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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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, governments have intervened in rural credit markets with policies that mandate banks to target a fixed share of their portfolios to agriculture, typically at subsidized rates (Besley, 1994).[1] While these initiatives have expanded the supply of credit to farmers, evidence suggests that many targeted individuals remain unaware of the existence of such programs or lack information about eligibility criteria, application procedures, or loan terms offered.[2] 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 government credit programs affects their take-up among farmers. 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 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] For example, India mandates banks to allocate at least 18% of credit to agriculture, while Brazil requires commercial banks to allocate at least 30% of demand deposits to rural credit.

[2] 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. At the launch of the program in 2007, the Department of Telecommunications identified an initial list of potential tower locations, all situated in rural areas without mobile phone coverage at the time. Our identification strategy compares locations where phone towers were proposed and eventually constructed (treatment group), with locations where phone towers were also proposed but eventually not constructed (control group). Towers in the control group were canceled or relocated after on-site assessments, 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 reflects greater participation in government credit programs that farmers inquire about when calling agricultural advice centers. Notably, 80% of the increase in credit-related calls to Kisan Call Centers concerns such programs, including Kisan Credit Cards. In line with this, the SMIS-driven expansion of mobile coverage resulted in 2.7 additional Kisan Credit Card accounts per 1,000 farmers and an average increase in borrowing of 810 Rupees per farmer for a one standard deviation rise in coverage.[3] By contrast, we find no significant effect on standard agricultural loans, indicating that the overall increase in borrowing is concentrated in Kisan Credit Cards – consistent with a mechanism in which improved access to program-specific information plays an important role.

To better understand the nature of this increase in borrowing, we examine how Kisan Credit Card loans are used. These loans may finance either consumption or investment, and the BSR data allow 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 implied by our estimates. The IV results suggest that each call to Kisan Call Centers corresponds to 0.8 additional farmers gaining access to credit from commercial and regional rural banks. Focusing on the elasticity of access to government credit programs with respect to program-related calls, the estimates imply that each such call is associated with 1.8 additional Kisan Credit Card accounts. While callers actively seek information when contacting Kisan Call Centers – and are therefore likely to act on it – these magnitudes also suggest that

[3] 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.

information diffuses from callers to non-callers. Several features of our setting may help explain this pattern, as both the expansion of mobile coverage and the characteristics of callers favor broad diffusion of information. First, mobile coverage in treated areas likely facilitates not only transmission to callers' immediate contacts but also wider, indirect diffusion through second- or third-degree ties by lowering communication costs across the network. Second, diffusion is further reinforced by the central position of callers within local networks: survey evidence shows that they are positively selected on education (Gandhi and Johnson, 2017), and prior research shows that more educated farmers are both more connected (Varshney et al., 2022) and more effective at seeding information within communities (Banerjee et al., 2024).

Finally, we discuss potential mechanisms behind the results. Mobile phone towers installed under the SMIS program may alleviate information frictions, thereby facilitating the uptake of interest-subsidized loans offered through government credit programs. An alternative 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 without a 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 that, after the construction of the first SMIS tower in a location, calls to Kisan Call Centers increase faster in areas where the majority of the local population speaks the same language as call centers' agronomists. In addition, 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.

Finally, while we cannot fully separate the effect of information about credit programs from other types of information – such as guidance on seeds, fertilizers, or irrigation – that farmers receive via Kisan Call Centers, the composition of borrowing offers some indications. In particular, the increase in borrowing via Kisan Credit Cards is concentrated in consumption loans rather than investment loans. The latter are typically used to finance input purchases and more directly reflect changes in production practices. We interpret this pattern as suggestive of an effect operating through farmers accessing information about credit programs rather than changing their production practices.

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, 7,871 sites across 500 districts were identified as potential tower locations. Villages or clusters of villages with at least 2,000 inhabitants and lacking mobile signal were prioritized. Of the total sites identified, 7,353 towers were eventually constructed. A second Phase was planned to extend coverage to even more sparsely populated regions, but it was never implemented.

We obtained data on SMIS tower deployment from the Center for Development of Telematics (C-DoT) - the consulting arm of the Department of Telecommunications of India. The dataset includes the geographical coordinates of both the originally proposed and the effectively constructed towers, as well as the operational date of each one (which we refer to as the construction date for simplicity). Among the towers confirmed as constructed, we exclude 350 for which the construction date is missing, leaving 7,003 towers for our empirical analysis. Figure 1 displays the monthly rollout pattern. Construction activity effectively began in January 2008 and concluded in May 2010, with the majority of towers becoming operational 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

[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).

