × Post × RRB			–85.6
			(55.7)
N	29,283	29,283	29,283
Cell FE	Yes	Yes	Yes
Baseline Controls × Year FE	Yes	Yes	Yes
Other Controls × Year FE	Yes	Yes	Yes
State × Year FE	Yes	Yes	Yes
Banks at Baseline	Yes	Yes	Yes

Notes: This table reports heterogeneous reduced-form effects of treatment by density of financial institutions in the sub-district of Kisan Call Centers on the share of farmers with credit (Panel A) and credit per farmer (Panel B). 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. Comm Banks is the density of commercial banks (per 100,000) in the sub-district within which the kisan call center is located divided by the standard deviation of this density in our sample. We construct similar measures for Primary Agricultural Credit Societies (PACS) and Regional Rural Banks (RRB). The bank branch density is obtained by dividing the number of branches of financial institutions in the sub-district in 2006 by the population in the sub-district (obtained from the 2011 Population Census). 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. Banks at baseline controls for the number of that bank type in a cell in 2001, interacted with Treat × Post. Standard errors are clustered at the sub-district level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

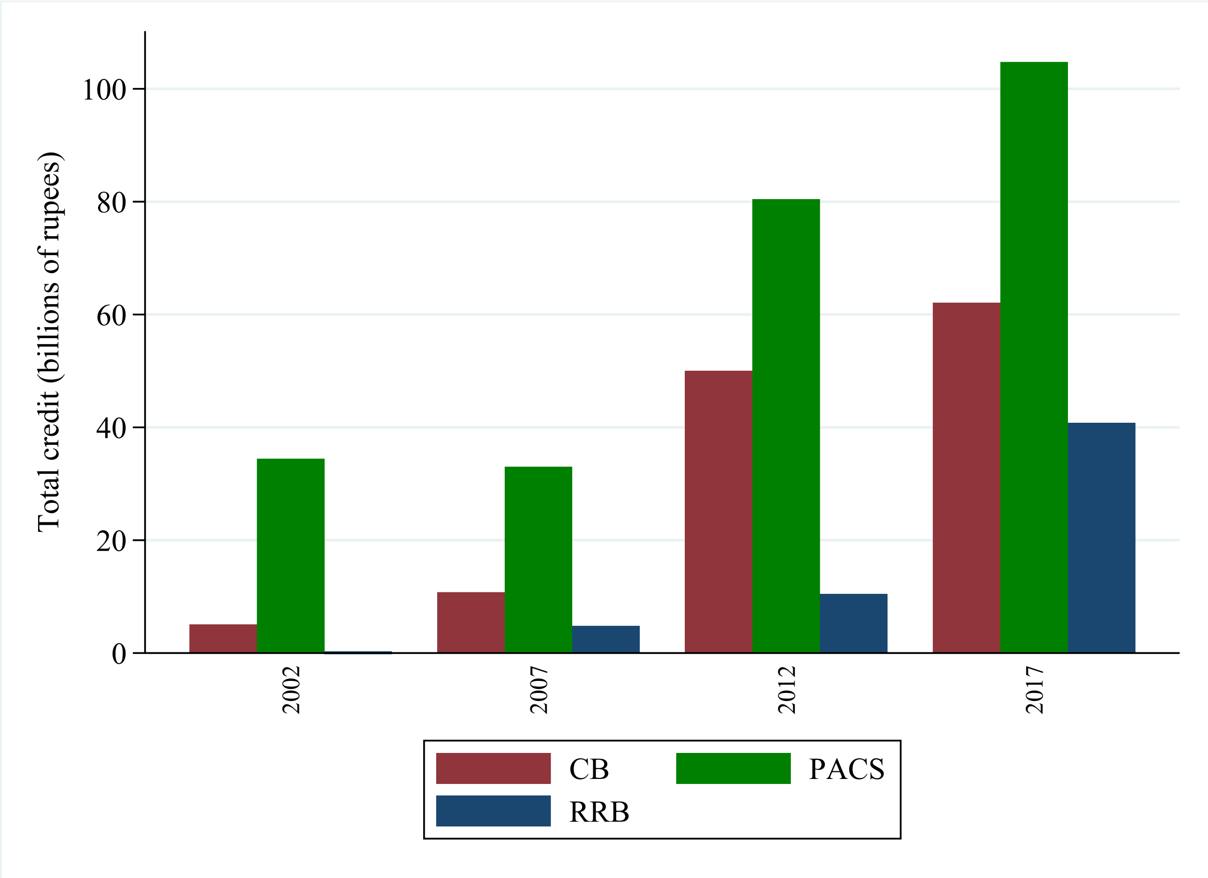
Appendix Figures

Figure A1: Treatment and Control cells under the SMIS Program



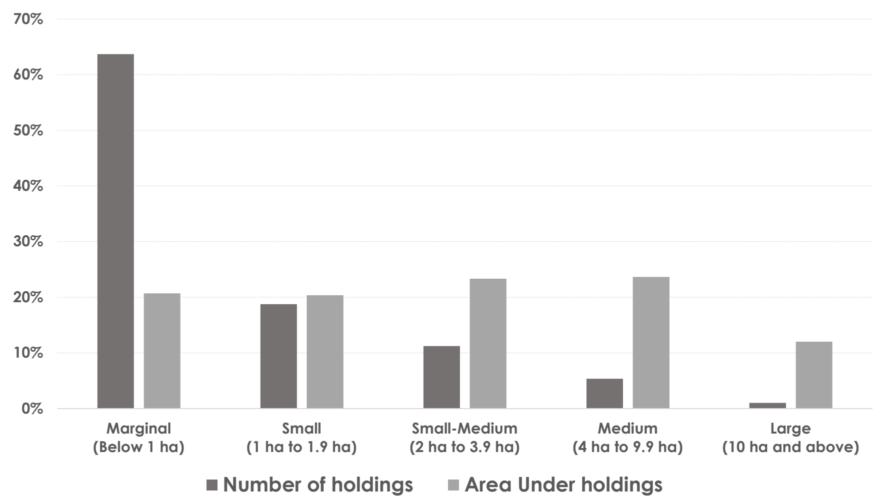
Notes: The figure shows the 8,451 cells used in the empirical analysis distributed across treatment (red) and control (blue). State borders are marked in black. Treatment cells are those that are both proposed *and* covered by mobile tower under SMIS. Control cells are those that are proposed *and not* covered by mobile towers under SMIS.

Figure A2: Aggregate Credit by Lender Type



Notes: This figure shows aggregate credit by lender type in our sample of cells, as observed in the AIS. 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	999.1**	4.5	–17.8
	(451.6)	(51.1)	(24.9)
N	29,185	29,185	29,185
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 sub-district level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table A2: Heterogeneity: By Lender

	Commercial Banks (1)	PACS (2)	RRB (3)
Panel A: Share of farmers with credit			
Coverage	–0.001	0.055**	–0.003
	(0.012)	(0.023)	(0.007)
Panel B: Credit per farmer			
Coverage	25.3	1,043.2***	0.2
	(154.3)	(391.5)	(0.5)
N	29,185	29,185	29,185
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 sub-district level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table A3: Heterogeneity: By Holding Size

	Very Small (1)	Small (2)	Semi-Medium (3)	Medium (4)	Large (5)
Panel A: Share of farmers with credit					
