Information Frictions and Take-up of Government Credit Programs*

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Abstract

Governments in most developing countries offer subsidized credit programs to the agricultural sector, yet farmers often lack information on these programs. We study the impact of information frictions on credit take-up by exploiting the construction of mobile phone towers in previously unconnected areas of India. Areas receiving towers experience an increase in farmers' calls to call-centers for agricultural advice and higher take-up of agricultural loans. Loan uptake rises particularly for government credit programs that farmers inquire about. New loans are mostly used for consumption in times of adverse weather shocks. Higher credit participation does not lead to higher default rates.

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JEL Classification: G21, Q16, E51

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1 Introduction

Farmers in developing countries often face limited access to formal financial services due to market failures such as information asymmetries, lack of competition among lenders and weak contract enforcement (Karlan and Morduch, 2010; Karlan et al., 2016). Using these market failures as a justification for policy, many governments have intervened in rural credit markets over the past decades – primarily by subsidizing agricultural credit – in the hope that higher take-up would facilitate the adoption of modern technologies and help farmers absorb income shocks and smooth consumption (Besley, 1994). While these initiatives have expanded the supply of credit to farmers, evidence suggests that many targeted individuals remain unaware of the programs existence 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, who are also more likely to be eligible for government credit programs.

In this paper, we study how relaxing information frictions about credit programs affects credit take-up among farmers, 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. This data allows us to study the impact of tower construction on both the number of calls and the type of questions that farmers ask.

To study the impact of potential access to information on credit take-up we use the branch-level agricultural credit data from the Basic Statistical Return (BSR) maintained by the Reserve Bank of India (RBI). This data covers agricultural credit originated by all commercial banks and regional rural banks aggregated at the branch-level. The data allows us to observe overall agricultural lending as well as lending via Kisan Credit Cards, a large government program offering credit to farmers at subsidized rates. It includes information on number of borrowing accounts, outstanding balance, loan use, interest rates charged and default. We complement the BSR dataset with data on credit originated by cooperative banks (PACS) collected via the Agricultural Input Survey that accompanies the Indian Agricultural Census.

The main identification challenge is to identify a plausible control group, given the endogenous location of new mobile phone towers. To address this issue, we exploit an

[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).

institutional feature of the implementation of the SMIS program. The Department of Telecommunications in India identified an initial list of potential tower locations, all situated in rural areas without mobile phone coverage at the time the program was launched in 2007. 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 either canceled or relocated, typically to increase population coverage or due to technical challenges related to the slope of the terrain or issues connecting the tower to the power grid in the initially proposed site.

We show that treatment and control areas are balanced on initial observable characteristics 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. Consistent with our identification assumption, treated and control areas exhibit similar pre-trends in credit outcomes in the years leading up to 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 the 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 a faster increase in farmers' calls to Kisan Call Centers. Call-level data from Kisan Call Centers contains information on the question asked by the farmer and the answer provided by the agronomist. We categorize calls based on the topic of each question. We document a significant increase in both the 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 how to access government credit programs, including how to obtain Kisan Credit Cards. This is consistent with underserved demand for agriculture-related information in the areas targeted by the program.

We then study the effect of expanding mobile phone coverage on credit outcomes. Using data from BSR, which cover commercial and regional rural banks, we find that areas with a one standard deviation larger increase in mobile phone coverage had 33.5 more borrowing accounts per 1,000 farmers and a larger increase in agricultural credit of approximately 8,000 Indian Rupees (about 120 USD) per farmer. We find consistent patterns using the AIS, which captures access to credit from cooperative banks (PACS): coverage expansion driven by SMIS tower construction led to increases in both the share of farmers with PACS credit and the average PACS credit per farmer. Event studies further support our findings, showing no significant pre-trends in credit outcomes, a gradual increase following tower introduction, and persistent effects up to a decade after the SMIS program began.

We next examine whether the positive impact of mobile phone coverage on agricultural credit take-up is consistent with higher participation in government credit programs that farmers inquire about when calling call centers for agricultural advice. Indeed, 80% of the increase in credit-related calls to Kisan Call Centers are inquiries about such programs, which includes Kisan Credit Cards. We find that the mobile coverage expansion generated by the SMIS program led to 2.7 more Kisan Credit Card accounts per 1,000 farmers, and higher borrowing of 810 Rupees per farmer for a standard deviation increase in mobile coverage.[2] Importantly, we study the effect of the SMIS program on standard agricultural loans that are not extended through Kisan Credit Cards, and find non statistically significant changes. In sum, the mobile coverage expansion generated by the SMIS program led to a higher increase in take up concentrated in Kisan Credit Cards loans, consistent with a mechanism in which improved access to program-specific information plays an important role.

Kisan Credit Card loans can be used for consumption or investment purposes, and the BSR data allows us to separate between these two outcomes. Our results suggest that the impact of mobile phone coverage on Kisan Credit Card loans is exclusively driven by consumption loans, with no effects on investment loans. This is consistent with farmers using this program to smooth consumption when affected by negative shocks. Indeed, we find that the impact of mobile coverage on credit outcomes is larger in areas with higher agricultural income volatility, and that credit use increases in years with low rainfall, which tend to be associated with lower agricultural yields and therefore lower agricultural income.

We also investigate the effects on interest rates and default. Ex-ante, the impact of a credit expansion on interest rates is ambiguous. Relaxation of information frictions that help farmers access subsidized (below market) rates might lower average rates in a given area, but might also lead to entry of riskier borrowers. We find negative but statistically insignificant coefficients when estimating the effect of mobile coverage on local average interest rates. In line with the results on interest rates, we also find a negative and mostly insignificant impact of mobile coverage expansion on local default rates. In sum, the results provide no evidence that credit expansion following tower construction was associated with a deterioration in the average risk profile of borrowing farmers.

We quantify the magnitude of the credit take-up response to farmers' calls, as implied by our estimates. The IV results suggest that each call to Kisan Call Centers corresponds to an increase of 0.8 farmers gaining access to credit from commercial and regional rural banks.[3] When focusing on the elasticity of access to government credit programs relative

[2]We document similar results when using data on the diffusion of Kisan Credit Cards among rural households from the Socio-Economic and Caste Census of India (SECC), and show that take up of credit from cooperative banks is concentrated in loans with short maturity and taken by small and medium farmers, consistent with the targeting of government credit programs.

[3]We find an elasticity of 1.4 farmers with access to credit per call when using data for cooperative banks (PACS).

to calls specifically inquiring about such programs, our estimates imply that each of these calls is associated with 1.8 additional Kisan Credit Card accounts.

Although callers are actively seeking information when contacting Kisan Call Centers – and are therefore likely to act upon it – these magnitudes can only be rationalized if information spreads from callers to non-callers. We discuss several aspects of our setting that might contribute to explaining this level of diffusion. First, mobile phone coverage in treated areas likely facilitates not only the transmission of information from callers to their immediate social contacts, but also broader, indirect diffusion among farmers who are not directly connected. By lowering communication costs across the network, mobile coverage enables information to circulate more widely and even among non-callers through second- or third-degree ties. This effect is likely magnified by the central position of callers within local social networks. Survey evidence shows that callers to Kisan Call Centers are positively selected on characteristics such as 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). Prior work has shown that seeding information with such central individuals can substantially enhance diffusion within communities (Banerjee et al., 2024).

Finally, we discuss mechanisms behind the results. Our preferred interpretation of the results is that the mobile phone towers installed under the SMIS program helped alleviate information frictions, thereby facilitating the uptake of interest-subsidized loans offered through government credit programs. A potential concern with this interpretation is that the expansion of mobile phone coverage may stimulate local economic activity more broadly (e.g., Jensen, 2007; Aker and Mbiti, 2010), increasing local income and thus farmers' demand for credit to expand their operations. Under this alternative channel, increased credit take-up could occur even in the absence of any reduction in 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., 2024). 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 Kisan Call Centers increase faster in areas where the majority of the local population speaks 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. Taken together, these results are consistent with a reduction in information frictions driving the effect of mobile phone coverage on credit take-up.

Related Literature

Our paper contributes to several strands of the literature at the intersection of information and communication technologies (ICT), financial access, and development. A growing body of work has examined the economic impacts of ICT in low-income settings (Jensen, 2007; Aker and Mbiti, 2010). Recent studies have shown how Internet and mobile connectivity can improve labor market efficiency through better job matching (Hjort and Tian, 2025), facilitate firm entry by reducing coordination costs (Chiplunkar and Goldberg, 2022), and enable financial innovation through new screening technologies in banking (D'Andrea and Limodio, 2024). In contrast to most of this work, which emphasizes private-sector adoption or market-level outcomes, we focus on financial inclusion among smallholder farmers and the role of government-led programs in enabling it. Specifically, our setting highlights how the interplay between government-sponsored mobile infrastructure expansion (SMIS) and agricultural advisory services (Kisan Call Centers) can reduce information frictions that hinder access to formal credit. This context allows us to focus on the specific role of information – rather than connectivity in general – in shaping credit take-up in underserved rural areas.

This contribution connects us to a broader literature on information frictions in credit markets in developing countries. Several studies document limited awareness of formal financial products and the often modest effects of information interventions. Dupas et al. (2014) show that limited knowledge and distrust constrain loan take-up in Kenya. De Mel et al. (2011) find more positive impacts from information sessions on microfinance loans in Sri Lanka, while Cole et al. (2011) document how financial education programs are less effective than monetary incentives in promoting bank account adoption in India and Indonesia. Compared to these studies, we focus on information frictions around a government credit program offered by a trusted institution, featuring especially favorable terms for farmers.

Within the ICT and finance literature, we build on studies that examine how mobile technologies shape financial behavior. Jack and Suri (2014) show that mobile money improves risk-sharing and consumption smoothing. Karlan et al. (2016) show that SMS reminders from banks help clients achieve their savings goals, which in turn can have positive effects on their income growth (Dupas and Robinson, 2013; Karlan et al., 2014; Aggarwal et al., 2023). Our paper contributes to this literature by showing how the diffusion of mobile phones enables farmers to learn about existing government credit programs, thereby promoting credit take-up. In this sense, our results also relate to work by Custódio et al. (2024) and Humphries et al. (2020) on subsidized credit take-up in high-income settings, which highlights the importance of timely information and perceived eligibility in driving program participation.[4]

[4] In related work, Bettinger et al. (2012) studies the effect of providing information on college financial aid programs on take-up rates of such programs in the US, and documents that providing information

Our analysis also relates to the extensive literature evaluating the impact of mobile phone-based agricultural extension programs on agricultural outcomes through randomized controlled trials (see Aker, Ghosh, and Burrell (2016) and Fabregas, Kremer, and Schilbach (2019) for recent reviews). For example, Casaburi et al. (2019) and Cole and Fernando (2021) 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 affects the 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 Kisan Call Centers in particular. Our first study in this agenda, Gupta et al. (2024), documents the importance of language barriers between farmers and the call center 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. (2024), 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. (2023) documents that Indian villages gaining access to the road network via a large infrastructure program experience an increase in loan take-up.[5]

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, including a discussion of magnitudes and potential mechanisms. Then, in Section 4, we discuss robustness tests on the main results. Section 5 offers concluding remarks.

without assistance in the application process does not significantly improve the probability of applying for government financial aid. DellaVigna and Linos (2022) compares the effects of "nudges" between RCTs run by US government agencies and RCTs published in academic journals, documenting positive and significant effects on take-up of government programs for both, with the larger magnitudes documented in academic papers ascribed to publication bias.

[5]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, Agarwal et al. 2024).

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 clusters 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 on which the construction of the tower is completed and the tower becomes operational. For simplicity, in the remainder of the paper we refer to this date as the date of construction. From the 7,353 towers constructed under Phase I of the SMIS program we remove 350 towers for which the construction date is missing. This leaves us with 7,003 mobile towers used in our empirical analysis. Figure 1 shows a timeline of construction of these towers by month. As shown, the construction of towers effectively started in January of 2008 and ended in May of 2010, with most towers being introduced between the second half of 2008 and the first half of 2009.

To measure the diffusion of mobile phone coverage in India we use data provided by the Global System for Mobile Communication Association (GSMA), the association representing the interests of the mobile phone industry worldwide. The data is collected by GSMA directly from mobile operators and refers to the GSM network, which is the dominant standard in India with 89 percent of the market 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.[6]

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.[7] 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 Farmers' Calls to Kisan Call Centers

Data on farmers' calls is from the Kisan Call Centers initiative. Kisan Call Centers 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, which answer calls from all Indian states.

Data on calls to Kisan Call Centers is from the Department of Agriculture, and is publicly available on the Open Government Data (OGD) Platform of India starting from 2006.[8]

Panel (a) of Figure 3 reports the total number of calls received by Kisan Call Centers per year between 2006 and 2017. As shown, Kisan Call Centers received less than 1,000 calls per year in the first period after its introduction; calls increased to around 1 million per year by 2012, and up to around 4.5 million per year by the end of the sample period in 2017. Overall, the dataset has 21,710,852 total calls for the years 2006 to 2017.

The data does not report the exact transcript of the conversation between the farmer and the agricultural advisor, but only a brief description of the topic of the call as reported by the Kisan Call Center advisor. We use the text of this description to categorize calls into nine groups. Panel (b) of Figure 3 and Table A1 report the decomposition of calls

[6] 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).

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

[8] The data can be accessed at `https://www.data.gov.in/datasets_webservices/datasets/6622307`. This version of the paper uses the January 2024 extraction.

by category. The two main categories are represented by calls in which farmers ask for information on weather forecasts (35%) or advice on how to deal with pests affecting their crops (32%).

We identify 751,744 calls in which farmers ask for information about agricultural credit, which represent 3.5% of total calls. As shown in Table A1, in the majority (73%) of credit-related calls, farmers ask for information about government credit programs. In particular, they ask about eligibility criteria, what are the loan terms offered and how to access them. In most cases, the description of the call does not report the name of the specific program the farmer is asking for information about, as call center advisors often describe it as "government program". We believe that most such calls are related to the Kisan Credit Card program, partly because it is the main government credit program for farmers, and partly because, when a specific government program is named, it is most often the Kisan Credit Card. We describe the Kisan Credit Card program in more detail in section 2.3.

2.3 Agricultural Credit Data

Data on credit to agriculture is from two main sources: the Basic Statistical Returns (BSR) dataset maintained by the Reserve Bank of India and the Agricultural Input Survey (AIS). The main providers of credit to farmers in India are commercial banks, regional rural banks and cooperative banks (Primary Agricultural Credit Societies, or PACS). Figure A1 shows the outstanding amount of agricultural loans originated by these different types of lenders during the period studied in the paper. The BSR data covers agricultural loans originated by commercial banks and regional rural banks, while we use data from the AIS to study agricultural credit originated by PACS. We describe these datasets in more detail below.

2.3.1 BSR dataset

We use data on agricultural credit from the Basic Statistical Returns (BSR) dataset maintained by the Reserve Bank of India. The data covers all branches of commercial banks and regional rural banks in India, which report to the RBI. We focus exclusively on lending to individuals who operate in the agricultural sector (i.e. we exclude lending to firms and other institutions). Our working dataset contains branch-level information on outstanding end-of-year loan balances, interest rates (average across loans originated by a branch, weighted by balance), and share of non-performing loans. The data covers 127,395 unique branches for the period between 2002 and 2014.

The focus of our paper is on farmers' information about government credit programs. One of the most important of such programs is Kisan Credit Cards. These cards were introduced in 1998 by the Reserve Bank of India to offer agricultural loans at subsidized interest rates. The objective of the program is to facilitate access to credit for small and marginal farmers, thus reducing dependence on informal moneylenders and with the hope of improving agricultural productivity. Kisan Credit Cards are issued by most financial institutions, including commercial banks, cooperative banks (PACS) and regional rural banks. The screening process includes checks for farmer's identity, landholding records and history of cultivation. In the past two decades, Kisan Credit Cards have become an important source of credit for farmers. According to a report by the National Bank for Agriculture and Rural Development, they have grown to constitute up to 40 percent of total agricultural credit in India (Bista et al., 2012). We observe a similar percentage for commercial and regional rural banks covered in the BSR data used in this paper.

One advantage of the BSR data is that it separately identifies lending to farmers via Kisan Credit Cards. This information is only available from 2008, and so there is limited scope to study pre-trends before the introduction of SMIS. Still, this data allows us to study the impact of tower construction on the diffusion of Kisan Credit Cards accounts, as well as to compare loans originated under the Kisan Credit Card scheme vs normal loans to farmers.

Figure 4 reports the average size distribution of Kisan Credit Card (KCC) loans and non-KCC loans. The two distributions exhibit substantial overlap in terms of loan size. One notable feature of KCC loans is their concentration around 300,000 Rupees - the maximum loan size eligible for subsidized interest rates under the scheme.[9]

In contrast, differences in interest rates between the two types of loans are more pronounced. On average, credit extended through the KCC program carries lower rates: 9.6% compared to 12.4% for other agricultural loans, as shown in Table 1. Figure 4 further highlights this gap: interest rates on KCC borrowing are heavily concentrated at the 7% subsidized rate, while rates on non-KCC loans follow a more continuous distribution, ranging from 7% to 17%.[10]

2.3.2 Agricultural Input Survey dataset

Data on agricultural credit originated by PACS is sourced from the Agricultural Input Survey (AIS). The AIS 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.[11]

[9] Recall that the BSR data is at the bank branch level. Thus, each observation in Figure 4 represents the average loan size and the average interest rate (weighted by loan size) of agricultural loans originated by a given bank branch in a given year.

[10] Note that, despite subsidized loans under the KCC program should all receive an interest rate of 7%, we do see in the data KCC loans with rates above 7%. Loans under KCC with rates above 7% tend to be larger, and often above the 300,000 Rupees limit, which might explain the fact that they are priced differently.

[11] The Agricultural Input Survey runs from 1^{st} July to June 30^{th} of the following year. In the paper, we refer to each survey by the calendar year in which it ends.

The survey uses a two-stage stratified design. In the first stage, the sub-districts (or tehsils) of India serve as the strata, and within each sub-district, 7% of villages is selected at random. In the second stage, within each selected village, the entire list of operational holdings is first grouped into five size categories (Marginal: below 1 ha; Small: 1-1.99 ha; Semi-medium: 2-3.99 ha; Medium: 4-9.99 ha; and Large: 10 ha and above). Then, a simple random sample of four holdings is drawn from each size group (or all holdings are included if there are four or fewer). Selected farmers 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 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).

2.3.3 Socioeconomic and Caste Census dataset

Finally, we obtain data on household ownership of Kisan credit cards from the Socioeconomic and Caste Census (SECC). The SECC aims at collecting information on socio-economic status, caste and indicators of poverty for all households across India. One of the primary objectives is to collect reliable data that can be used to help target government programs more effectively, especially those aiming at poverty reduction. The data collection effort started in 2011 and concluded in 2012.

The SECC collects information on whether a member of the household has a Kisan Credit Card with a credit limit of more than Rs. 50,000. Given the maximum credit limit on Kisan Credit Cards is Rs. 300,000, we think that this variable captures the majority of households in which at least one member has a Kisan Credit Card.

2.4 Matching Datasets at Cell-level

We use a grid of 10×10 km cells to match information from the datasets presented above, which come at different levels of geographical aggregation. In what follows we explain how we map each dataset into cells.