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 comes from the Kisan Call Centers initiative. This program, launched by the Indian Ministry of Agriculture in the mid-2000s, established a nationwide network of 21 facilities offering free agricultural advice to farmers via landline or mobile phone. Each call is handled by a trained agronomist, who tailors recommendations to the agroclimatic conditions of the caller's region. These facilities serve farmers across all Indian states.

Call records from the Kisan Call Centers are compiled by the Department of Agriculture and are publicly available on the Open Government Data (OGD) Platform of India starting from 2006.[8] Panel (a) of Figure 3 shows the annual volume of calls between 2006 and 2017. Fewer than 1,000 calls were received annually in the early years following the program's introduction; by 2012, the figure had grown to roughly 1 million per year, reaching approximately 4.5 million by 2017. In total, the dataset contains 21,710,852 calls over the period 2006-2017.

While the dataset does not include verbatim transcripts of conversations between farmers and advisors, it does provide short summaries of call topics as recorded by the Kisan Call Centers staff. We use these summaries to categorize calls into nine groups. Panel (b) of Figure 3 and Table A1 present the distribution across categories. The most frequent inquiries concern weather forecasts (35%) and pest management (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, call descriptions do not mention the specific program the farmer is asking about, as advisors often record it simply as a "government program". We believe that these calls primarily concern the Kisan Credit Card program, both because it is the main government credit program for farmers and because, when a program is named explicitly, it is most often the Kisan Credit Card. We describe the Kisan Credit

[7] We use Gridded Population of the World, Version 4 data, assuming uniform population density within each 10×10 km cell. For each cell and year, we combine population with data on the share of area under mobile phone coverage to estimate the fraction of individuals reached by the signal, and then aggregate across cells to obtain national coverage..

[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.

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

The Basic Statistical Returns (BSR) dataset covers all branches of commercial banks and regional rural banks in India, which report to the Reserve Bank of India. 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 number of borrowing accounts, 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 years 2002 to 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]

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 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 maturity and size of the borrowers in hectares.

[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.

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 BSR is at the bank branch level. Due to numerous inconsistencies with their reported physical address, we re-compute the geographical coordinates of all bank branches using 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 on PACS from the AIS are reported at the district level, covering the universe of 524 districts in India. We map this information to the cell level by allocating agricultural credit originated by PACS in each district across its cells, in proportion to the share of PACS branches located in each cell. As shown in Figure A2, PACS branches are more widely distributed than commercial and regional rural banks. Data on the location of PACS branches is sourced from the Village Census. 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.

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.[12]

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

[12] 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).

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 for control cells. Column 2 reports the results of a regression of each cell-level initial characteristic (standardized) on the binary treatment indicator. Thus, point estimates can be interpreted as the conditional difference between treatment and control. 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 in column (2), treatment and control cells are balanced with respect to initial observable characteristics, including specialization in agriculture (agricultural employment share, percent of irrigated land, crop suitability and composition), access to agricultural markets,[13] rainfall volatility, both the level and pre-trends in local income as proxied by nightlights, and distance to the nearest town. 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 PACS, commercial banks, and regional rural banks. Treatment and control cells are further balanced in terms of the diffusion of ethnic and linguistic minorities, measured by the share of the population belonging to scheduled castes and by whether the majority speaks a first language other than the official state language. Finally, we examine political alignment by comparing vote shares for the two main parties – Bharatiya Janata Party (BJP) and Indian National Congress (INC) – in the 2004 national parliamentary elections, the last before SMIS, and again find no significant differences.

Beyond these baseline observables, it is also important to verify that SMIS tower placement was not systematically correlated with other major rural programs implemented in the same period. Such overlap could confound our estimates if, for example, areas prioritized for SMIS were also systematically prioritized for roads, electricity, or banking expansion. We therefore test for balance on the targeting rules of contemporaneous initiatives: the PMGSY road construction program, which targeted villages above population thresholds of 500 and 1,000 (Asher and Novosad, 2020; Agarwal et al., 2023); the RGGVY rural electrification program, which initially targeted 300-person villages and later extended to 100-person villages (Burlig and Preonas, 2024); the RBI's branch expansion policy,

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

which targeted districts below the national average population-to-branch ratio (Cramer, 2021; Young, 2018); and the farmer debt waiver program introduced during the global financial crisis (Giné and Kanz, 2018). As shown, treated and control cells do not differ significantly with respect to any of these criteria.