Coverage	0.017	0.011	0.010**	0.006**	0.002**
	(0.015)	(0.007)	(0.005)	(0.003)	(0.001)
Panel B: Credit per farmer					
Coverage	158.2	235.9*	245.7**	180.8**	38.6**
	(174.7)	(135.9)	(120.4)	(88.3)	(19.5)
N	29,185	29,185	29,185	29,185	29,185
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 sub-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	0.0509	1,099.7
Standard Errors (Baseline)	[0.0257]**	[503.4]**
Spatial Correlation, threshold: 50 km	[0.0190]***	[386.7]***
Spatial Correlation, threshold: 150 km	[0.0187]***	[393.3]***
Spatial Correlation, threshold: 300 km	[0.0187]***	[414.3]***
Spatial Correlation, threshold: 500 km	[0.0168]***	[386.1]***
Panel B: RF Results		
Tower × Post	0.0109	235.5
Standard Errors (Baseline)	[0.0055]**	[105.8]**
Spatial Correlation, threshold: 50 km	[0.0041]***	[82.8]***
Spatial Correlation, threshold: 150 km	[0.0040]***	[84.2]***
Spatial Correlation, threshold: 300 km	[0.0040]***	[88.7]***
Spatial Correlation, threshold: 500 km	[0.0036]***	[82.7]***
N	29,185	29,185
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 5. 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 (1)	RF (2)	IV (3)
Panel A: Share of farmers with credit			
Coverage	0.014***		0.054*
	(0.004)		(0.030)
Tower × Post		0.011*	
		(0.006)	
Panel B: Credit per farmer			
Coverage	320.8***		1,021.4*
	(79.2)		(593.9)
Tower × Post		203.2*	
		(116.7)	
N	29,170	29,170	29,170
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 sub-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	+Tower×Post ×Controls
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Share of farmers with credit						
Tower ×	0.013**	0.016***	0.013**	0.014**	0.014**	0.018**
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.008)
Tower × Post × 1(majority NS Speakers)	-0.029**	-0.029**	-0.028**	-0.030**	-0.031**	-0.035***
	(0.012)	(0.012)	(0.013)	(0.013)	(0.013)	(0.013)
Panel B: Credit per farmer						
Tower ×	301.713***	351.966***	260.380**	304.102***	308.692***	328.199**
	(115.299)	(119.573)	(111.540)	(110.535)	(114.953)	(158.100)
Tower × Post × 1(majority NS Speakers)	-805.476***	-825.754***	-679.558**	-776.637***	-831.475***	-811.625***
	(287.012)	(286.951)	(298.181)	(295.747)	(293.678)	(302.917)
	28,930	28,930	28,930	28,930	28,930	28,930
Baseline Controls × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Other Controls × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Cell FE	Yes	Yes	Yes	Yes	Yes	Yes
State × Year FE	Yes	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. Column 6 includes simultaneously all the interactions in Columns 2 to 5. 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 sub-district level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.