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.

Calls to Kisan Call Centers are geo-located at the sub-district level and we assign them proportionally to all cells whose centroid is contained in the sub-district. On average, there are 27 cells per subdistrict.

Credit data on commercial banks and rural regional banks from the Basic Statistical Return is at the bank branch level. A separate dataset maintained by the RBI reports the geographical coordinates and the address of each bank branch. We perform a validation exercise on the geographical coordinates reported in this data. Due to numerous inconsistencies with their reported physical address, we re-compute the geographical coordinates of all bank branches using the Google Maps API. The procedure is described in detail in Appendix B.1. A second challenge is that borrowers might not be located in the same cell where the branch is located. Indeed, data from the Indian Human Development Survey (IHDS) shows that individuals often travel as far as 40km to reach the closest bank branch, with an average distance of 5km. We allocate agricultural credit originated by a bank branch to the surrounding cells assuming a catchment area with a radius of 50 km around each branch. Within the 50 km radius, allocation of agricultural credit is determined by cell size in terms of number of farmers and distance to the bank branch, with a decay function whose parameters are obtained by matching IHDS responses about distance to the nearest branch. Appendix Section B.2 describes this allocation rule in detail.

Finally, 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). Data on Commercial Banks and Regional Rural Banks is observed in the BSR dataset at branch-level and therefore we rely on BSR data for those lenders. For PACS, we map district-lender information to the cell level by allocating agricultural credit originated by PACS in a given district across the cells of that district proportionally to the share of PACS branches in each cell within that district. As shown in Figure A2, PACS branches are more capillary distributed than commercial and regional rural banks.

Data on the location of PACS branches is sourced from the Village Census.[12] This neutral assignment rule implies that $Credit_{it}^{PACS} = Credit_{dt}^{PACS} \times \frac{Branches_{idt}^{PACS}}{Branches_{dt}^{PACS}}$, where $Credit_{it}^{PACS}$ is the agricultural credit from PACS in cell i located in district d and year t.

Summary statistics for all outcome variables at the cell-level are reported in Table 1.

[12]Location of Land Development Bank (PLDB) branches is not available. 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).

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 where towers were initially proposed but eventually not constructed.[13]

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 A3 reports the geographical distribution across India as a whole. Our final regression sample consists of 8,426 unique cells, of which 6,280 (75 percent) in the treatment group and 2,146 (25 percent) in the control group.

Our identification strategy relies on the assumption that locations where a tower was proposed but ultimately not constructed serve as a valid control group for those that did receive a tower. A key concern in this setting is that, while all proposed locations met uniform eligibility criteria, relocation or cancellation decisions were not random. Conversations with C-DoT officials responsible for the implementation of the program indicate that such decisions were typically based on logistical considerations – such as terrain ruggedness, lack of access to the electricity grid, or the opportunity to reach a larger population from an alternative site. These factors are observable in our data. Table 2 shows that treatment status is positively associated with population and power supply, and negatively associated with terrain ruggedness – patterns consistent with the implementation details shared by program officials.

Thus, our main identification assumption is that conditional on terrain ruggedness, availability of connection to the power grid and potential population covered, control cells are a good counterfactual for treated cells. In Table 3 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. Column 1 reports the mean of each cell-level initial characteristic, column 2 reports the results of a regression of the binary treatment indicator on each cell-level

[13]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).

initial characteristic separately, and column 3 reports the results of regressing the binary treatment indicator on all cell-level initial characteristics in a single regression. All regressions include state fixed effects and controls for the main determinants of tower relocation, namely terrain ruggedness, connection to the power grid and population.

As shown, treatment and control cells are uncorrelated with initial observable characteristics including measures of specialization in agriculture (agricultural employment share, percent of irrigated land, crop suitability and composition), access to agricultural markets, rainfall volatility, level and pre-trends in local income as proxied by nightlights, and distance to the nearest town.[14] We also test for differences in the presence of communication infrastructure and banking institutions, as captured by landline connections, post offices and the initial presence of branches of different types of lenders (PACS, commercial banks, regional rural banks). Treatment and control cells are also balanced in terms of diffusion of ethnic and linguistic minorities, as captured by the share of population that belongs to scheduled castes and a dummy capturing whether the majority of local population speaks as a first language one that is not the official language of the state where they live. Finally, we test for differences in vote share for the two main political parties – Bharatiya Janata Party (BJP) and India National Congress (INC) – in the 2004 national parliamentary elections, the last before the introduction of SMIS, and find no significant differences.

The multivariate regression results reported in column (3) of Table 3 show that only the presence of an education facility is statistically different between treatment and control cells, and therefore we control for it in all specifications. As additional support for our identification strategy, we document with event-study graphs that there are no pre-existing trends in the main outcome variables in the period before the introduction of SMIS towers.

A potential concern with our identification strategy is that treated cells in our sample might be treated by multiple government programs at the same time. This would happen if, for example, areas selected for the SMIS tower construction program were also selected by other government initiatives targeting rural areas, such as the road construction program PMGSY introduced in 2000 (Asher and Novosad, 2020; Agarwal et al., 2023), the rural electrification program RGGVY introduced in 2005 (Burlig and Preonas, 2024), the RBI program providing incentives to Indian banks to open new branches in underbanked districts introduced in 2005 (Cramer, 2021; Young, 2018) and the debt waiver program for farmers introducing with the global financial crisis (Giné and Kanz, 2018). Because such programs targeted areas with certain observable characteristics, we can explicitly test for these potential dynamic confounders. In particular, the rural road construction program targeted villages with population exceeding 500 and 1,000 inhabitants, the rural electrification program targeted 300-person villages in its first round and 100-person villages in its second round, and the RBI policy targeted districts below the national average of

[14]We construct access to agricultural markets for each cell following Chatterjee (2023).

population-to-bank-branch ration. Table 3 shows that treated cells are not significantly different than control cells in terms of share of villages above the aforementioned thresholds, in terms of their probability to be located in a banked district, or in terms of the measure of exposure to the debt waiver program proposed by Giné and Kanz (2018).

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. Notice that this effect is not purely 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:

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

The outcome variable *Coverage* is the share of land covered by the mobile phone network in cell i, state s and year t. $\mathbb{1}$ (Tower) 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 credit outcomes in the Agricultural Input Survey, which is run at 5-year intervals and available for 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 that emerge as unbalanced between treatment and control cells in Table 3. 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 4 reports the first-stage results. The estimated coefficient in column (1) indicates that cells covered by new SMIS towers have a 8 percentage points larger increase in the share of land covered by mobile phone signal after the introduction of SMIS, relative to the control group. The magnitude of the point estimate is stable when adding cell controls interacted with year fixed effects. 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 54.5 in column (2).

Finally, because mobile coverage is reported by operators at yearly level, we can 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 10 percentage points by the end of the sample period.

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 normalized by number of farmers. We present three specifications: an OLS regression showing the correlation between mobile phone coverage and calls per farmer, a reduced form regression, and a 2SLS specification of the form:

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

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 three versions of the outcome variable: (i) the total number of calls to Kisan Call Centers, (ii) the number of calls involving credit-related inquiries, and (iii) the subset of credit-related calls in which farmers ask about government-sponsored credit programs. All variables are expressed in calls per 1,000 farmers. We estimate this specification focusing on the years 2002, 2007, 2012 and 2017 to match the waves of the Agricultural Input Survey.

The results are reported in Table 5. Panel A shows that higher mobile phone coverage is positively and significantly correlated with calls per farmer. The reduced form estimates in Panel B show that cells where SMIS towers were constructed experience a larger increase in calls per farmer relative to counterfactual cells where towers were proposed but not constructed.

Our main quantification exercise focuses on the IV coefficients reported in Panel C. The estimate in column (1) indicates that a one standard deviation increase in mobile network coverage (0.46) is associated with 41 additional calls to Kisan Call Centers per 1,000 farmers following the introduction of the SMIS program. Column (2) shows that the same increase in coverage corresponds to 2.1 more credit-related calls per 1,000 farmers, while column (3) indicates an increase of 1.7 calls related to government credit programs per 1,000 farmers over the same period.

Figure 7 reports an event study of the reduced form effect of SMIS tower construction on calls per 1,000 farmer around the introduction of SMIS towers in each cell. As shown, we find relatively small and not statistically significant effects in the years preceding the SMIS program, and positive and significant effects in the post-SMIS period.

3.4 Agricultural Credit

3.4.1 Main effects on credit take-up and credit per farmer

Table 6 reports the results on the effect of mobile phone coverage on credit outcomes. As described in Section 2.3, we observe agricultural credit from commercial banks and regional rural banks in the data from the BSR, and agricultural credit originated by PACS in the data from the Agricultural Input Survey. Each data source allows us to construct two main outcomes: share of farmers with credit and monetary value of credit (in Rupees) per farmer.

As in the previous section, for each outcome, we present three specifications: an OLS regression, a reduced form regression of the effect of SMIS tower construction on credit outcomes, and an IV specification in which we instrument mobile coverage with SMIS tower construction.

We start by focusing on outcomes sourced from the BSR data. The data reports the number of borrowing accounts and the amount of outstanding balance in those accounts for agricultural loans in each bank branch and year. In column (1) we focus on number of borrowing accounts normalized by number of farmers in a given cell. The IV coefficient reported in panel C implies that cells with a one standard deviation larger increase in coverage had 0.033 more borrowing accounts per farmer (or 33.5 more accounts per 1,000 farmers) after the introduction of SMIS towers. In column (2) we focus on agricultural credit (in Indian Rupees, INR) per farmer. As shown, the IV coefficient implies that cells with a one standard deviation larger increase in coverage experience a larger increase in agricultural credit of about 8,000 INR per farmer after the introduction of SMIS towers.[15]

Next, in columns (3) and (4), we focus on agricultural credit originated by Primary Agricultural Credit Societies (PACS), sourced from the Agricultural Input Survey. Instead of the number of borrowing accounts, the AIS reports the number of farmers with credit and total amount of agricultural credit originated by PACS in each district and year. We describe the allocation rule used to map this information at the cell-level in Section 2.4. As shown, we find that coverage diffusion driven by SMIS tower construction leads to

[15] This corresponds to around 120 USD per farmer in additional agricultural credit at an exchange rate of INR to USD of 0.015.

an increase in the share of farmers with access to credit from PACS, as well as PACS credit per farmer. In particular, the IV coefficient in Panel C implies that cells with a one standard deviation larger increase in coverage experienced a 5.7 percentage points larger increase in the share of farmers with credit after the introduction of SMIS. Next, in column (3) of Table 6 we focus on credit per farmer, finding results consistent with the positive effects on credit take-up. In particular, column (3) shows that cells with a standard deviation larger increase in mobile coverage experienced a 1,300 Rupees larger increase in credit per farmer.

Taken together, the estimates in columns (1) and (3) indicate an increase of about 90 more farmers with access to credit per 1,000 farmers – and about 9,500 additional Rupees of agricultural credit per farmer – for a standard deviation larger increase in coverage (about half the area of a 10×10 km cell).[16] The combined increase amounts to about 58% of the total credit per farmer received from PACS, commercial banks and regional rural banks reported in Table 1, underscoring the economic relevance of the effect.

Because BSR credit outcomes are observed yearly, we can perform an event-study analysis in which we interact the treatment dummy with year fixed effects and plot the estimated βs from the regression below:

$$y_{ist} = \alpha_i + \alpha_{st} + \sum_{\substack{k=-5 \\ k \neq -1}}^{5} \beta_k \mathbb{1}\left(\text{Tower}\right)_{is} \times year_t + \delta_t X_{is} + \varepsilon_{ist}. \tag{3}$$

where the outcomes are accounts per farmer and credit per farmer from the BSR dataset, and k indexes years relative to tower construction. Figure 8 reports the coefficient estimates and 95 percent confidence intervals. As shown, we find no evidence of differential pre-existing trends in credit outcomes between treated and control cells before the construction of the first SMIS tower. By year 5 after SMIS tower construction, the reduced form estimates increase up to about 0.08 more borrowing accounts and 2000 more Rupees of credit per farmer. Figure 9 reports similar event study for credit from PACS, for which data is observed in 4 waves. Also in this case we see no differential effect of treatment on credit outcomes before SMIS tower construction, and positive and persistent effects in the 2 waves of the post period.

Overall, the results reported in Table 6, Figure 8 and Figure 9 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 facilitates take-up of agricultural credit. Still, several important open questions remain. First, are the positive effects 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

[16] This is under the assumption that each borrowing account measures in the BSR data corresponds to an individual farmer.

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.

Before proceeding, however, we discuss the differences in magnitude between OLS and IV estimates and the potential sources of bias in the OLS that can drive it. As shown, the 2SLS estimates are two to three times larger in magnitude than the OLS estimates. 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 grid cells of 10 X 10 km. Another possible 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 informational gap is larger in these areas, 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.

3.4.2 Take-up of government credit programs

As shown in Section 3.3, the vast majority (80%) of the increase in credit-related calls to Kisan Call Centers is represented by calls in which farmers ask for information about government-sponsored credit programs. In Section 2.3 we discuss how Kisan Credit Cards are one of the main government programs to facilitate access to credit to farmers. These cards offer short-term loans for small and marginal farmers at subsidized interest rates.

The BSR data allows us to separately identify commercial banks' lending to farmers via Kisan Credit Cards starting from 2008. Although we do not observe Kisan Credit Card diffusion before the introduction of SMIS towers, we can estimate a cross-sectional regression which relates Kisan Credit Card outcomes at cell level in the post-SMIS period (years 2011-12) to mobile coverage instrumented via tower construction.

The results of this test are reported in columns (1) to (4) of Table 7. The OLS estimates show a positive correlation between mobile coverage expansion and standard loans. However, when we exploit plausibly exogenous variation in coverage driven by the SMIS tower construction program we find positive and significant effects for Kisan Credit Cards and non statistically significant changes in standard agricultural loans. The magnitude of the IV coefficients in columns (1) and (3) imply that cells with a standard deviation larger increase in mobile coverage have 2.7 more Kisan Credit Card accounts per 1,000 farmers, and 810 Rupees per farmer higher borrowing via Kisan Credit Cards in the years 2011-12. Note that in this table we focus on Kisan Credit Card diffusion in the years 2011-12 to match the timing of the Census studied in column (5) and described below. We obtain qualitatively similar and quantitatively larger estimates if using average diffusion across all the post SMIS years. Overall, we find that the mobile coverage expansion generated by the SMIS program led to a higher increase in take-up that was concentrated in Kisan Credit Cards loans, consistent with a mechanism in which improved access to program-specific information plays an important role.

We investigate further the take-up of Kisan Credit Cards among farmers using 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 limit of 50,000 Rupees or more.[17] We match SECC data with cells in our sample using the SHRUG2.0 dataset created by the Data Development Lab.

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 a limit above 50,000 Rupees. The results are reported in column (5) of Table 7. The IV coefficient indicates that cells with a standard deviation larger increase in mobile coverage experience a 3.4 percentage points larger increase in the share of agricultural households where at least one member has a Kisan Credit Card. The magnitude of the IV coefficient in column (5) is substantially larger than the one in column (1). This is at least in part due to the fact that the SECC covers Kisan Credit Card borrowing from all lenders, while the BSR data covers commercial banks and regional rural banks. In addition, there are differences in the construction of the two outcomes: while the SECC reports the share of households with at least one card, the BSR data captures the ratio of number of Kisan Credit Cards accounts over number of farmers.

Of course, the identification assumptions behind the results presented in Table 7 are stronger than the ones behind the panel analysis. 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 suggestive evidence that the expansion of agri-

[17] 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).

cultural credit in treated areas of our sample was at least in part driven by take-up of government-sponsored credit programs, about which farmers ask the majority of credit related questions to Kisan Call Centers.

Because data on Kisan Credit Card is observable yearly from 2008 to 2014, and SMIS tower construction occurred between 2008 and 2010 in different cells, we can estimate an event study that includes either one or two pre-periods for cells that received their towers in 2009 and 2010. The results are reported in Figure 10. We find no pre-trends in Kisan Credit Card adoption and a gradual increase in the post period that reached 0.01 more accounts per farmer and about 1500 Rupees higher credit per farmer by year 5 after SMIS tower construction.

Finally, we investigate whether the effects on PACS lending are consistent with an expansion in the take-up of government credit programs, and of Kisan Credit Cards in particular. In Table A2 we estimate IV regressions capturing the effect of coverage on agricultural credit from PACS by maturity and by farm size. We find that the effects on credit per farmer are driven by a relative increase in short term loans. We also report effects by size of the borrower. Size categories reported by the Agricultural Input Survey include: small farms (below 2 hectares), medium farms (2 to 10 hectares) and large farms (10 hectares and above).[18] When splitting the sample by holding size the magnitude of the point estimates of the effect of mobile phone coverage on PACS lending are larger for smaller farms and monotonically decreasing in farm size. These heterogeneous effects are consistent with a credit expansion driven by government subsidized loans, as Kisan Credit Cards loans tend to be short-term (less than 12 months) and their primary beneficiaries are small and marginal farmers.

3.4.3 Heterogeneous Effects by Loan Use, Agricultural Income Volatility and Shocks

Kisan Credit Card loans may be used for either consumption or investment purposes, and the BSR data allow us to distinguish between these two categories. In Table A3, we replicate the cross-sectional specification from Table 7, disaggregating outcomes by loan purpose. The results indicate that the effects of mobile coverage expansion on Kisan Credit Card lending are entirely driven by an increase in consumption loans, with no statistically significant impact on investment loans.

It is important to note that, according to the BSR data, 95% of the outstanding balance and 96% of Kisan Credit Card accounts are classified as consumption loans. Within our sample, the average outstanding balance is Rs. 286,115 for consumption loans and Rs. 318,699 for investment loans.

These results are consistent with the interpretation that farmers use Kisan Credit Card

[18] According to the Agricultural Input Survey of 2007, small farms (below 2 hectares) constitute the majority (82.4 percent) of agricultural holdings in India. In terms of area farmed, each size category represents a relatively similar share of total agricultural land.

loans primarily to smooth consumption in the face of adverse shocks.[19] We explore this hypothesis by examining heterogeneous effects of mobile coverage on agricultural credit in regions with varying levels of income volatility and exposure to weather shocks.

Table A4 presents results by agricultural income volatility, measured at the cell level using the standard deviation of agricultural yields over time. We proxy agricultural yields with intra-annual changes in NDVI (Normalized Difference Vegetation Index), a satellite-based measure of vegetation cover.[20] We define high-volatility areas as those with above-median standard deviation in this measure. The estimates in Table A4 show larger credit responses to mobile coverage in high-volatility areas across all outcomes. The difference is statistically significant for the number of accounts per farmer in commercial and regional rural banks (column 1), while differences for other outcomes are not statistically distinguishable from zero.

We further test whether agricultural credit increases more in years with adverse weather conditions, using rainfall data from the Global Precipitation Climatology Centre (GPCC). We calculate rainfall z-scores for each cell by subtracting the area's average rainfall from its current value and dividing by its standard deviation. Cell-years with positive z-scores (above their historical mean) are classified as high-precipitation, while those with negative or zero z-scores are classified as low-precipitation. The results reported in Table A5 provide some evidence of stronger responses during adverse weather conditions. In particular, the BSR data show significantly higher credit use in low-rainfall years – typically associated with lower yields and negative income shocks – with a statistically significant difference in credit amount per farmer. This is consistent with mobile coverage facilitating access to credit in response to weather-related income shortfalls. In contrast, the effects on credit from PACS are relatively similar across precipitation levels, showing no significant variation between positive and negative shock years.