The multivariate regression results in column (3) confirm overall balance across treatment and control cells, with the F-test failing to reject the null that observables are jointly equal to zero. The only statistically significant difference is the presence of an education facility, which we control for in all specifications along with the baseline controls. In Section 3.4 below, we provide additional support for our identification strategy by showing event-study graphs that reveal no pre-existing trends in the main outcome variables prior to the introduction of SMIS towers.

3.2 First Stage

The first-stage regression estimates the effect of tower construction on mobile phone coverage in the sample of cells initially selected for SMIS. By design, all such cells had zero coverage in the baseline year 2007. Treated cells – those that received a tower – are therefore expected to experience larger increases in coverage after the program. Importantly, this effect is not purely mechanical: the outcome variable is the actual mobile coverage reported by Indian telecommunication companies to GSMA, rather than the predicted increase based on SMIS tower locations. This distinction matters because the tower construction program we use for identification was not the only factor driving changes in mobile coverage in India during this period.

Our first-stage regression is as follows:

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

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 described in the previous section. Baseline cell-level 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.[14]

Table 4 reports the first-stage results. Column (1) shows that cells with new SMIS towers experienced an 8-percentage-point larger increase in land covered by mobile signal after the program, relative to the control group. The magnitude of the estimate remains virtually unchanged when adding cell controls interacted with year fixed effects in column (2), consistent with the overall balance in observables between treated and control cells. The Kleibergen-Paap first-stage F-statistic is 54.5, which is above conventional thresholds for weak instruments.

To further illustrate these first-stage results, we exploit the yearly reporting of coverage by operators to estimate the effect of tower construction by year. The results are shown in Figure 6. Recall that mobile coverage is zero for all cells in our sample until the start of the SMIS program in 2008. This is by construction: the program targeted areas without pre-existing coverage and we remove from our sample any targeted area with even partial mobile coverage in the pre-SMIS period. Between 2008 and 2012, treated cells experience faster growth in coverage relative to control cells, with the gap widening to about 10 percentage points and then stabilizing at that level through 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.[15] 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

[14] There are 2,346 sub-districts in our sample.

[15] Number of farmers is sourced from the 2001 Population and Village Census of India. The data is available at the village level. We use village centroids to match villages to cells.

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. Column (1) shows 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 after the introduction of the SMIS program. Column (2) indicates that the same increase corresponds to 2.1 more credit-related calls per 1,000 farmers, and column (3) to 1.7 additional calls concerning government credit programs per 1,000 farmers.

Figure 7 reports an event study of the reduced form effect of SMIS tower construction on calls per 1,000 farmers. To estimate this regression, we assign calls to relative years around tower construction based on the month in which a given SMIS tower was constructed in a given cell. For example, if a tower was constructed in June of 2009, the calls in relative year $t = 0$ for that cell will include all calls in the period between June 2009 and May 2010. As documented in Figure 3, there are very few calls to Kisan Call Centers between 2006 and 2008, which explains why our point estimates are tightly estimated zeros in most of the pre-period. However, starting from the first year in the post-period, cells where SMIS towers were constructed at $t = 0$ experience a positive and significant increase in calls per farmer relative to the control group. As shown, the estimated coefficients increase from 0.5 to 9 calls per 1,000 farmers during the first five years after SMIS tower construction.

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 BSR data, and agricultural credit originated by PACS in the AIS data.