3.4.4 Interest Rates and Default

The BSR data allow us to observe both the average interest rate and the default rate on agricultural loans originated at the branch level. In Table 8, we examine the impact of mobile coverage expansion on these outcomes.

Column (1) shows that areas experiencing greater expansion in mobile coverage due to the construction of SMIS towers saw a relative decline in the average interest rate on agricultural loans. The OLS estimate indicates a negative and statistically significant effect, while the reduced-form and IV estimates are also negative but imprecisely estimated

[19]Indeed, 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). See on this also Ghosh and Vats (2022), who study the real and financial effects of a guaranteed income scheme for small farmers in India.

[20]See Asher and Novosad (2020), Asher et al. (2022), and Gupta et al. (2024) for recent applications of NDVI as a proxy for agricultural productivity in India.

and not statistically significant at conventional levels. The magnitude of the IV coefficient suggests that a one standard deviation increase in coverage is associated with a 0.25 percentage point reduction in the average interest rate on agricultural loans.

Ex ante, the effect of credit expansion on interest rates is theoretically ambiguous. Easing information frictions may enable more farmers to access subsidized (below-market) loans, thereby lowering average rates. However, it could also lead to the inclusion of riskier borrowers, which might increase average rates. As shown in Figure 4, the distribution of average interest rates on Kisan Credit Cards across branches features a pronounced mass at the 7 percent minimum, consistent with the subsidized nature of the product. At the same time, the large within-product variation in rates likely reflects differences in borrower characteristics. In this context, the results in column (1) suggest that improved information access did not increase the average risk profile of borrowers, at least insofar as such risk is reflected in interest rates.

Consistent with the findings on interest rates, columns (2) and (3) of Table 8 show a negative, though mostly statistically insignificant, effect of mobile coverage expansion on both the share of accounts classified as non-performing and the share of agricultural credit outstanding that is non-performing. Under the RBI definition, a non-performing asset is a loan with payments at least 90 days overdue. Overall, the credit expansion facilitated by SMIS tower construction does not appear to have increased average default rates in the post-implementation period.

3.5 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 5 and Table 7. For this quantification, we focus on the 2SLS estimates, which are easily interpretable as the impact of SMIS-induced changes in mobile phone coverage on calls per farmer and credit per farmer.

Table 5 shows that cells with a standard deviation larger increase in mobile coverage experience 1.7 more calls about government credit programs per thousand farmers after the introduction of the SMIS program. The results in Table 7 imply that cells with a standard deviation larger increase in mobile coverage experience 2.7 more Kisan Credit Card accounts per thousand farmers in commercial and regional rural banks. The ratio of the estimated effect on credit access divided by the estimated effect on calls implies an increase of 1.6 additional Kisan Credit Card accounts per call asking for information about government credit programs.

These magnitudes suggest that a substantial share of farmers both act on the information received from call centers and contribute to its diffusion within their communities, including to those who do not place calls themselves. Several features of the setting support this interpretation. First, farmers proactively contact Kisan call centers to obtain information about credit programs, rather than being approached by lenders, indicating deliberate information-seeking behavior. As detailed in Section 2.3 and illustrated in Figure 4, Kisan Credit Cards offer significantly lower interest rates than comparable non-subsidized loans, making them particularly attractive. Furthermore, expanded mobile phone coverage in treated areas facilitates the transmission of information from callers to non-callers, as well as among non-callers.

Finally, survey evidence shows that farmers calling Kisan call centers are selected in terms of their personal characteristics and their role in local communities. In particular, a survey implemented in 2017 by the Indian Centre for Management in Agriculture (Gandhi and Johnson, 2017) indicates that callers are – on average – more educated than the average farmer in India, the majority of them having completed secondary education.[21] Existing evidence in the literature shows that more educated farmers are also more likely to be part of the social network of other farmers.[22] Existing studies have also shown that seeding information with a selected group of individuals that are central in their local network can be a powerful tool to disseminate information within a community (Conley and Udry, 2010; Beaman et al., 2021; Banerjee et al., 2024).

3.6 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. However, a potential challenge with this interpretation is that the arrival of mobile phone coverage in a given region can promote credit take-up via mechanisms other than access to information. 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.

To make progress in the direction of isolating the role of information, we follow Gupta et al. (2024) 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 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 99 non-official languages spoken in the country.[23] This

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

[22] 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. 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).

[23] The 2011 Census identifies 121 languages spoken in India, 22 of which are part of the Eight Schedule

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 11 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 the official language of Odisha. While this area has a similar diffusion of agriculture as the rest of Odisha (panel b) and has experienced an expansion in mobile phone coverage similar to the rest of the State (panel c), phone calls by farmers to Kisan Call Centers from this area have been significantly lower (panel d). This example is illustrative of a statistical trend that we observe across all our sample.

We re-estimate the reduced form specification for the main outcomes including interactions capturing the differential effect of SMIS towers across cells with a different initial share of state official language speakers as follows:

$$\begin{aligned} y_{ist} &= \alpha_i + \alpha_{st} + \beta_1 \mathbb{1}\,(\text{Tower})_{is} \times Post_t \times \mathbb{1}(\text{majority state speakers}_{is}) \\ &+ \beta_2 \mathbb{1}\,(\text{Tower})_{is} \times Post_t \times \mathbb{1}(\text{majority non-state speakers}_{is}) \\ &+ \gamma \mathbb{1}\,(\text{Tower})_{is} \times Post_t \times C_{is} + \delta_t X_{is} + \eta_{ist} \end{aligned} \tag{4}$$

where β_1 captures the effect of tower construction on outcomes in cells where the majority of the local population speaks the official language of the state, and β_2 captures the effect of tower construction on outcomes in cells where the majority of the local population speaks either a non official language or an official language that is not the one of the state where they live.[24] In this specification we include among the initial cell-level controls X_{is} interacted with time fixed effects also the share of non-state language speakers in a given cell.

The empirical model described in equation (4) 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. However, 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

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.

[24]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.

also variation driven by other local conditions. To address this concern, we augment our model by including triple interactions of treatment status times *Post* with measures of agricultural specialization (share of population employed in agriculture, share of irrigated land), geographical isolation (distance to nearest town), local economic development (night lights intensity), the share of population that belongs to a scheduled caste and a measure of access to agricultural markets (Chatterjee, 2023). These potential confounders are represented by C_{is} in equation (4).

The results are reported in Table 9. We find positive and statistically significant effects of tower construction on calls and access to credit in areas where the majority of the local population face lower language barriers with agricultural advisors. The estimates for β_2 are instead either negative or close to zero, and not statistically significant for all outcomes. Table 9 also reports the p-value of the difference between β_1 and β_2, which shows that this difference is statistically significant for most outcomes. Taken together, the results in Table 9 indicate that the positive impact of tower construction on calls and credit outcomes is significantly attenuated in areas where the majority of the local population faces language barriers when accessing Kisan Call Centers. This is consistent with an information mechanism driving the effect of mobile phone coverage on credit take-up.

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. For example, farmers who learn about new seeds or improved agricultural practices via Kisan Call Centers might demand more credit to adopt such technologies, even if they are fully informed about the subsidized credit programs available to them.

Isolating which specific type of information explains the increase in credit take-up documented in the data is more 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 advisors gain potential access to different types of information, which include information about credit programs but also information about agricultural technologies such as high yielding variety seeds, fertilizers and irrigation techniques. Access to information about agricultural technologies can indirectly foster credit demand to adopt them.

However, the results support the importance of access to information about credit programs. We observe that farmers use Kisan Call Centers to ask information about credit programs available to them, which indicates the existence of an informational gap for this type of products. The results presented in Section 3.4.2 indicate that areas receiving SMIS towers experience higher take-up of Kisan Credit Card loans, the largest government credit program that we can also observe in the data, and, importantly, no significant increase in non-Kisan Credit Cards loans. Finally, we find that the increase in loans taken via Kisan Credit Cards is mostly driven by consumption loans rather than investment loans. An increase in credit driven by farmers' learning about agricultural technologies and borrowing to pay for adoption would instead increase investment loans rather than consumption loans.

4 Robustness Tests

We present a set of robustness tests for the key results of the paper. First, we test the robustness of our estimates to spatial standard errors correction. Second, we show that results are robust to the use of alternative estimators proposed by the recent literature to analyze dynamic effects under staggered treatment. Third, we test for possible spillovers from the construction of mobile phone towers on surrounding cells. Fourth, we show that results are not driven by specific states in India. Fifth, we report a sensitivity analysis of the main results to the use of different decay parameters used in the credit allocation rule.

Standard errors correction. A well documented concern in studies whose identification strategy relies on geographical variation is that spatial correlation in the data can lead to incorrect computation of the standard errors. To partially address this concern, in all the specifications in the paper we cluster standard errors at the sub-district level, i.e. allowing the error term 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 adjusts standard errors by allowing to be correlated based on spatial proximity. The results are reported in Table A6. As shown, accounting for spatially correlated standard errors between 50 km and 500 km does not significantly affect the results. Compared to the baseline specification, the 2SLS estimates typically become more precise and the coefficients of interest remain statistically significant at conventional levels.

Alternative estimators for staggered diff-in-diff. As Figure 1 shows, the majority of the SMIS towers were established over two years: 2008 and 2009. Thus, when using yearly data, it is plausible to think of the SMIS program as a shock that happened in all treated cells at roughly the same time. Still, given the somewhat staggered nature of the treatment, we estimate event studies using relative years with respect to tower construction. We also test the robustness of our estimates on credit using alternative estimators for staggered difference-in-differences research design proposed in the literature, including Sun and Abraham (2021); Borusyak et al. (2024); Callaway and Sant'Anna (2021). Figure A4 presents the event-time estimates of tower placement on bank credit per farmers from these estimators. Our main estimates remain robust to these alternative estimation methodologies.

Spillovers from towers constructed in surrounding cells. The spatial proximity between treated and control cells has the potential to generate spillovers from tower placement. We formally test for spillovers using the methodology proposed in Berg et al. (2021). Specifically, for every cell i we construct the variable Share treated$_{id}$, defined as the share of treated cells within the same sub-district d in which cell i is located, excluding the treatment status of the focal cell. We then estimate potential spillover effects by examining how Share treated$_{id}$ affects the outcomes of interest, using the following specification:

$$\Delta y_{ids} = \alpha_s + \beta_1 \; 1(\text{Tower})_i + \beta_2 \text{ Share treated}_{id} + \gamma X_{ids} + \epsilon_{ids} \tag{5}$$

where Δy is the difference in the averages of the dependent variables in the years after and before the cell received a mobile phone tower under the SMIS program. To account for the fact that spillover effects might be different across treated and control cells, we also estimate a version of equation (5) in which we interact Share treated$_{id}$ with dummies identifying treated and control cells as follows:

$$\begin{aligned} \Delta y_{ids} \;&=\; \alpha_s + \beta_1 \; 1(\text{Tower})_i + \beta_T \text{ Share treated}_{id} \times 1(\text{Tower})_i \\ &+\; \beta_C \text{ Share treated}_{id} \times (1 - 1(\text{Tower})_i) + \gamma X_{ids} + \epsilon_{ids} \end{aligned} \tag{6}$$

Table A7 reports the results from estimation equations (5) and (6) on the main credit outcomes. Columns (1) and (4) report our baseline treatment effects. Columns (2) and (5) show evidence consistent with no spillover effects from surrounding treated cells on average. Columns (3) and (6) show no heterogeneous effects of spillovers from surrounding treated cells on either the treated or the control cells.

Robustness to excluding specific States. An interesting question is whether the results are driven by any specific State in India or whether instead they represent a more general pattern that is observed across the country. In Figure A5 we report the 2SLS estimates on the main credit outcomes excluding one Indian State at the time. As shown, the magnitude of the documented effects does not depend on the exclusion of any specific State.

Sensitivity to decay parameter used in credit allocation rule. As described in Section 2.4 we allocate agricultural credit originated by a bank branch to the surrounding cells assuming a catchment area with a radius of 50 km around each branch and an allocation rule that gives more weights to cells that are closer to the branch and that have more farmers. To model the role of distance to the branch, we use a decay function whose key parameter is obtained by matching survey responses about how much people have to travel to reach the nearest branch. In appendix Section B.2 we explain the methodology and estimate the decay parameter used in our baseline specification (0.8). As a robustness on the choice of this parameter, in Table A8 we replicate the main results on credit outcomes using decay parameters ranging from 0.4 to 0.8. As shown, the estimates are relatively stable to the choice of this parameter.

5 Concluding Remarks

In this paper, we provide evidence on the effects of the expansion of mobile phone coverage on the take-up of agricultural credit in rural areas of India by exploiting variation generated by the construction of new towers in previously unconnected regions. 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.

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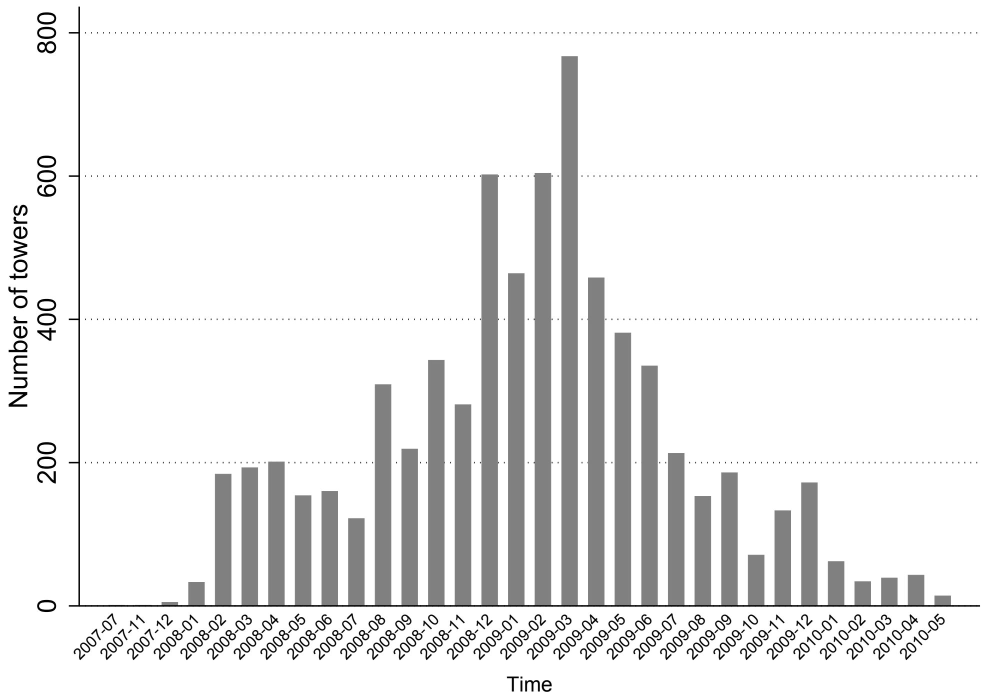
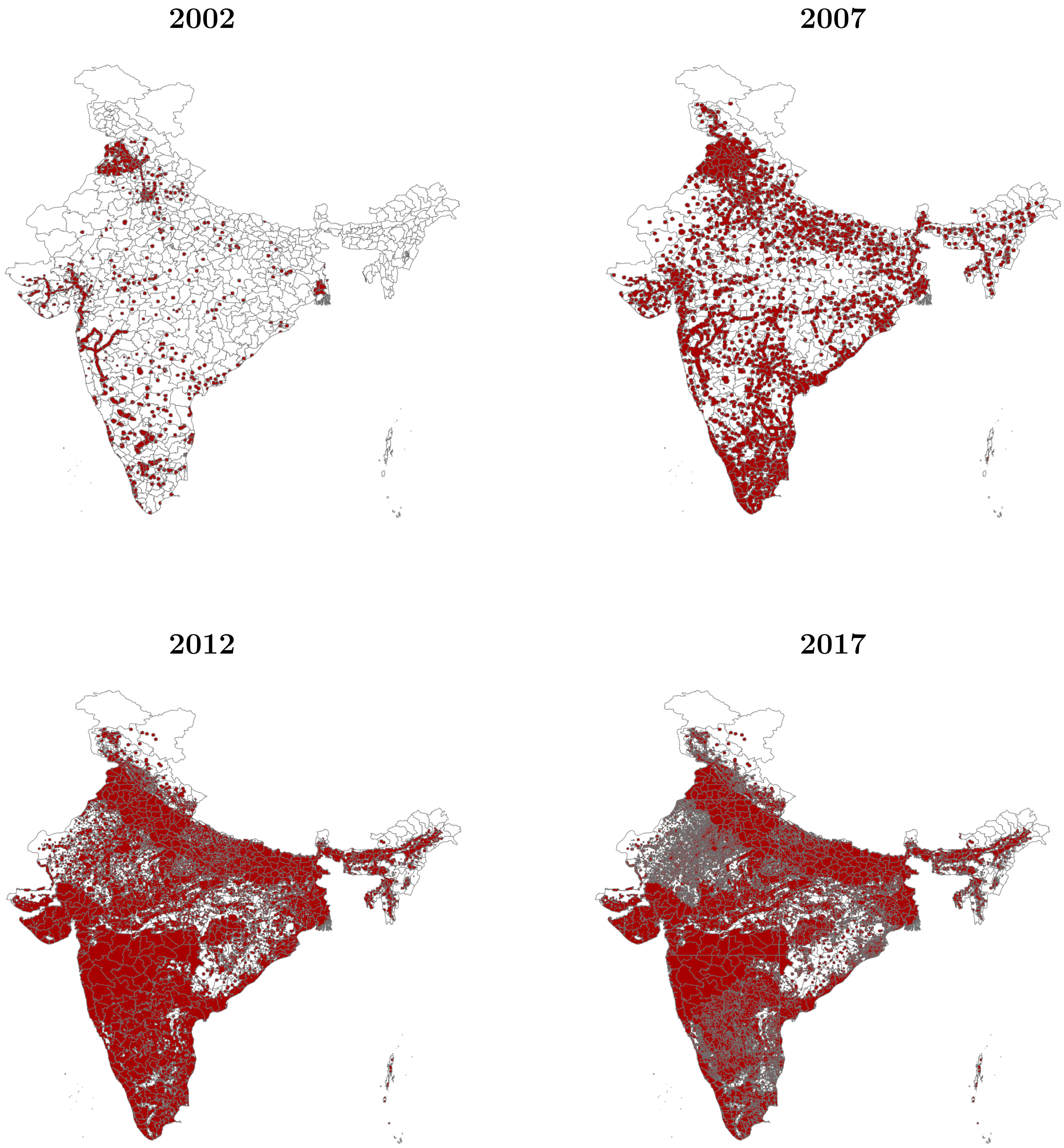
Figures

Figure 1: Timeline of tower construction under SMIS Phase I



Notes: Source: Department of Telecommunications, India

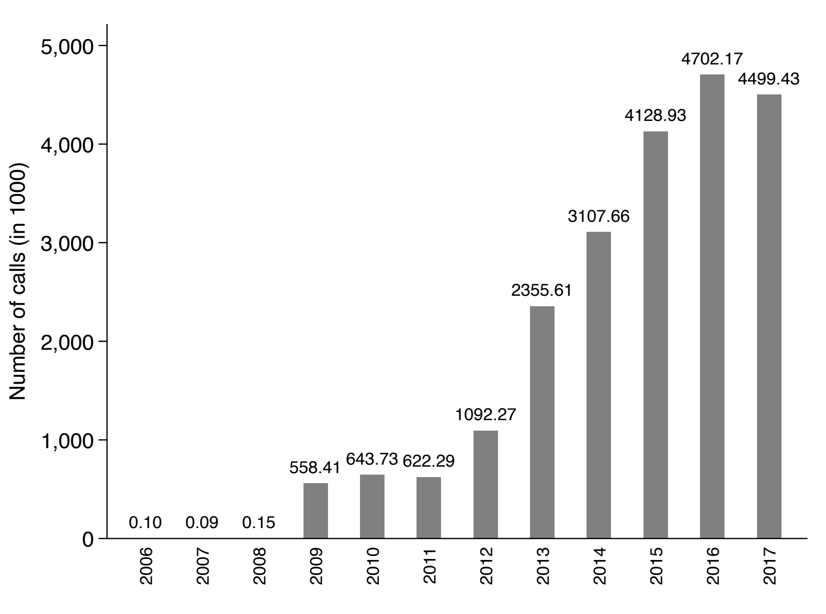
Figure 2: Mobile Phone Coverage Evolution, India 2002-2017



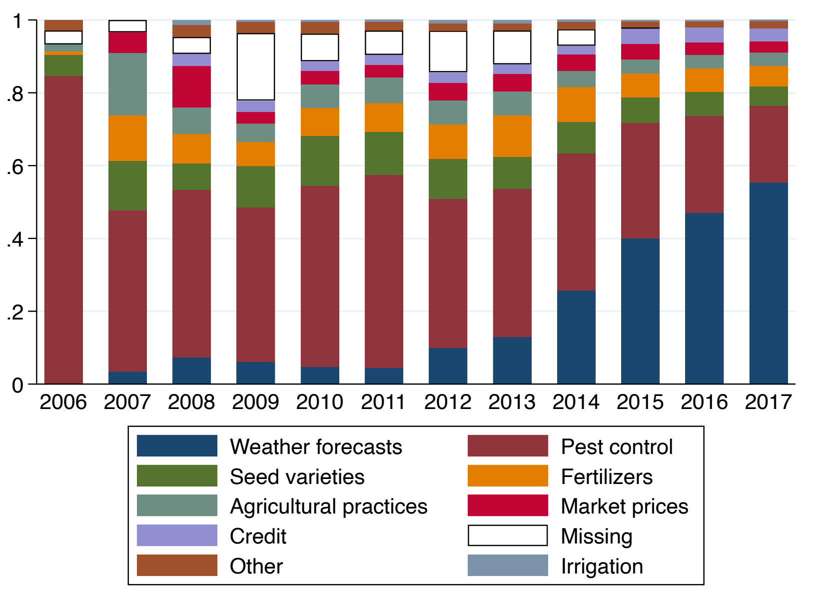
Notes: The figure reports geo-referenced data on mobile phone coverage for all of India at five-year intervals between 2002 and 2017. Source: GSMA.

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

(a) Number of calls by year



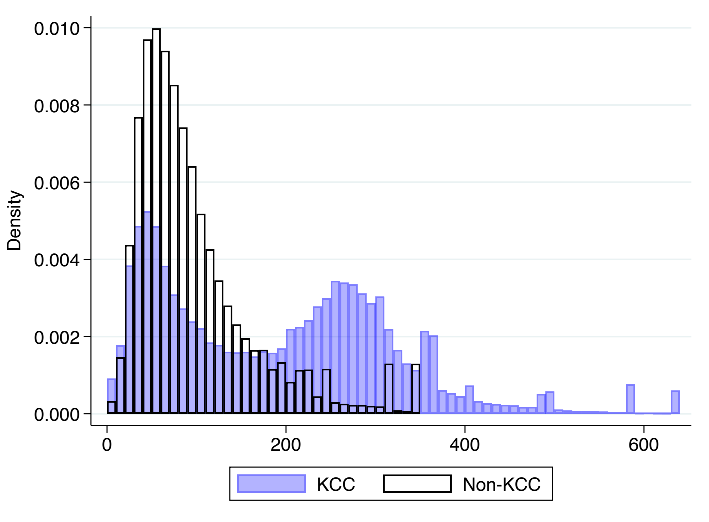
(b) Composition of calls by year



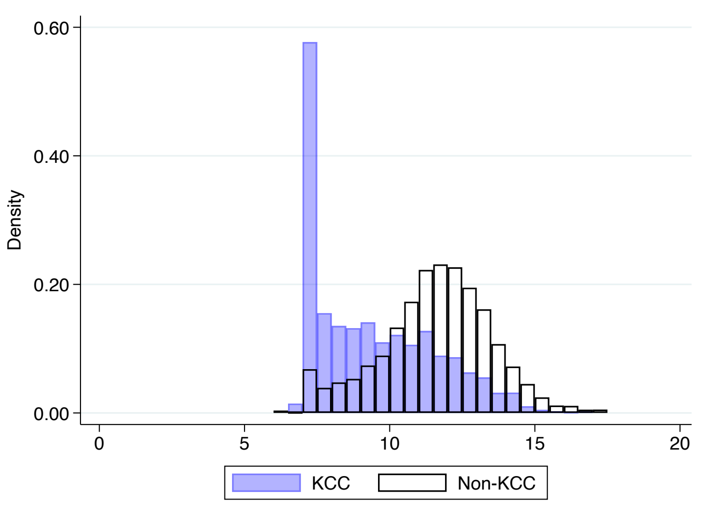
Notes: Source: Authors' calculations based on the data on calls to Kisan Call Centers made available on the Open Government Data (OGD) Platform of India `https://www.data.gov.in/` as of January 2024.

Figure 4: Average Interest rates and Credit per account across bank branches

(a) Credit per account

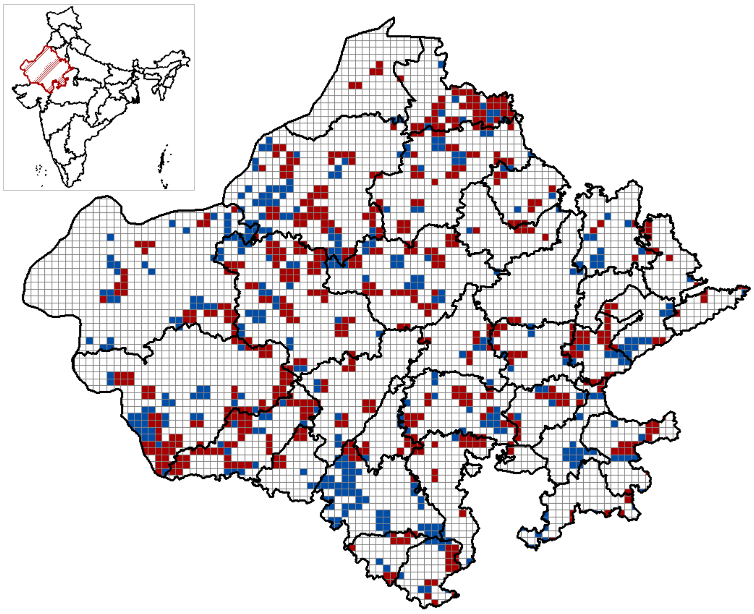


(b) Interest rates



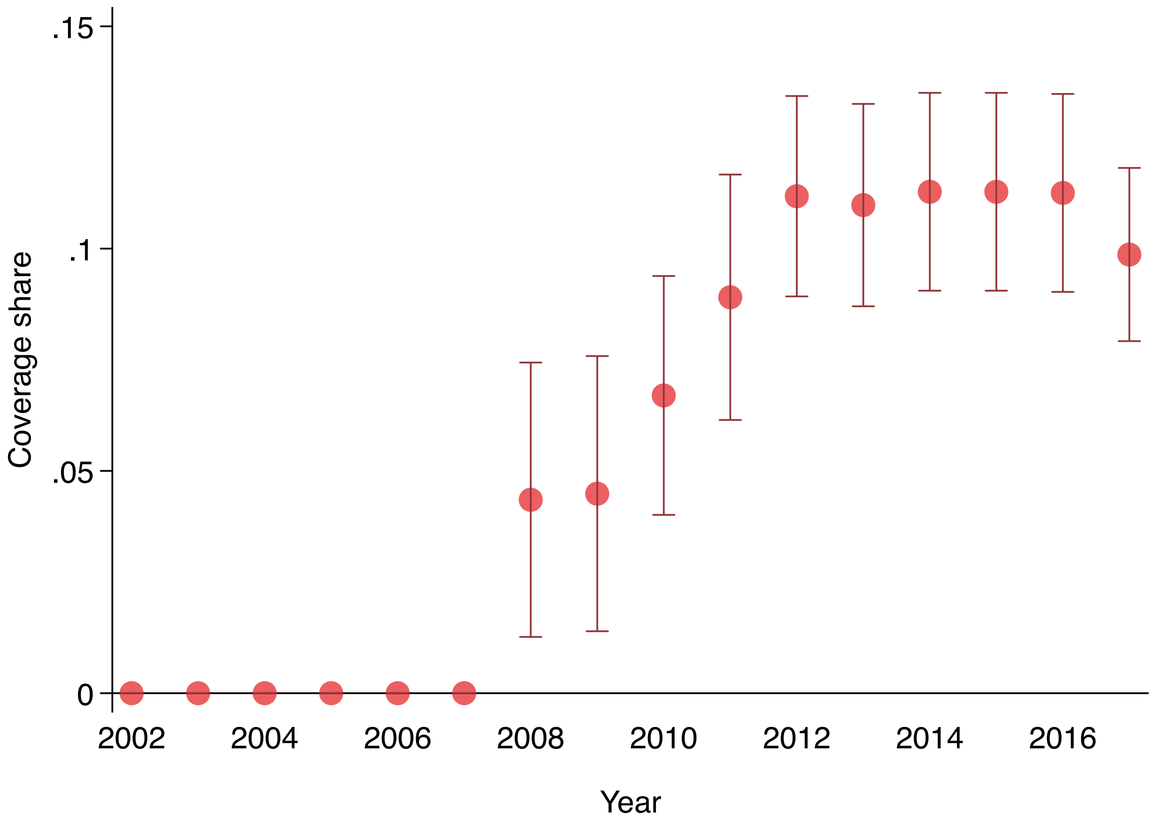
The graph plots the distribution of credit per account (panel a) and interest rates (panel b) separately for Kisan Credit Card (KCC) and non-Kisan Credit Card (non-KCC) credit as reported in the branch-level BSR data. Credit per account is in thousands and winsorized at the 95th percentile. Interest rate is winsorized at the 1st and 99th percentiles.

Figure 5: Treatment and Control Cells
Rajasthan State



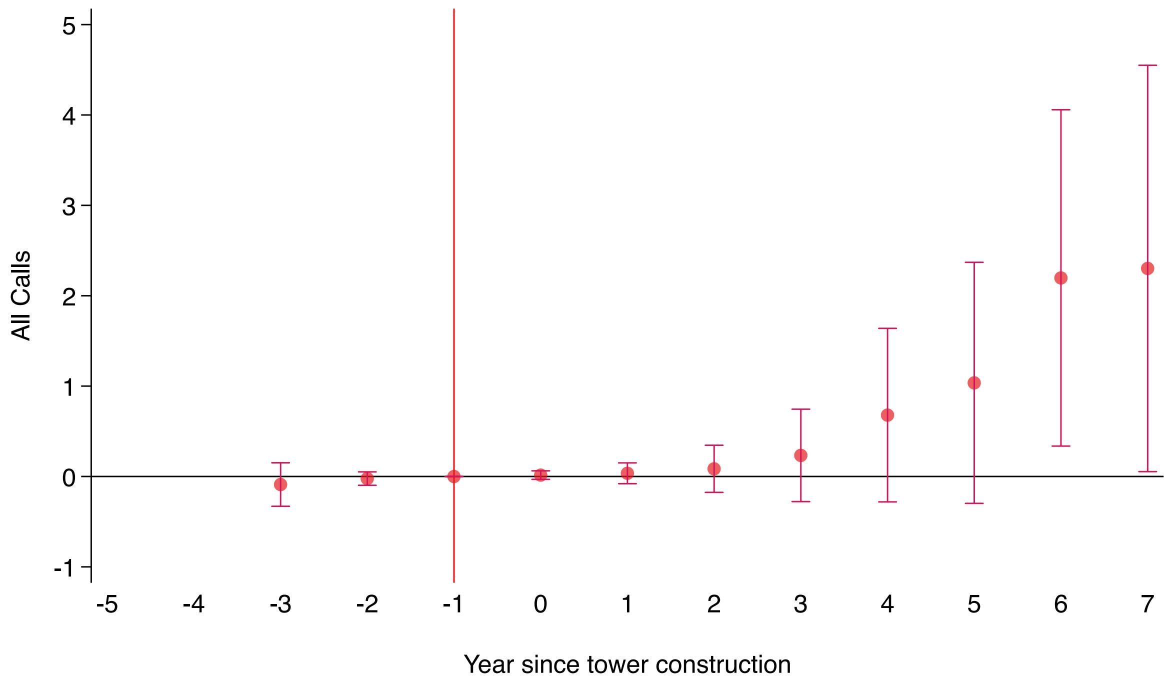
Notes: Treatment (red) and control (blue) cells for the state of Rajasthan. District boundaries are labeled in black. Treatment cells are those that are both proposed *and* covered by mobile tower under SMIS Phase I. Control cells are those that are proposed *and not* covered by mobile tower under SMIS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

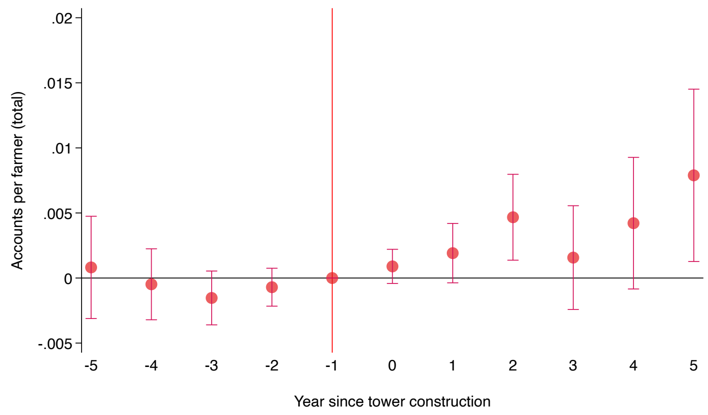
Figure 7: Reduced Form Effects of Tower Construction on Calls: Event Study



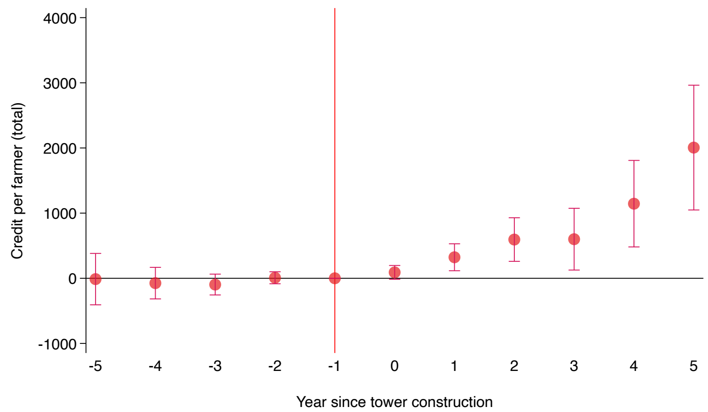
Notes: This figure presents the reduced-form estimates of the SMIS tower construction program on number of calls per 1000 farmers to Kisan Call Center using specification (3). We normalize the coefficients in year before tower construction to 0. The dependent variable is winsorized at the 5% level. 95% confidence intervals represented by vertical bars.

Figure 8: Reduced Form Effects of Tower Construction on Credit Outcomes: Event Study (Commercial Banks and Regional Rural Banks)

(a) Accounts per farmer



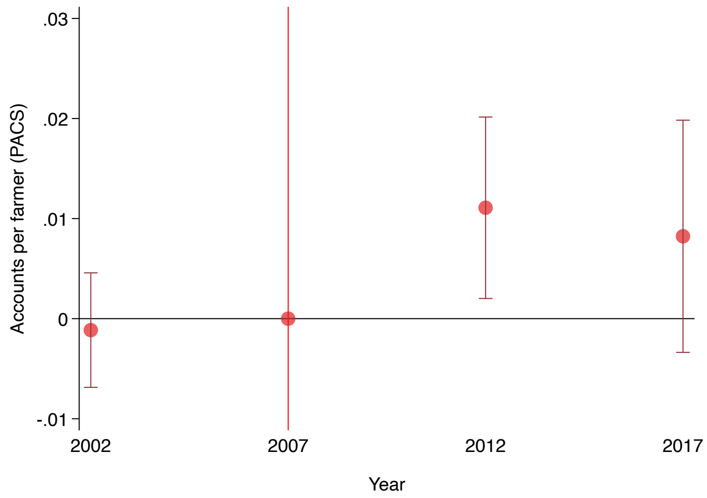
(b) Credit per farmer



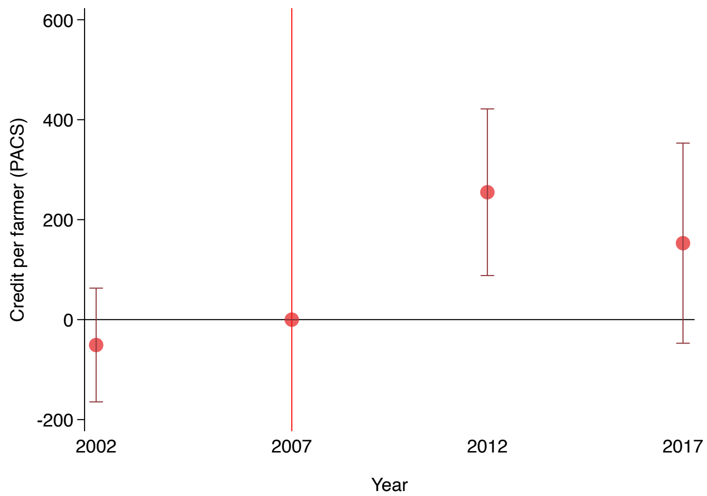
Notes: This figure presents the reduced-form estimates of the SMIS tower construction program on the credit accounts per farmers (panel a) and credit per farmer (panel b) as reported by the commercial and regional rural banks using specification (3). We normalize the coefficients in the year before tower construction to 0. We use data from the branch-level Basic Statistical Return (BSR) maintained by the Reserve Bank of India (RBI) and the 2001 Population Census to compute the outcome variables. We divide the total number of accounts with agricultural credit (from the BSR data) by the number of farmers found in a cell (from the 2001 Population Census) to obtain the credit accounts per farmer. We divide the agricultural credit outstanding in a cell (from the BSR 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 variables are winsorized at the 5% level. 95% confidence intervals represented by vertical bars.