We start by focusing on outcomes sourced from the BSR data, which report the number of borrowing accounts and the amount of outstanding balance in those accounts for agricultural loans. In column (1) we focus on borrowing accounts per farmer in a given cell. The IV coefficient 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. The IV coefficient implies that cells with a one standard deviation larger increase in coverage experienced a larger increase in agricultural credit of about 8,000 INR per farmer.[16]

[16] This corresponds to around 120 USD per farmer in additional agricultural credit at an exchange

We then turn to credit outcomes from the AIS, which provide information on the number of farmers with PACS credit and the total amount of PACS credit. As shown in columns (3) and (4), SMIS-driven coverage expansion increased both the share of farmers with PACS credit and PACS credit per farmer. In particular, the IV coefficient in column (3) of Panel C implies that cells with a one standard deviation larger increase in coverage experienced a 5.7 percentage point larger increase in the share of farmers with PACS credit. Column (4) further shows that the same increase in coverage is associated with about 1,300 INR more PACS credit per farmer.[17]

Taken together, the IV estimates in columns (1) and (3) imply that a one standard deviation larger increase in coverage (about half the area of a 10×10 km cell) corresponds to roughly 90 more farmers with access to credit per 1,000 farmers.[18] The estimates in columns (2) and (4) further indicate an increase of about 9,500 Rupees of agricultural credit per farmer. The combined increase amounts to about 58% of total credit per farmer received from PACS, commercial banks, and regional rural banks, as 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:

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

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-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 2,000 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

rate of INR to USD of 0.015.

[17] It is worth noting that the IV estimates are two to three times larger than the OLS estimates. The most likely explanation for this is measurement error in the coverage data: the licensed data are aggregated across all operators, with submissions that likely vary in quality and without information on signal strength. Both sources of measurement error are particularly relevant at fine geographies such as 10×10 km grid cells.

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

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 by other changes to the local economy brought about by access to mobile phones? Third, what do our estimates suggest about the relationship between farmers' calls and credit take-up? The rest of the paper attempts to address these questions.

3.4.2 Take-up of government credit programs

As shown in section 3.3, the SMIS-induced expansion of mobile phone coverage triggered demand for information about government programs when farmers called Kisan Call Centers. We now present evidence consistent with this information affecting farmers' credit decisions.

Beginning in 2008, the BSR data separately report commercial banks' lending to farmers through standard agricultural loans and through Kisan Credit Cards, the main government credit program for farmers. Although the sample period does not allow us to observe Kisan Credit Cards diffusion before the introduction of SMIS towers, we can estimate a cross-sectional regression that relates lending outcomes at the cell level in the post-SMIS period (2011-12) to mobile coverage instrumented with tower construction. The results are reported in Table 7.[19]

The OLS estimates suggest that mobile coverage expansion is correlated with greater lending to farmers through both standard agricultural loans and Kisan Credit Cards. The IV estimates, however, show significant effects only for Kisan Credit Cards: a one standard deviation increase in coverage leads to 2.7 additional Kisan Credit Cards accounts per 1,000 farmers and 810 Rupees more borrowing per farmer through this program (columns 1 and 3). No corresponding effects appear for standard agricultural loans (columns 2 and 4), suggesting that the impact of mobile coverage was concentrated in Kisan Credit Cards, consistent with a mechanism where improved access to program-specific information plays a central role.

We further investigate Kisan Credit Cards take-up using data from the Socio-Economic and Caste Census (SECC), conducted by the Ministry of Rural Development in 2011-12. Among other household characteristics, the SECC records whether agriculture is the main source of income and whether the household holds a Kisan Credit Card with a credit limit of at least 50,000 Rupees.[20] The estimates in column (5) of Table 7 confirm

[19] We focus on 2011-12 to match the timing of the Census analyzed in column (5) of the Table.

[20] According to a NABARD survey of 714 farmers across five Indian states, this threshold represents about one-third of the average loan value under KCCs (166,320 Rs). Minimum loans ranged from 5,000 Rs in Bihar to 25,000 Rs in Karnataka, while maximum loans ranged from 82,600 Rs in Assam to 2,500,000 Rs in Punjab (Mani, 2016, p.43).

that mobile coverage increased the share of agricultural households holding such a card: the IV coefficient implies that a one standard deviation increase in coverage raises this share by 3.4 percentage points. This effect is substantially larger than the corresponding estimate in column (1), partly because the SECC covers Kisan Credit Card borrowing from all lenders, whereas the BSR data cover only commercial and regional rural banks. In addition, the SECC measure is based on whether a household has at least one card, while the BSR outcome is the ratio of KCC accounts to the number of farmers.