Figure 9: Reduced Form Effects of Tower Construction on Credit Outcomes: Event Study (PACS)

(a) Share of farmers with credit (PACS)



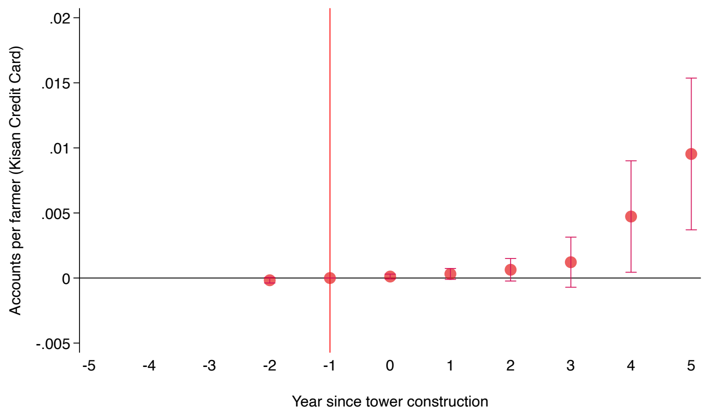
(b) Credit per farmer (PACS)



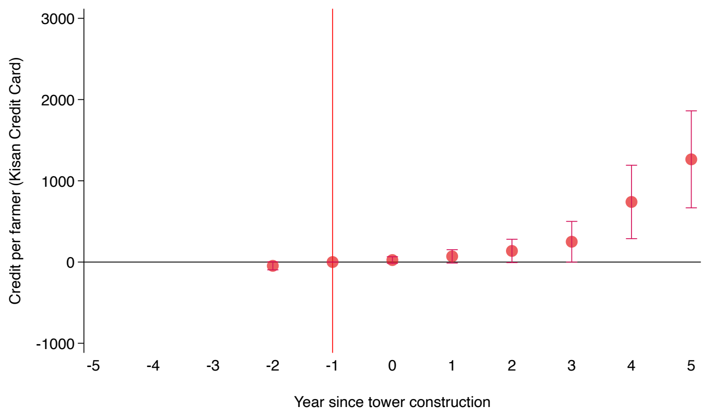
Notes: This figure presents the reduced-form estimates of the SMIS tower construction program on the share of farmers with credit (panel a) and credit per farmer (panel b) using specification (3). We normalize the coefficients in the year before tower construction to 0. We use data from the Agricultural Input Survey (AIS) 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 variables are winsorized at the 5% level. 95% confidence intervals represented by vertical bars.

Figure 10: Reduced Form Effects of Tower Construction on Credit Outcomes: Event Study (Kisan Credit Cards)

(a) Accounts per farmer



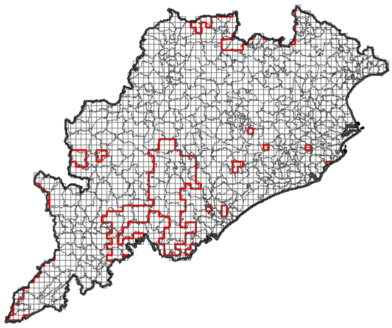
(b) Credit per farmer



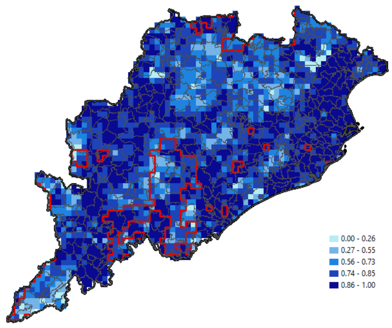
Notes: This figure presents the reduced-form estimates of the SMIS tower construction program on the account per farmers (panel a) and credit per farmer (panel b) as reported by the commercial and regional rural banks and classified under the category of Kisan Credit Cards loans using specification (3). We normalize the coefficients in the year before tower construction to 0. We use data from the branch-level Basic Statistical Return (BSR) maintained by the Reserve Bank of India (RBI) and the 2001 Population Census to compute the outcome variables. We divide the total number of accounts with Kisan Credit Card credit (from the BSR data) by the number of farmers found in a cell (from the 2001 Population Census) to obtain the credit accounts per farmer. We divide the Kisan Credit Card credit outstanding in a cell (from the BSR 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 variables are winsorized at the 5% level. 95% confidence intervals represented by vertical bars.

Figure 11: Coverage and Farmers Calls by Language in the State of Odisha

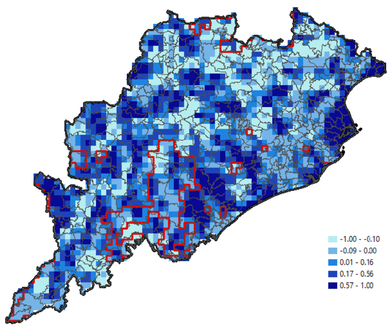
(a) Non-official language speakers



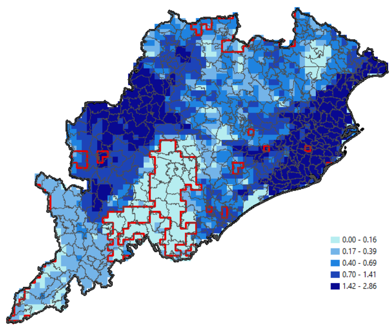
(b) Share of farmed land



(c) Change in mobile coverage



(d) Change in calls to Kisan Call Centers



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

Tables

Table 1: Summary Statistics

	Data Source	N	Mean	SD
Coverage share	GSMA coverage data	29,186	0.448	0.455
Number of calls per 1000 farmers	Kisan Call Center			
All calls		29,186	32.343	87.317
Credit calls		29,186	1.456	4.554
Government programs credit calls		29,186	1.125	3.756
Share of farmers with credit				
PACS	Agricultural Input Survey	29,186	0.117	0.156
Commercial banks and RRBs	Basic Statistical Return (RBI)			
All loans		29,186	0.204	0.172
Kisan Credit Cards		16,164	0.078	0.104
Credit per farmer				
PACS	Agricultural Input Survey	29,186	2,014.8	3,025.1
Commercial banks and RRBs	Basic Statistical Return (RBI)			
All loans		29,186	14,336.2	17,703.7
Kisan Credit Cards		16,164	6,877.7	8,992.8
Banks' non-performing assets (NPA)	Basic Statistical Return (RBI)			
Share of NPA accounts		28,944	0.100	0.085
Share of NPA credit		28,944	0.092	0.084
Average interest rates	Basic Statistical Return (RBI)			
All		28,944	11.8	1.6
Kisan Credit Cards		15,955	9.6	1.5
Non-Kisan Credit Cards		28,904	12.4	1.5
Share of rural households with KCC	Socio Economic and Caste Census	8,152	0.041	0.046

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. Coverage share is calculated using the GSMA coverage data. Mobile phone coverage data comes from GSMA. Data on calls comes from the Kisan Call Center data maintained by the Ministry of Agriculture. Bank agricultural credit variables comes from the branch-level Basic Statistical Return (BSR) maintained by the Reserve Bank of India (RBI). PACS agricultural credit outcomes come from the Agricultural Input Survey (AIS). The share of agricultural households with Kisan Credit Cards is computed using the Socio Economic and Caste Census (SECC), which was obtained from SHRUG. We utilize four rounds spanning five years between 2002 to 2017 corresponding to the AIS data.

Table 2: Determinants of tower relocation and treatment status

	1(Tower)			
	(1)	(2)	(3)	(4)
Log population (2001)	0.079***			0.062***
	(0.011)			(0.013)
Power Supply		0.112***		0.040
		(0.034)		(0.034)
Ruggedness			-0.058***	-0.040***
			(0.015)	(0.015)
Observations	8,426	8,426	8,426	8,426
R-squared	0.078	0.070	0.074	0.082
State FE	Yes	Yes	Yes	Yes

Notes: The table reports the baseline correlates of receiving a SMIS tower (1(Tower)). The unit of observation is a 10 $\times$ 10 km cell. Column (1) documents the correlation between 1(Tower) and (log) population; Column (2) documents the correlation between 1(Tower) and power supply; Column (3) documents the correlation between 1(Tower) and terrain ruggedness. Column (4) documents the estimates from a multivariate regression with 1(Tower) as the dependent variable and (log) population, power supply and terrain ruggedness as the independent variables. The sample includes all cells with zero cell phone coverage in 2006. All specifications include state fixed effects. All regressions are weighted by the agricultural population in the cell. Standard errors clustered at sub-district level are reported in brackets. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table 3: Predictive power of pre-existing cell characteristics on treatment status

	Control Means (1)	Treated – Control (2)	1(Tower) (3)
Agri Workers/Working Pop.	0.283	0.003	0.026
		(0.030)	(0.082)
Log Distance to Nearest Town (kms)	3.333	-0.055*	-0.014
		(0.033)	(0.012)
Percent Irrigated	0.299	0.039	0.008
		(0.035)	(0.033)
Percent area under Kharif Crops	0.264	0.034	0.039
		(0.034)	(0.059)
Log (crop suitability)	8.341	-0.003	0.005
		(0.019)	(0.014)
Log Night Lights (2001)	0.638	0.007	-0.002
		(0.030)	(0.015)
Night lights growth (1996-2001)	0.081	-0.051	-0.010
		(0.048)	(0.010)
Agri Market Competition	0.101	0.016	0.019
		(0.023)	(0.051)
Rainfall Volatility	18.194	-0.039	-0.001
		(0.031)	(0.001)
Number of ...			
... Landline Telephone connections	24.150	-0.072	-0.000
		(0.051)	(0.000)
... Post Offices	3.366	-0.043	-0.003
		(0.033)	(0.003)
... Credit Facilities (PACS and Banks)	1.442	0.036	-0.031
		(0.032)	(0.063)
... Agricultural Credit Society Facility	1.220	0.043	0.035
		(0.031)	(0.063)
... Commercial Bank Branches	0.214	-0.010	0.028
		(0.035)	(0.064)
... Regional Rural Bank Branches	0.208	0.013	0.002
		(0.036)	(0.004)
Population Share of ...			
... Share of Scheduled Castes	0.140	0.040	0.044
		(0.042)	(0.094)
1(majority NS Speakers)	0.108	-0.052	-0.044
		(0.034)	(0.035)
... Share of male population	0.514	0.021	0.179
		(0.030)	(0.437)
Availability of ...			
... Drinking Water Facility	0.994	0.010	0.127
		(0.022)	(0.188)
... Education Facility (Schools and Colleges)	0.877	-0.069**	-0.135**
		(0.029)	(0.054)
... Recreation Facility	0.059	0.010	0.009
		(0.019)	(0.035)
... Medical Facility (Hospitals and Clinics)	0.334	0.009	0.012
		(0.033)	(0.030)
... Landline Telephone Office	0.167	-0.061*	-0.014
		(0.034)	(0.011)
... Communication Facility	0.357	0.040	0.053
		(0.024)	(0.104)

Continued . . .

. . . Continued

	Control Means (1)	Treated − Control (2)	1(Tower) (3)
... Bus Connectivity Facility	0.344	0.039	0.025
		(0.024)	(0.102)
... Tar (paved) Road Connectivity	0.473	-0.001	-0.016
		(0.026)	(0.027)
Rural Electrification program targeting ...			
% villages with pop > 100	0.957	-0.028	-0.077
		(0.023)	(0.086)
% villages with pop > 300	0.836	-0.003	0.043
		(0.027)	(0.062)
Rural Road program targeting ...			
% villages with pop > 500	0.702	0.006	0.028
		(0.030)	(0.050)
% villages with pop > 1000	0.448	0.001	-0.027
		(0.034)	(0.037)
Cell in banked district (Bank-branch expansion)	0.142	0.021	0.029
		(0.024)	(0.020)
Bailout Share (Debt Relief Program)	0.558	-0.019	-0.007
		(0.042)	(0.018)
Political leaning ...			
Vote Share of BJP (2004)	0.334	0.026	0.056
		(0.031)	(0.046)
Vote Share of INC (2004)	0.295	-0.021	-0.030
		(0.035)	(0.043)
Baseline Controls		Yes	Yes
State FE		Yes	Yes

Notes: This table tests whether initial characteristics predict the construction of a SMIS tower (1(Tower)) in a given cell conditional on the cell being included in the list of potential tower locations from the Ministry of Telecommunication. Column (1) reports the mean in the control group for the variables. Column (2) reports the differences in the means between the treatment and control for the variable, controlling for state fixed effects and baseline controls for determinants of tower relocation, namely (log) total population, power supply and ruggedness. We normalize the independent variables to have mean zero and standard deviation of one. Column (3) reports the estimate from a multivariate regression of the binary treatment indicator (1(Tower)) on all cell characteristics in a single regression, controlling for state fixed effects and baseline controls for determinants of tower relocation, namely (log) total population, power supply and ruggedness. All estimates apart from Bailout Share, Vote Share of BJP (2004) and Vote Share of INC (2004) come from the multivariate regression in the primary sample of 8,426 cells. The estimates on Bailout Share, Vote Share of BJP (2004) and Vote Share of INC (2004) are reported from a multivariate regression that also includes these three covariates along with other covariates, and comes from the sample of 7,139 cells. All variables are measured at baseline from the 2001 Population & Village Census, and the Election Commission of India. Covariate include share of working population in agriculture; (log) distance to the nearest town (in kms); percentage of cell area irrigated; percentage of cell area cropped with eight major Kharif Crops; (log) of crop suitability from SHURG data; (log) night lights intensity; growth in night lights intensity; access to agricultural markets; rainfall volatility as measured by standard deviation of rainfall in the cell between 2000 and 2007; number of landline telephone connections in the village, number of post office in the village, number of credit facilities (bank and credit societies), number of primary agricultural societies (PACS), number of commercial bank branches, number of regional rural bank branches, share of population that is (i) scheduled caste or (ii) male; whether the cell's majority population speaks a non-scheduled language; average number of villages in a cell with availability of (i) drinking water facility (ii) educational facility (schools) (iii) recreation facility (iv) medical facility (hospitals or clinics) (v) communication facility (post office or telephone) (iv) bus connectivity (v) tar (paved) road; share of villages in the cell with population above (i) 100 (ii) 300 (iii) 500 (iv) 1000; whether the cell was in an underbanked district as per national bank branch expansion policy; whether the cell was in a district that have above median share or bailout under agricultural debt relief; the share of votes for BJP and INC in the 2004 national elections. Standard errors are clustered at the sub-district level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table 4: First Stage

	Coverage share	
	(1)	(2)
Tower × Post	0.0788***	0.0787***
	(0.0107)	(0.0107)
Kleibergen-Paap F statistic	54.379	54.493
Observations	29,186	29,186
Number of cells	8,426	8,426
Cell FE	Yes	Yes
State × Year FE	Yes	Yes
Baseline controls × Year FE	Yes	Yes
Other controls × Year FE	No	Yes

Notes: This table reports the effects of receiving a tower under the SMIS program on cellphone tower coverage in the cell. 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. Coverage share is defined as the share of cell area covered by GSMA. Baseline controls include (log) total population, power supply and ruggedness. Other controls include educational facilities. All controls are at baseline from the 2001 Population & Village Census and are interacted with year fixed effects. All specifications include state-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 calls per 1,000 farmers

	# of calls per 1000 farmers		
	All calls (1)	Credit calls (2)	Gov credit calls (3)
Panel A: OLS			
Coverage	17.501***	1.244***	0.951***
	(3.832)	(0.212)	(0.174)
Panel B: Reduced Form			
Tower × Post	7.012***	0.369**	0.295**
	(2.654)	(0.151)	(0.124)
Panel C: IV			
Coverage	89.135***	4.686**	3.748**
	(34.284)	(1.860)	(1.533)
Observations	29,186	29,186	29,186
Number of cells	8,426	8,426	8,426
Cell FE	Yes	Yes	Yes
State × Year FE	Yes	Yes	Yes
Baseline controls × Year FE	Yes	Yes	Yes
Other controls × Year FE	Yes	Yes	Yes

Notes: This table reports the effects of mobile phone coverage on the share of calls to the Kisan Call Centers per 1000 farmers. Panel A reports the OLS estimates, Panel B reports the reduced form estimates of receiving a tower under the SMIS program, and Panel C reports the IV-2SLS estimates where we instrument mobile phone coverage using treatment status under the SMIS program. Columns (1) reports the effects on all calls; Column (2) reports the effects on calls about credit programs; Column (3) reports the effects on government-program related credit calls. Tower is a binary indicator which equals 1 if for cells that received a tower under the SMIS program. Post is a binary indicator which equals 1 after 2007. Coverage is the share of cell area under GSMA 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 (log) total population, power supply and ruggedness. Other controls include educational facilities. All controls are at baseline from the 2001 Population & Village Census and are interacted with year fixed effects. All specifications include state-year fixed effects. The dependent variables are winsorized at the 5% level. 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 Credit Take-up

	Accounts per farmer in BSR (1)	Credit per farmer in BSR (2)	Share of farmers with PACS credit in AIS (3)	PACS credit per farmer in AIS (4)
Panel A: OLS				
Coverage	0.037***	6020.890***	0.036***	804.381***
	(0.006)	(910.865)	(0.008)	(136.208)
Panel B: Reduced Form				
Tower × Post	0.006*	1553.557***	0.010**	223.881***
	(0.004)	(519.121)	(0.004)	(83.174)
Panel C: IV				
Coverage	0.074*	18087.925***	0.126**	2846.008***
	(0.044)	(6033.697)	(0.057)	(1066.333)
Observations	29,186	29,186	29,186	29,186
Number of cells	8,426	8,426	8,426	8,426
Cell FE	Yes	Yes	Yes	Yes
State × Year FE	Yes	Yes	Yes	Yes
Baseline controls × Year FE	Yes	Yes	Yes	Yes
Other controls × Year FE	Yes	Yes	Yes	Yes

Notes: This table reports the effects of mobile phone coverage on credit take-up and credit per farmer. Panel A reports the OLS estimates, Panel B reports the reduced form estimates of receiving a tower under the SMIS program, and Panel C reports the IV-2SLS estimates where we instrument mobile phone coverage using treatment status under the SMIS program. The data is computed using the branch-level Basic Statistical Return (BSR) maintained by the Reserve Bank of India (RBI), Agricultural Input Survey (AIS) and the 2001 Population Census of India. We divide the number of farmers with credit (from the BSR data and AIS data) by the number of farmers found in a cell (from the 2001 Population Census) to obtain the share of farmers with bank credit and PACS credit, respectively. We divide the agricultural credit in a cell (from the BSR data and AIS data) by the number of farmers found in a cell (from the 2001 Population Census) to obtain the bank credit per farmer in rupees and PACS credit per farmers in rupees, respectively. 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 2007. Coverage is the share of area in a cell that is covered by GSMA mobile coverage. 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 (log) total population, power supply and ruggedness. Other controls include educational facilities. All controls are at baseline from the 2001 Population & Village Census and are interacted with year fixed effects. All specifications include state-year fixed effects. The dependent variables are winsorized at the 5% level. Standard errors are clustered at the sub-district level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table 7: The Effect of Tower Construction on Kisan Credit Cards

	Accounts per farmer(BSR)		Credit per farmer(BSR)		Share of households
	KCC	non-KCC	KCC	non-KCC	with KCC from SECC
	(1)	(2)	(3)	(4)	(5)
Panel A: OLS					
Coverage	0.0028***	0.0679***	768.1412***	5658.5721***	0.0241***
	(0.0004)	(0.0067)	(121.9924)	(541.8979)	(0.0028)
Panel B: Reduced Form					
Tower	0.0004*	-0.0010	136.2550**	332.1703	0.0057***
	(0.0002)	(0.0043)	(64.8221)	(317.4717)	(0.0015)
Panel C: IV					
Coverage	0.0059**	-0.0137	1809.4438**	4411.1656	0.0751***
	(0.0030)	(0.0569)	(854.3858)	(4166.9458)	(0.0210)
Observations	8,340	8,340	8,340	8,340	8,151
State FE	Yes	Yes	Yes	Yes	Yes
Baseline controls	Yes	Yes	Yes	Yes	Yes
Other controls	Yes	Yes	Yes	Yes	Yes

Notes: This table reports the effects of mobile phone coverage on share of farmers with Kisan Credit Card accounts and credit per farmer through Kisan Credit Card. Panel A reports the OLS estimates, Panel B reports the reduced form estimates of receiving a tower under the SMIS program, and Panel C reports the IV-2SLS estimates where we instrument mobile phone coverage using treatment status under the SMIS program. The data is computed using the branch-level Basic Statistical Return (BSR) maintained by the Reserve Bank of India (RBI) and the 2001 Population Census of India. We divide the number of farmers with credit classified as Kisan Credit Card versus not (from the BSR data) by the number of farmers found in a cell (from the 2001 Population Census) to obtain the share of farmers with KCC credit and non-KCC credit, respectively. We divide the agricultural credit in a cell classified as Kisan Credit Card versus not (from the BSR data) by the number of farmers found in a cell (from the 2001 Population Census) to obtain the KCC and non-KCC credit per farmer in rupees. The data from SECC (Column (5)) 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 area in a cell that is covered by GSMA mobile coverage in 2011. 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 (log) total population, power supply and ruggedness. Other controls include educational facilities. All controls are at baseline from the 2001 Population & Village Census. All specifications include state-year fixed effects. The dependent variables are winsorized at the 5% level. Standard errors are clustered at the sub-district level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table 8: The Effect of Tower Construction on Default and Interest Rates

	Average interest rates (1)	Share of NPA accounts (2)	Share of NPA credit (3)
Panel A: OLS			
Coverage	-0.249***	-0.021***	-0.015**
	(0.059)	(0.007)	(0.007)
Panel B: Reduced Form			
Tower × Post	-0.047	-0.003	-0.002
	(0.035)	(0.003)	(0.003)
Panel C: IV			
Coverage	-0.595	-0.037	-0.022
	(0.444)	(0.042)	(0.042)
Observations	28,917	28,917	28,917
Number of cells	8,388	8,388	8,388
Cell FE	Yes	Yes	Yes
State × Year FE	Yes	Yes	Yes
Baseline controls × Year FE	Yes	Yes	Yes
Other controls × Year FE	Yes	Yes	Yes

Notes: This table reports the effects of mobile phone coverage on average interest rates, share of accounts classified as non-performing (NPA) and share of credit classified as non-performing. Panel A reports the OLS estimates, Panel B reports the reduced form estimates of receiving a tower under the SMIS program, and Panel C reports the IV-2SLS estimates where we instrument mobile phone coverage using treatment status under the SMIS program. The data is computed using the branch-level Basic Statistical Return (BSR) maintained by the Reserve Bank of India (RBI) and the 2001 Population Census of India. Columns (1) reports the effects on average interest rate on agricultural loans; Column (2) reports the effects on the share of agricultural credit accounts classified as non-performing (NPA); Column (3) reports the effects on the share of agricultural credit classified as non-performing (NPA). 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 area in a cell that is covered by GSMA mobile coverage. 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 (log) total population, power supply and ruggedness. Other controls include educational facilities. All controls are at baseline from the 2001 Population & Village Census and are interacted with year fixed effects. All specifications include state-year fixed effects. Standard errors are clustered at the sub-district level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

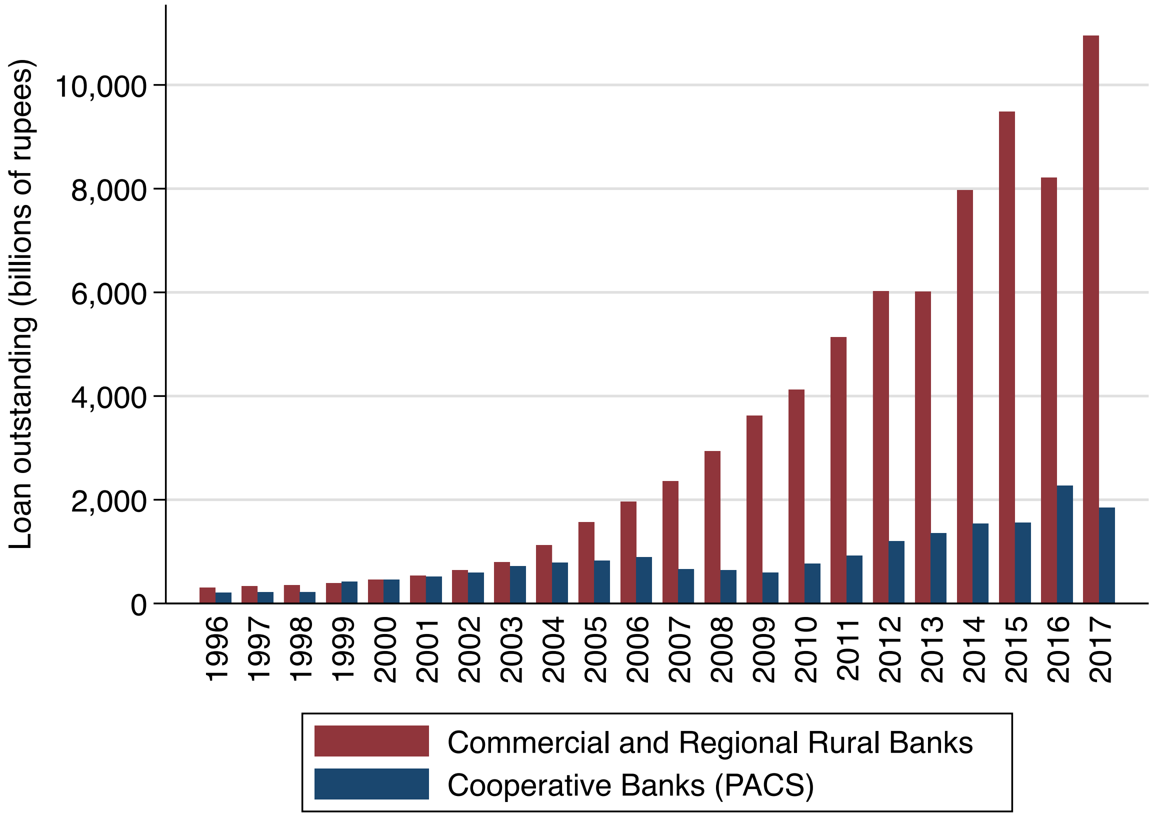
Table 9: Heterogeneous Effects by Language

	# of calls per 1000 farmers			Accounts per farmer	Credit per farmer	Share of farmers with	PACS credit per farmer
	All calls	Credit calls	Gov credit calls	in BSR	in BSR	PACS credit in AIS	in AIS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Tower × Post × 1(non-majority NS Speakers)	6.763*	0.685***	0.573***	0.007	1493.654**	0.019***	284.447**
	(3.693)	(0.210)	(0.174)	(0.005)	(720.602)	(0.007)	(129.801)
Tower × Post × 1(majority NS Speakers)	-8.984	0.006	0.040	-0.007	-1155.934	-0.002	-248.435
	(6.590)	(0.312)	(0.255)	(0.013)	(1592.769)	(0.012)	(249.986)
p-value (diff.)	0.01	0.01	0.02	0.26	0.08	0.07	0.02
N	28,931	28,931	28,931	28,931	28,931	28,931	28,931
Cell FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Baseline controls × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Other controls × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Agriculture × Tower × Post	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Distance to town × Tower × Post	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Nightlights (2006) × Tower × Post	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Share SC × Tower × Post	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Agri. Market Comp. × Tower × Post	Yes	Yes	Yes	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 calls to Kisan Call Center, credit take-up and credit outstanding per farmer. The data is computed using the branch-level Basic Statistical Return (BSR) maintained by the Reserve Bank of India (RBI), Agricultural Input Survey (AIS) and the 2001 Population Census of India. We divide the number of farmers with credit (from the BSR data and AIS data) by the number of farmers found in a cell (from the 2001 Population Census) to obtain the share of farmers with bank credit and PACS credit, respectively. We divide the agricultural credit in a cell (from the BSR data and AIS data) by the number of farmers found in a cell (from the 2001 Population Census) to obtain the bank credit per farmer in rupees and PACS credit per farmers in rupees, respectively. 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. 1(non-majority NS speakers) is a binary variable that takes the value of 1 if more than 50% of the population speaks one of the 22 official (scheduled) languages. 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 (log) total population, power supply and ruggedness. Other controls include share of agricultural work, share of irrigated land, availability of educational facilities, medical facilities, lending facilities, number of commercial banks, telephones per capita, distance to nearest town, nightlights intensity in 2006, share of scheduled caste, agricultural competition 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. All specifications include state-year fixed effects. All specifications also control for the following baseline characteristics interacted with (Tower × Post): agricultural work and share of irrigated land (agriculture), distance to nearest town, nightlights intensity in 2006, share of scheduled caste, and agricultural market competition. Baseline characteristics are standardized to have mean 0 and standard deviation 1. The dependent variables are winsorized at the 5% level. Standard errors are clustered at the sub-district level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

A Appendix Figures and Tables

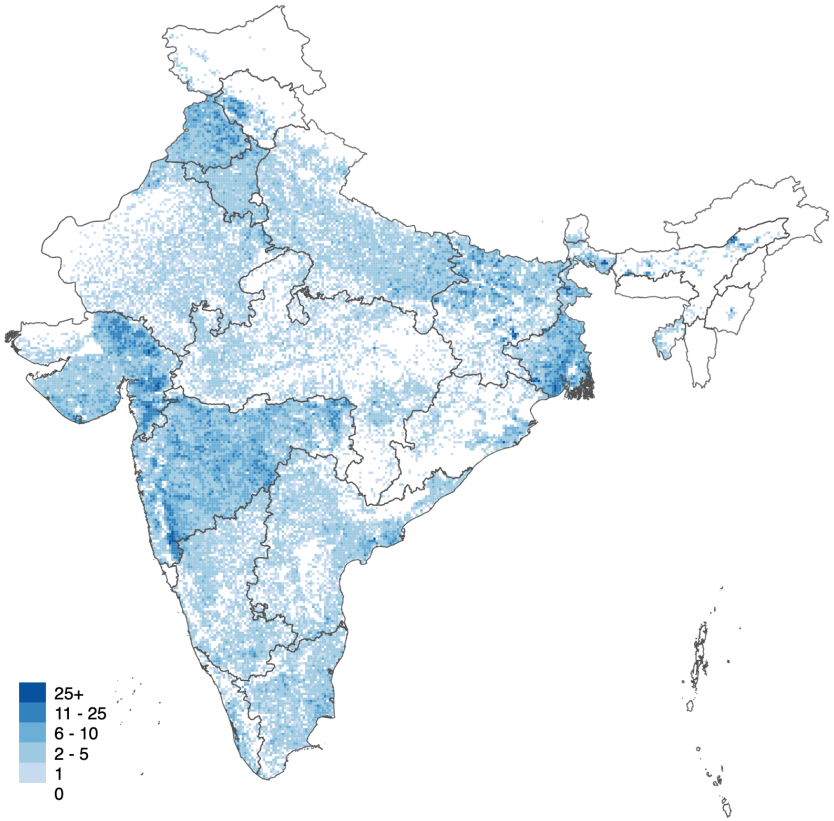
Figure A1: Aggregate Agricultural Credit by Lender Type



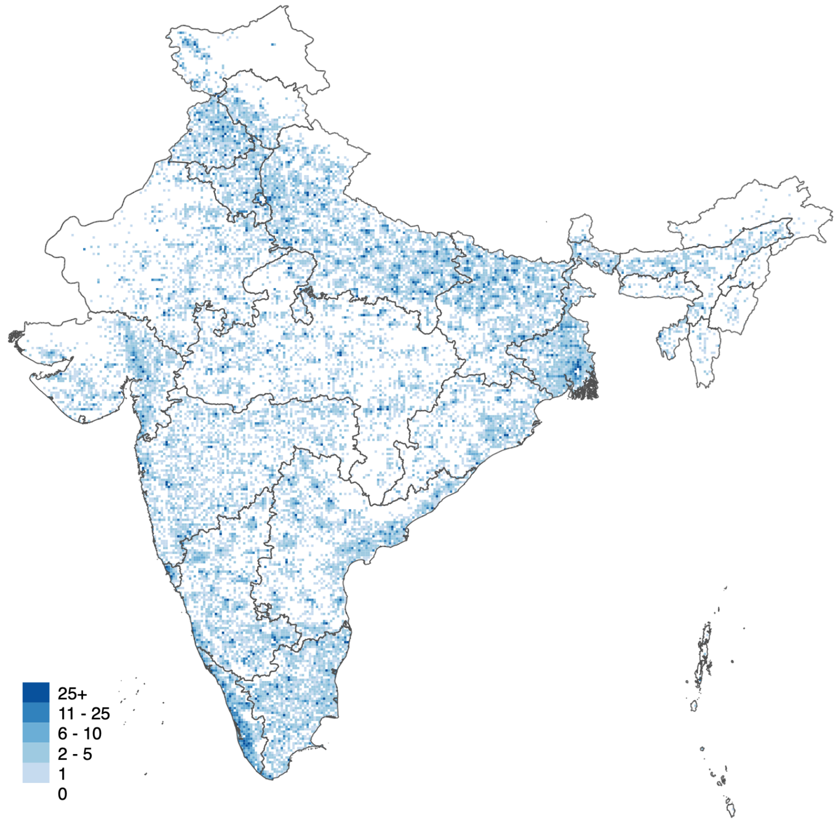
Notes: This figure shows aggregate agricultural credit by commercial and regional rural banks, and Primary Agricultural Credit Societies (PACS). Data is sourced from the Reserve Bank of India and the National Bank for Agriculture and Rural Development (NABARD).

Figure A2: Distribution of bank branches across India

(a) PACS

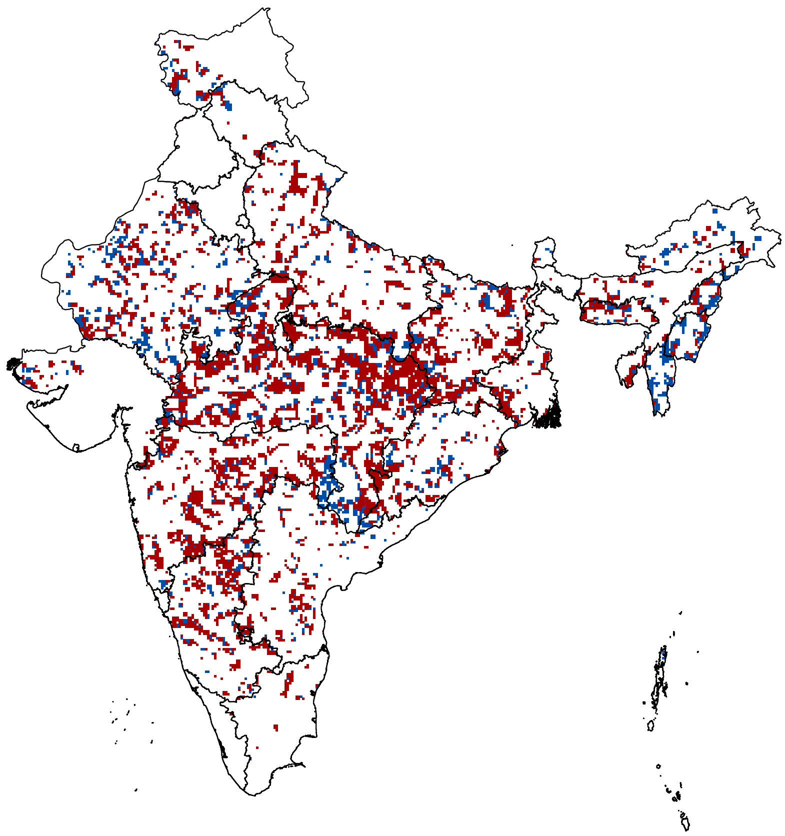


(b) Commercial and Regional Rural Banks



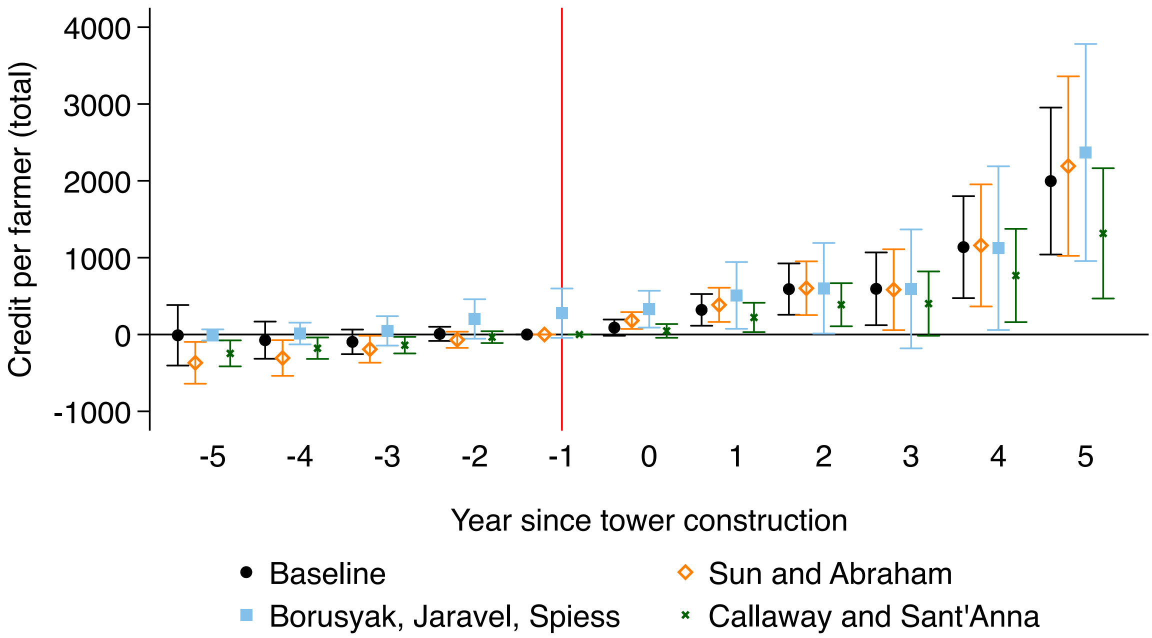
Notes: The figure plots the number of branches of Primary Agricultural Credit Societies (PACS) (panel a) and bank branches (panel b) across cells as reported in the year 2001. Information on PACS is obtained from the 2001 Census and information on commercial and rural bank branches comes from data from the Reserve Bank of India (RBI).

Figure A3: Treatment and Control cells under the SMIS Program



Notes: The figure shows the 8,426 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 A4: Robustness to alternative staggered event study estimators

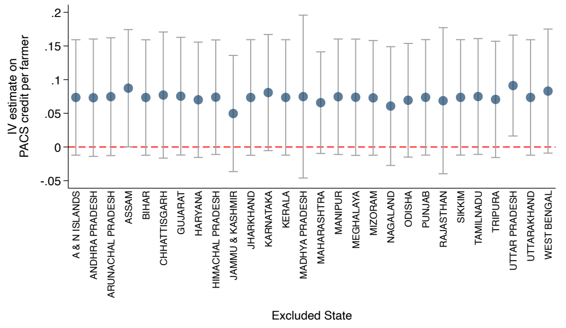


Notes: The figure test for the robustness of our estimates on bank credit per farmer using alternative estimators for staggered difference-in-differences research design proposed in the literature, including Sun and Abraham (2021); Borusyak et al. (2024); Callaway and Sant'Anna (2021). The baseline estimates using specification (3) are reported as black dots. The data is computed using the branch-level Basic Statistical Return (BSR) maintained by the Reserve Bank of India (RBI), Agricultural Input Survey (AIS) and the 2001 Population Census of India. We divide the agricultural credit in a cell (from the BSR data and AIS data) by the number of farmers found in a cell (from the 2001 Population Census) to obtain the bank credit per farmer in rupees and PACS credit per farmers in rupees, respectively. 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 (log) total population, power supply and ruggedness. Other controls include educational facilities. All controls are at baseline from the 2001 Population & Village Census and are interacted with year fixed effects. All specifications include state-year fixed effects, baseline controls-year fixed effects and other controls-year fixed effects. The dependent variables are winsorized at the 5% level. 95% confidence intervals represented by vertical bars.

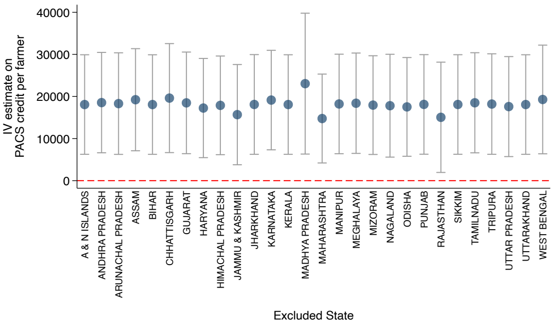
Figure A5: Robustness: Leave out one state at a time

A. Bank Credit (from BSR)

i. Share of farmers with bank credit

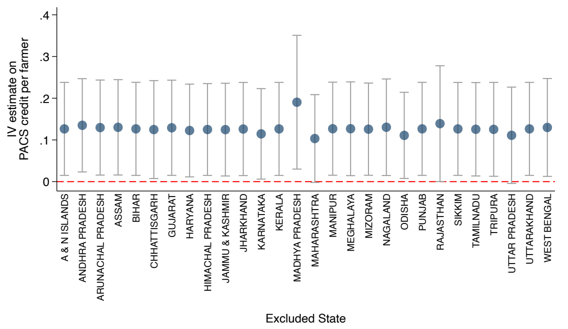


ii. Bank credit per farmer

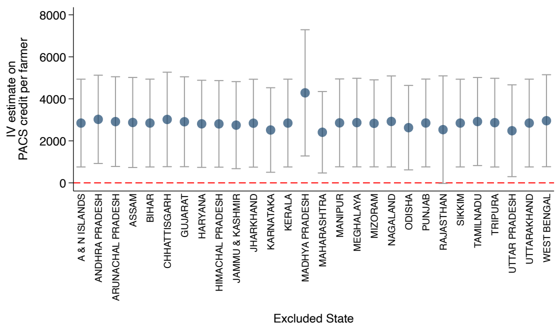


A. PACS Credit (from AIS)

i. Share of farmers with PACS credit



ii. PACS credit per farmer



Notes: The figure reports robustness of IV-2SLS estimates of receiving mobile phone coverage on our measure of credit take-up after excluding one-state at a time from our sample. Each estimate is plotted from a separate regression for the dependent variable of interest on instrumented GSMA coverage using treatment status under the SMIS program. The excluded state within each regression is specified as the label on the horizontal axis. The data is computed using the branch-level Basic Statistical Return (BSR) maintained by the Reserve Bank of India (RBI), Agricultural Input Survey (AIS) and the 2001 Population Census of India. We divide the number of farmers with credit (from the BSR data and AIS data) by the number of farmers found in a cell (from the 2001 Population Census) to obtain the share of farmers with bank credit and PACS credit, respectively. We divide the agricultural credit in a cell (from the BSR data and AIS data) by the number of farmers found in a cell (from the 2001 Population Census) to obtain the bank credit per farmer in rupees and PACS credit per farmers in rupees, respectively. 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 (log) total population, power supply and ruggedness. Other controls include educational facilities. All controls are at baseline from the 2001 Population & Village Census and are interacted with year fixed effects. All specifications include state-year fixed effects, baseline controls-year fixed effects and other controls-year fixed effects. The dependent variables are winsorized at the 5% level. 95% confidence intervals represented by vertical bars.

Appendix Tables

Table A1: Calls by Category

Category	Count	Percent (%)
Panel A: Calls by category		
Weather forecasts	7,547,599	34.76
Pest control	6,901,085	31.79
Seed varieties	1,645,715	7.58
Fertilizers	1,618,206	7.45
Agricultural practices	963,836	4.44
Market prices	836,518	3.85
Credit	751,744	3.46
Missing	678,040	3.12
Other	669,915	3.09
Irrigation	98,194	0.45
Total	21,710,852	100.00
Panel B: Credit calls (% of total credit calls)		
Government program-related credit calls	548,419	72.95
Non-government program-related credit calls	203,325	27.05
Total	751,744	100.00

Notes: The table shows the distribution of calls made to the Kisan Call Center across various categories of query types (Panel A). Panel B further decomposes the calls classified as credit related queries into (i) government program-related credit calls; and (ii) non-government program-related credit calls.

Table A2: Heterogeneity: By Maturity and Holding Size

	Short	Medium	Long
	(1)	(2)	(3)
Panel A: By Maturity			
Outcome: PACS credit per farmer in AIS			
Coverage	3152.3***	-80.6**	-21.8
	(1124.7)	(35.9)	(19.7)
	Small	Medium	Large
	(1)	(2)	(3)
Panel B: By Holding Size			
Outcome: Share of farmers with PACS credit in AIS			
Coverage	0.076*	0.037**	0.001
	(0.044)	(0.015)	(0.001)
Outcome: PACS credit per farmer in AIS			
Coverage	1420.2**	1263.1***	91.9**
	(698.8)	(452.5)	(41.7)
Observations	29,186	29,186	29,186
Number of cells	8,426	8,426	8,426
Cell FE	Yes	Yes	Yes
State × Year FE	Yes	Yes	Yes
Baseline controls × Year FE	Yes	Yes	Yes
Other controls × Year FE	Yes	Yes	Yes

Notes: This table reports the IV-2SLS effects of being included under the SMIS program on the share of farmers with PACS credit and PACS credit per farmer by loan maturity (Panel A) and by farmers' holding size (Panel B). 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. Coverage is the share of area in a cell that is covered by GSMA mobile coverage, instrumented with treatment status under the SMIS program. 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. For Panel A, 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. For Panel B, Column 1 presents results for Small holdings (<2 ha), Column 2 presents results for Medium holdings (2-10 ha), Column 3 presents results for large holdings (>10 ha). Baseline controls include (log) total population, power supply and ruggedness. Other controls educational facilities. All controls are at baseline from the 2001 Population & Village Census and are interacted with year fixed effects. All specifications include state-year fixed effects. Standard errors are clustered at the sub-district level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table A3: Kisan Credit Card: consumption versus investment borrowings

	KCC (consumption)		KCC (investment)	
	Accounts	Credit	Accounts	Credit
	(1)	(2)	(3)	(4)
Coverage (2011)	0.00570**	1,751**	-5.92e-05	-47.29
	(0.00279)	(801.3)	(0.000195)	(58.91)
Observations	8,340	8,340	8,340	8,340
Number of cells	24	24	24	24
Cell FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Baseline controls	Yes	Yes	Yes	Yes
Other controls	Yes	Yes	Yes	Yes

Notes: This table reports the IV-2SLS effects of mobile phone coverage on share of farmers with Kisan Credit Card accounts and credit per farmer through Kisan Credit Card, decomposing the borrowing into borrowings classified as consumption purposes versus investment purposes. Coverage is the share of area in a cell that is covered by GSMA mobile coverage in 2011 instrumented using whether the cell received a cellphone tower under the SMIS program. 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 (log) total population, power supply and ruggedness. Other controls include educational facilities. All controls are at baseline from the 2001 Population & Village Census. All specifications include state fixed effects. The dependent variables are winsorized at the 5% level. Standard errors are clustered at the sub-district level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table A4: Heterogeneous treatment effects by Income Volatility in the region

	Accounts per farmer(BSR)	Credit per farmer (BSR)	Accounts per farmer(PACS)	Credit per farmer (PACS)
	(1)	(2)	(3)	(4)
Tower × Post × 1(High agricultural volatility)	0.011**	2128.055***	0.011	266.489**
	(0.005)	(780.518)	(0.007)	(124.967)
Tower × Post × 1(Low agricultural volatility)	-0.001	872.436	0.009	168.006
	(0.005)	(631.203)	(0.006)	(118.463)
p-value (diff.)	0.09	0.18	0.89	0.57
N	27,890	27,890	27,890	27,890
Baseline controls × Year FE	Yes	Yes	Yes	Yes
Other controls × Year FE	Yes	Yes	Yes	Yes
Cell FE	Yes	Yes	Yes	Yes
State × Year FE	Yes	Yes	Yes	Yes

Notes: This table reports the reduced-form heterogeneous treatment effects of receiving SMIS cell tower on credit take-up and credit outstanding per farmer by agricultural volatility of the region. All variable definitions are the same as in Table 6. 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 2007. To capture agricultural income volatility at cell level we use the standard deviation of agricultural yields. We proxy agricultural yields using the intra-annual change in NDVI (Normalized Difference Vegetation Index), an index of intensity of vegetation cover estimated using satellite images. We defined areas exposed to "high" agricultural income volatility as those with above median standard deviation of the agricultural income measure across years (1(high agricultural volatility)). The table reports the p-value on the difference between high vs low areas. 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 (log) total population, power supply and ruggedness. Other controls include share of educational facilities. All controls are at baseline from the 2001 Population & Village Census and are interacted with year fixed effects. All specifications include state-year fixed effects. The dependent variables are winsorized at the 5% level. Standard errors are clustered at the sub-district level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table A5: Heterogeneous treatment effects by Weather Shocks

	Accounts per farmer(BSR)	Credit per farmer (BSR)	Accounts per farmer(PACS)	Credit per farmer (PACS)
	(1)	(2)	(3)	(4)
Tower × Post × 1(Low Precipitation)$_{t-1}$	0.008*	2080.544***	0.009	215.315**
	(0.005)	(707.845)	(0.006)	(108.498)
Tower × Post × 1(High Precipitation)$_{t-1}$	0.003	717.707*	0.015**	263.796**
	(0.004)	(417.352)	(0.006)	(103.318)
p-value (diff.)	0.41	0.06	0.43	0.72
N	29,186	29,186	29,186	29,186
Baseline controls × Year FE	Yes	Yes	Yes	Yes
Other controls × Year FE	Yes	Yes	Yes	Yes
Cell FE	Yes	Yes	Yes	Yes
State × Year FE	Yes	Yes	Yes	Yes

Notes: This table reports the reduced-form heterogeneous treatment effects of receiving SMIS cell tower on credit take-up and credit outstanding per farmer in response to weather-induced agricultural shocks. All variable definitions are the same as in Table 6. 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 2007. We capture negative shocks as low rainfall years in a given cell using data from the Global Precipitation Climatology Centre (GPCC). We calculate rainfall z-scores for each cell by subtracting the area's average rainfall from its current value and dividing by its standard deviation. Cell-years with positive z-scores (above their historical mean) are classified as high-precipitation, while those with negative or zero z-scores are classified as low-precipitation. The table reports the p-value on the difference between areas the received a high precipitation versus low precipitation. 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 (log) total population, power supply and ruggedness. Other controls include share of educational facilities. All controls are at baseline from the 2001 Population & Village Census and are interacted with year fixed effects. All specifications include state-year fixed effects. The dependent variables are winsorized at the 5% level. Standard errors are clustered at the sub-district level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table A6: Robustness: Conley Standard Errors

	# of calls per 1000 farmers			Accounts per farmer	Credit per farmer	Share of farmers with	PACS credit per farmer
	All calls	Credit calls	Gov credit calls	in BSR	in BSR	PACS credit in AIS	in AIS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Coverage	89.135	4.686	3.748	0.074	18,087.9	0.126	2,846.0
Standard Errors clustered at the sub-district level (Baseline)	[34.284]***	[1.860]**	[1.533]**	[0.044]*	[6,033.7]***	[0.057]**	[1,066.3]***
Spatial Correlation, threshold: 50 km	[29.405]***	[1.687]***	[1.403]***	[0.029]**	[3,755.6]***	[0.039]***	[723.9]***
Spatial Correlation, threshold: 150 km	[35.764]**	[1.772]***	[1.473]**	[0.030]**	[4,139.6]***	[0.038]***	[711.8]***
Spatial Correlation, threshold: 300 km	[37.731]**	[1.867]**	[1.560]**	[0.030]**	[4,380.5]***	[0.038]***	[724.0]***
Spatial Correlation, threshold: 500 km	[39.739]**	[2.081]**	[1.750]**	[0.031]**	[4,519.8]***	[0.036]***	[644.4]***
N	28,931	28,931	28,931	28,931	28,931	28,931	28,931
Baseline controls × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Other controls × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cell FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table reports the IV-2SLS results for alternative spatial clustering across cells. All definitions and specifications are the same as in Table 5 and Table 6. 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. 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 (log) total population, power supply and ruggedness. Other controls include share of educational facilities. All controls are at baseline from the 2001 Population & Village Census and are interacted with year fixed effects. All specifications include state-year fixed effects. The dependent variables are winsorized at the 5% level. Standard errors are clustered at the sub-district level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table A7: Testing for Spillovers

	Δ Accounts per farmer(BSR)			Δ Credit per farmer(BSR)		
	(1)	(2)	(3)	(4)	(5)	(6)
1(Tower)	0.0088**	0.0091***	0.0182**	1856.3630***	1901.5454***	3461.9783***
	(0.0041)	(0.0035)	(0.0079)	(552.9109)	(474.2499)	(1103.5734)
Share treated$_{ids}$		-0.0019			-272.7488	
		(0.0080)			(1161.8248)	
1(Tower) $\times$ Share treated$_{ids}$			-0.0070			-1,140.688
			(0.0088)			(1304.4493)
(1-1(Tower)) $\times$ Share treated$_{ids}$			0.0127			2254.5524
			(0.0130)			(1850.0347)
Observations	7,411	7,411	7,411	7,411	7,411	7,411
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Baseline controls	Yes	Yes	Yes	Yes	Yes	Yes
Other controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table reports heterogeneous spillover effects on both treated and control groups, following the approach in Berg et al. (2021). Share treated$_{id}$ is defined as the share of treated cells within the same sub-district d, excluding the treatment status of the focal cell i. Tower is a binary indicator which equals 1 when a cell received a tower under the SMIS program. 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 (log) total population, power supply and ruggedness. Other controls include educational facilities. All controls are at baseline from the 2001 Population & Village Census. All specifications include state-year fixed effects. Standard errors are clustered at the sub-district level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table A8: Robustness to different decay parameters values

	Accounts per farmer in BSR (1)	Credit per farmer in BSR (2)	KCC Accounts per farmer in BSR (3)	KCC Credit per farmer in BSR (4)
Panel A: Decay parameter = 0.8 (Baseline)				
Coverage	0.074*	18087.925***	0.006**	1809.444**
	(0.044)	(6033.697)	(0.003)	(854.386)
Panel B: Decay parameter = 0.7				
Coverage	0.078*	18650.708***	0.006*	1841.549**
	(0.044)	(6108.125)	(0.003)	(871.959)
Panel C: Decay parameter = 0.6				
Coverage	0.082*	19099.561***	0.006*	1873.548**
	(0.044)	(6197.870)	(0.003)	(888.153)
Panel D: Decay parameter = 0.5				
Coverage	0.086*	19502.029***	0.006*	1903.469**
	(0.045)	(6286.941)	(0.003)	(903.315)
Panel E: Decay parameter = 0.4				
Coverage	0.089**	19835.307***	0.006*	1925.903**
	(0.045)	(6365.600)	(0.003)	(915.695)
Observations	29,186	29,186	8,340	8,340
Number of cells	8,426	8,426	8,340	8,340
Cell FE	Yes	Yes	No	No
State (× Year) FE	Yes	Yes	Yes	Yes
Baseline controls (× Year) FE	Yes	Yes	Yes	Yes
Other controls (× Year) FE	Yes	Yes	Yes	Yes

Notes: This table reports the IV-2SLS results for alternative decay parameters. All definitions and specifications are the same as in Table 6 and Table 7. 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 (log) total population, power supply and ruggedness. Other controls include share of educational facilities. All controls are at baseline from the 2001 Population & Village Census. In column 1 and column 2, all controls are interacted with year fixed effects. Column 1 and 2 include state-year fixed effects. Column 3 and 4 include all controls and state fixed effects. The dependent variables are winsorized at the 5% level. Standard errors are clustered at the sub-district level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

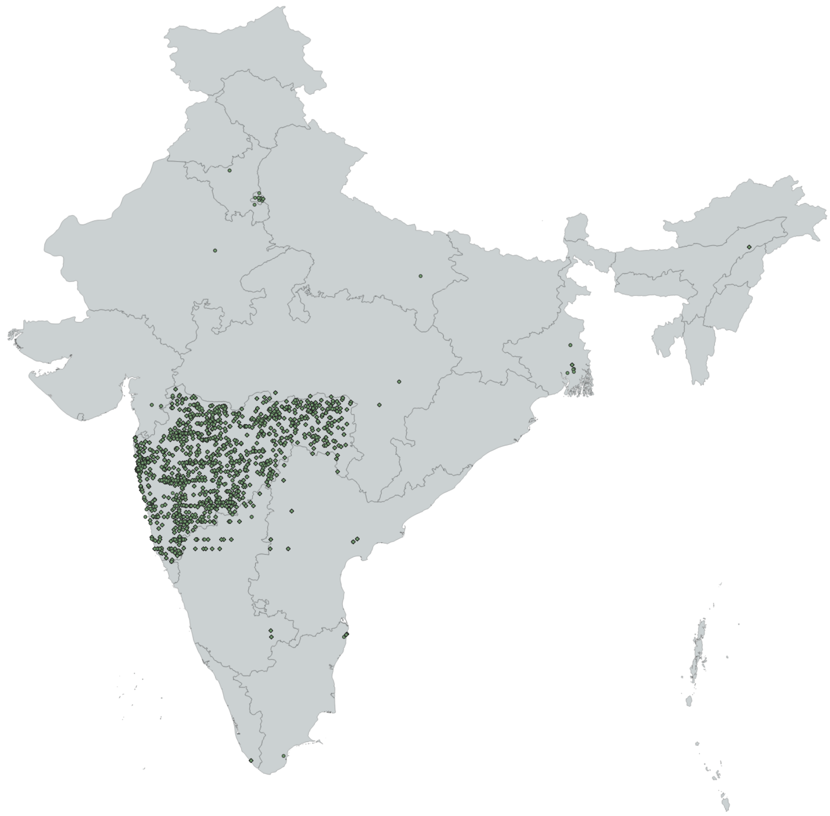
B Appendix: Bank Branch Location and Credit Allocation

B.1 Validating data on bank branch location via Google Maps API

According to data from the bank-branch location data maintained by the Reserve Bank of India (RBI), there are 164,192 branches of commercial banks and rural regional banks in India. The data reports geographical coordinates for 143,889 branches, and address information for 135,690 branches. For each of the 164,192 bank branches, the data reports either its coordinates or its address, or both.

We first assess the accuracy of bank-branch coordinates by comparing them to their corresponding addresses in the data. We find that several branch coordinates are located in states different from those reported in their addresses. For instance, Figure B1 plots the coordinates of all bank branches in the data that should be in Maharashtra according to their addresses in the data. As shown, several branches with address in Maharashtra have geographical coordinates in other states.

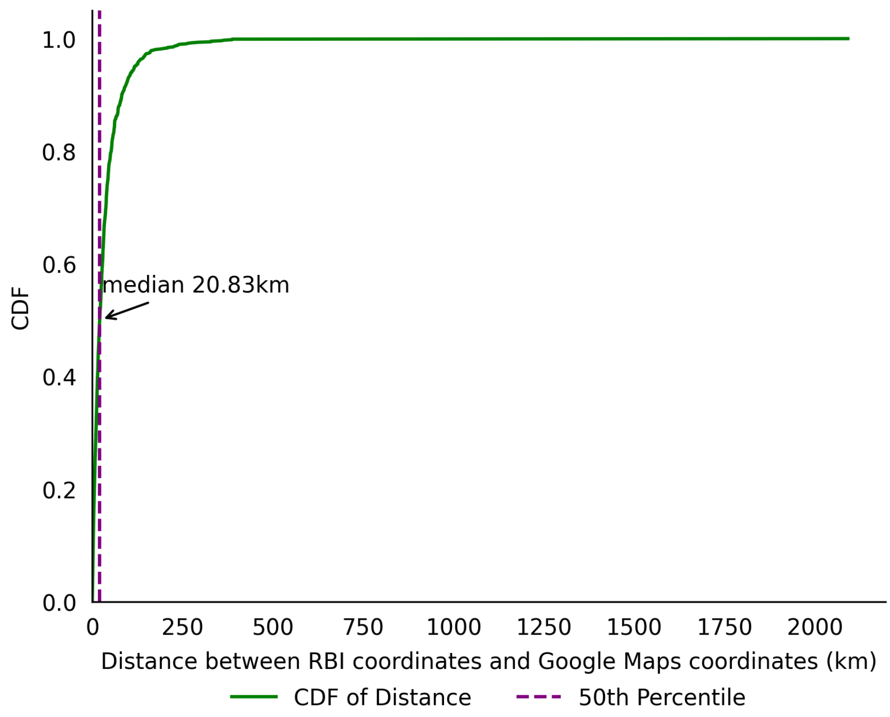
Figure B1: Bank branches with addresses in Maharashtra



Notes: The figure plots coordinates of all bank branches that *should* be located in Maharashtra based on their addresses in the bank-branch location data.

To further evaluate the accuracy of these coordinates, we test a 1% random sample of bank branch coordinates by entering their addresses into the Google Maps Places API. After obtaining an additional set of coordinates from Google Maps, we calculate the distance between the coordinates in the data and Google Maps coordinates. We find the two sources are relatively consistent for half of the observations – the median distance is 20.83 km, as shown in Figure B2. However, the disagreement can be substantial for certain branch locations, with a maximum distance of 2,082.39 km.

Figure B2: Distance between coordinates in the bank-branch location data and Google Maps coordinates based on a random sample



Notes: The figure shows the cumulative distribution function of the distance between bank branches' coordinates and their Google Maps coordinates acquired from Google Places API by entering bank branches' addresses.

Given the inaccuracy of the coordinates in the bank-branch location data, we use the Google Maps Places API to obtain more accurate coordinates for all bank branches reported in that dataset. Specifically query the Google Maps Places API in the following steps:

1. If the address in the bank address data contains a PIN (Postal Index Number) code, we create the query string by concatenating the state, district, bank name, branch name, and PIN code

   For example, we observe the following information in bank-branch location address dataset for a bank branch:

   - State: ANDHRA PRADESH
   - District: SRIKAKULAM
   - Bank: STATE BANK OF INDIA
   - Branch: AMADALAVALASA
   - Address: WARD NO.8, MAIN ROAD, AMADALAVALASA, AMADALAVALASA, 532185

We extract the PIN code from the street address in the branch location data, and create the query string as follows: "Bank + Branch + District + State + Pincode + India" – in this case "STATE BANK OF INDIA, AMADALAVALASA branch, SRIKAKULAM district, ANDHRA PRADESH, 532185 India".

2. If the street address reported in the branch location data does not contain a PIN code, or if the query string does not return any results from the Places API, we use a concatenation of "Bank + Branch + District + State + Address + India " as the query string, for example, "STATE BANK OF INDIA, AMADALAVALASA branch, SRIKAKULAM district, ANDHRA PRADESH, WARD NO.8, MAIN ROAD, India".[25]

3. If the address reported in the branch location data lacks a PIN code or provides no additional details beyond the state, district, and bank branch, or if the previous queries return no results, we use the concatenation of "Bank + Branch + District + State + India" as the query string, for instance, "STATE BANK OF INDIA, AMADALAVALASA branch, SRIKAKULAM district, ANDHRA PRADESH, India".

Using this procedure, we are able to identify the geo-location of 135,186 branches from Google Maps Places API out of a total of 135,690 branches with address information. Of these, 95.2% of Google Maps coordinates are classified as "bank" by Google Maps Places API[26]. 96.8% match the state and district in the addresses in the bank address dataset. 84.1% match the exact bank names in the addresses in the bank address dataset. 75.1% match the exact PIN code in the addresses in the bank address dataset.[27].

[25]We remove locality names that are already in bank name, branch name, districts, or states from street address to avoid duplication. In the above example ,"AMADALAVALASA" appear both in the street address and the branch name. We remove the duplicated "AMADALAVALASA" and simplify the input to "STATE BANK OF INDIA, AMADALAVALASA branch, SRIKAKULAM district, ANDHRA PRADESH, *WARD NO.8, MAIN ROAD*, India". This prevents overly long query strings and reduces the chance of generating noisy search results.

[26]This is from the "type" field of the Google Maps Places API response. Other non-bank types in of queried results include "atm", "finance", "locality", "point of interest", etc.

[27]We consider these three metrics lower-bounds since there have been changes in PIN code, bank names, and state – district boundaries over time. For example, five banks were merged with the State Bank of India in 2017, and the metric of matching on bank names does not adjust for mergers and acquisitions over time (see *The Economic Times* report on Feb 24, 2017).

Table B1: Identifying Branch Locations using Google Maps API

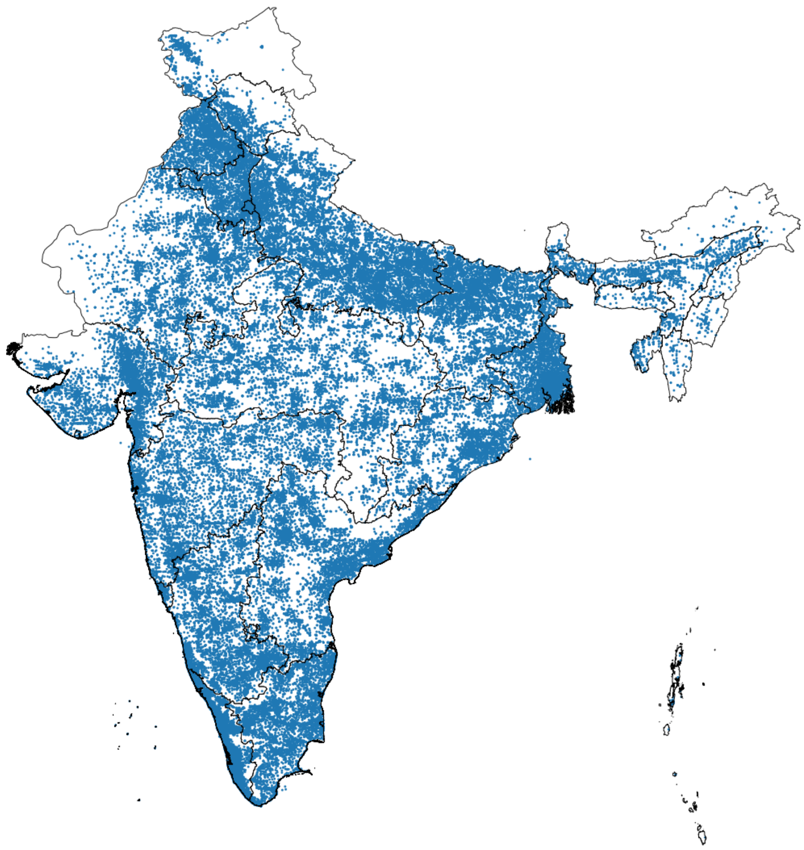
	(1) N inputs	(2) N found	(3) % GMaps inputs	(4) % total branches
Concatenation + Pincode	104,334	92,187	67.9	56.2
Concatenation + Address	37,417	23,387	17.2	14.2
Concatenation	20,116	19,612	14.5	11.9
Subtotal		135,186		82.3
N not in GMaps & in bank-branch location dataset		400		0.2
N not in GMaps & *not* in bank-branch location dataset		104		0.1
N no addresses & in bank-branch location dataset		28,502		17.4
Subtotal		164,192		100

Notes: This table lists the number of Google Maps inputs for each step outlined in the text (column 1), the number of branches found in Google Maps (column 2), the percent of branches found in Google Maps out of the number of input in each step (column 3), and the percent of branches found in Google Maps out of a total number of 164,192 branches (column 4). The term "concatenation" in the row-names refers to "Bank + Branch + District + State + India".

For branches we could not locate on Google Maps or lacked address information (17.4% of total branches), as well as a small number of branches whose Google Maps coordinates do not match the state and district of the address reported in the branch location data (1.2% of total branches), we use the *median* coordinates in that data. In this way, we obtain geo-locations of 164,088 branches[28]. Figure B3 plots the distribution of a universe of 164,088 bank branches in India after applying the Google Maps correction.

[28]The total number of branches in the union of branch location data and branch address dataset is 164,192. We are unable to locate 104 branches using either those data or Google Maps. These branches do not have coordinates information in the location dataset. Although they are present in the the address dataset, our queries to Google Maps Places API do not yield any result for these branches.

Figure B3: Geographical distribution of bank branches in the location dataset

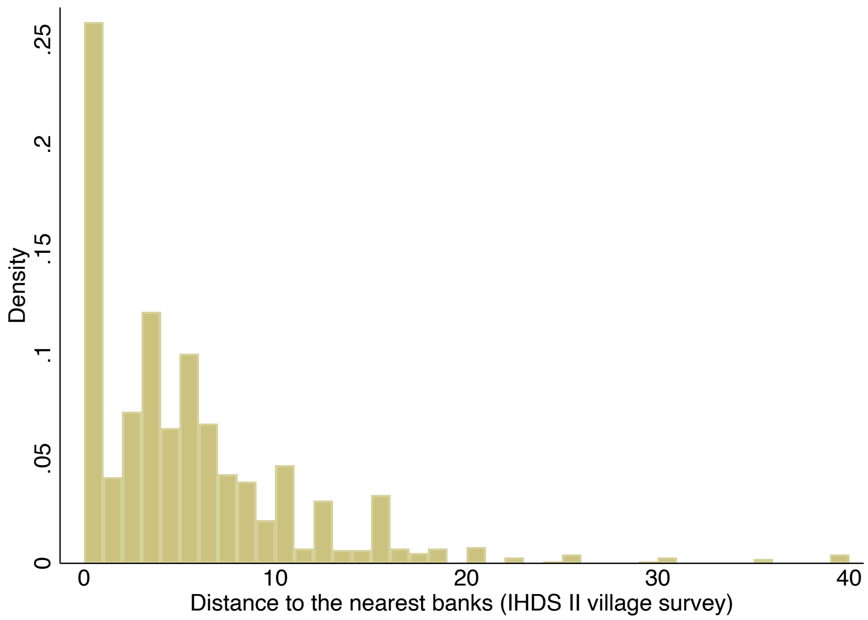


Notes: The figure plots the corrected bank branch locations after using the Google Maps Places API methodology described in Appendix B. The total number of branches is 164,088. The data covers branches of commercial banks and regional rural banks.

B.2 Allocation of bank credit to cells

The BSR data has 127,395 unique branches, out of which we have coordinates for 127,327. Recall that the BSR data does not report the location of borrowers. According to the second round of the Indian Human Development Survey (IHDS II)[29], the mean and median distance that people travel to reach the nearest bank branch in India are 5.09km and 4km, respectively, and the maximum distance is 40km. We expect the average distances to be higher in more rural areas.

Figure B4: Nearest distance to bank branches in IHDS II village survey

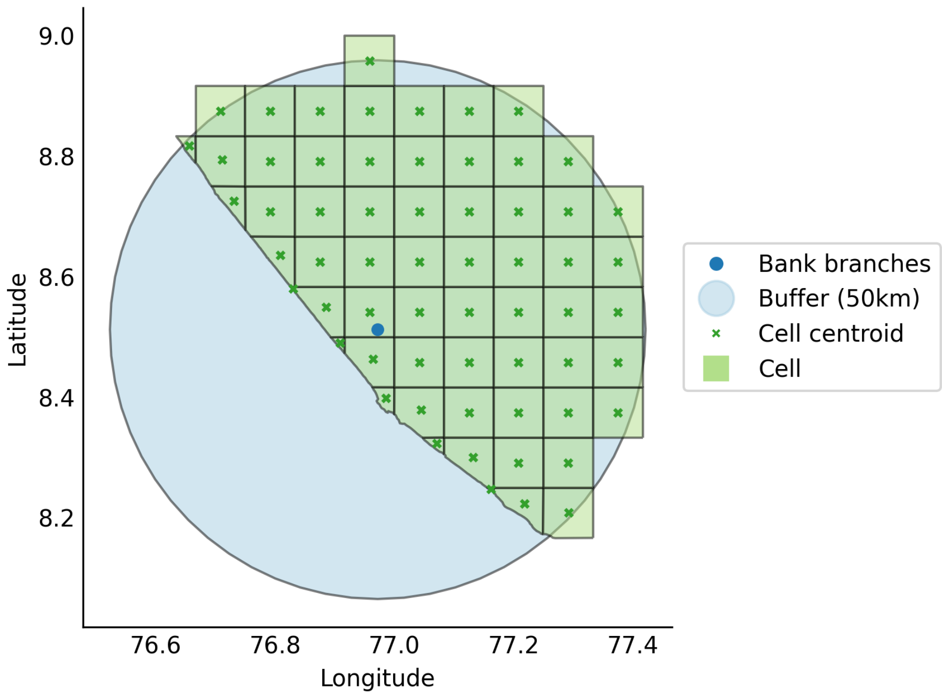


Notes: The figure shows the distribution of distance to the nearest bank branch in the Village Survey of IHDS II. The number of observations is 1,408.

To allocate credit originated by a given bank branch to the nearby areas we assume a 50 km catchment area of each bank branch. Specifically, for each branch, we identify all cells whose centroids are located within a 50 km Euclidean distance from the location of a given branch. Figure B5 provides an example of a bank branch located along the shoreline and its nearby cells.

[29] Available on IHDS website.

Figure B5: An example of a bank branch and its nearby cells



Notes: The figure illustrates the location of an example bank branch (blue dot) and its nearby cells (green squares). Nearby cells are defined as those with centroids falling within a 50 km Euclidean radius of the branch.

As the probability of traveling to farther bank branches decreases with distance, we use a polynomial decay function to assign more weight to the nearest cells. The decay function is defined as follows:

$$f(x) = \alpha \frac{1}{(x+1)^{\gamma}}, \quad \gamma > 0 \tag{7}$$

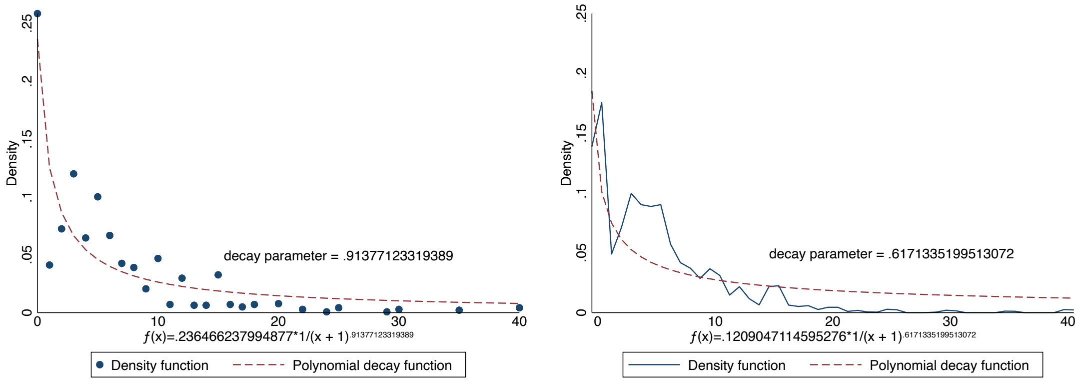
where x is the distance from the bank branch to the cell and γ is the decay rate.

We use the distribution of nearest distance to banks in Figure B4 to estimate the decay rate γ in Equation (7). The fitted polynomial decay function is shown in Figure B6a and B6b.

Figure B6: Estimates of the decay parameter

(a) Histogram density

(b) Kernel density



Notes: The figure shows the estimated decay parameter by fitting the polynomial decay function in Equation (7) to the density function of the distance to the nearest bank branch in the IHDS II Village Survey. Figure B6a fits the polynomial decay function to the density function in Figure B4. Figure B6b uses a kernel density function with Epanechnikov kernel and bandwidth equals to 1 to fit the polynomial decay function.

Finally, we use the following equation to allocate credit to nearby cells. The weights are increasing in the share of farmers in a given cell out of all farmers in the catchment area and decreasing in the distance between the cell and the bank branch as follows:

$$y_{ij} = \frac{N\_Farmers_i \, (d_{ij}+1)^{-\gamma}}{\sum_{k:d_{kj}\leq 50\text{km}} N\_Farmers_k \, (d_{kj}+1)^{-\gamma}} \cdot y_j \tag{8}$$

where y_{ij} is the credit allocated to cell i from bank branch j. $N\_Farmers_i$ is the number of farmers in cell i. d_{ij} is the distance between cell i's centroid and branch j. y_j is the total credit originated by branch j. The denominator normalizes the weights so that the sum of credits allocated to each nearby cells equals y_j.