Because Kisan Credit Card data are available annually from 2008 to 2014, and SMIS towers were rolled out between 2008 and 2010 across different cells, we can exploit this staggered timing to estimate an event study that tracks outcomes relative to the year of tower construction. Cells first covered in 2009 contribute one pre-treatment year, while those covered in 2010 contribute two. The results are shown in Figure 10. We find no evidence of pre-trends in Kisan Credit Card adoption and observe a gradual post-treamtent increase, reaching an additional 0.01 accounts per farmer and about 1,500 Rupees more 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).[21] 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.

[21] 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.

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 loans primarily to smooth consumption in the face of adverse shocks.[22] 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.[23] 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 further 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

[22] 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.

[23] 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.

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 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 discussed in Section 2.3 and illustrated in Figure 4, Kisan Credit Cards offer significantly lower interest rates than comparable non-subsidized loans, making the incentives to acquire and act upon such information particularly strong. Furthermore, expanded mobile coverage in treated areas enables rapid transmission of information from callers to non-callers, as well as within social circles of individuals who never contact the call centers directly. This makes call centers an entry point for broader local learning, rather than a channel affecting only direct users. Finally, survey evidence suggests that callers are positively 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, with 72% having completed higher secondary education.[24] Existing evidence indicates that more educated farmers are more likely to be embedded in other farmers' social networks.[25] 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. A potential challenge with this interpretation is that the arrival of mobile phone coverage in a given region could also promote credit take-up through other mechanisms. For instance, mobile coverage may stimulate local economic opportunities more broadly, raising incomes and, in turn, farmers' demand for credit to expand their operations.

To make progress in isolating the role of information, we follow Gupta et al. (2024) and exploit an institutional feature of Kisan Call Centers: calls from each state are answered in

[24] Table 2.8, page 19 in Gandhi and Johnson (2017).

[25] 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).

the state's official language. This creates a language barrier for individuals whose mother tongue is not that official language – either because they speak another of India's official languages or one of the 99 non-official languages spoken in the country.[26] Even among areas receiving similar mobile phone coverage through SMIS towers, farmers' ability to access information can therefore vary by local language.

Figure 11 presents 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, allowing the effect of SMIS towers to vary with the share of state official language speakers in the cell:

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

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 (MajOS_{is}), and β_2 captures the effect in cells where the majority speaks either a non-official language or an official language different from that of their state of residence (MajNOS_{is}). A key concern is that language distribution across areas is not random: cells where most residents do not speak the state's official language may also be more specialized in agriculture, more geographically isolated, or less economically developed – factors that could independently shape the response to mobile coverage. In such cases, the interaction between coverage and language composition may partly capture these local conditions. To address this concern and isolate the effect of language barriers on information access, we extend the model by adding triple interactions of treatment status times *Post* with measures of agricultural specialization (share employed in agriculture, share of irrigated land), geographical isolation (distance to the nearest town), local economic development (night lights intensity), the share of scheduled caste population, and access to agricultural markets (Chatterjee, 2023). These potential confounders are denoted C_{is} in equation (4). We also include the

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

share of non-state language speakers among the baseline cell-level controls X_{is} interacted with time fixed effects.

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.

Overall, we interpret our evidence as strongly supportive of an information mechanism driving the effect of mobile phone coverage on credit take-up. Farmers actively use Kisan Call Centers to inquire about government credit programs, and areas receiving SMIS towers exhibit higher take-up of Kisan Credit Card loans – the main subsidized program observable in our data – but no increase in standard agricultural loans. Consistent with this interpretation, we also find stronger effects in areas where, despite gaining mobile coverage, farmers face language barriers that limit access to Kisan Call Centers.

Finally, while we cannot fully separate the effect of program-specific information from other types of advice – such as guidance on seeds, fertilizers, or irrigation, which could also stimulate credit demand – the composition of borrowing offers some indications. The increase in the use of Kisan Credit Cards is concentrated in consumption loans rather than investment loans, which are typically used to finance input purchases and more directly reflect changes in production practices. We interpret this pattern as suggestive of an effect operating through farmers accessing credit programs rather than changing their production practices.

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 test for possible spillovers from the construction of mobile phone towers on surrounding cells. Third, we show that results are not driven by specific states in India. Fourth, 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.

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 A4 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. The findings underscore the role of information frictions as a binding constraint in the adoption of rural credit programs (e.g., Byerlee et al., 2008; Duflo et al., 2007) and highlight the potential for low-cost communication technologies to enhance the reach and impact of government interventions in agriculture.

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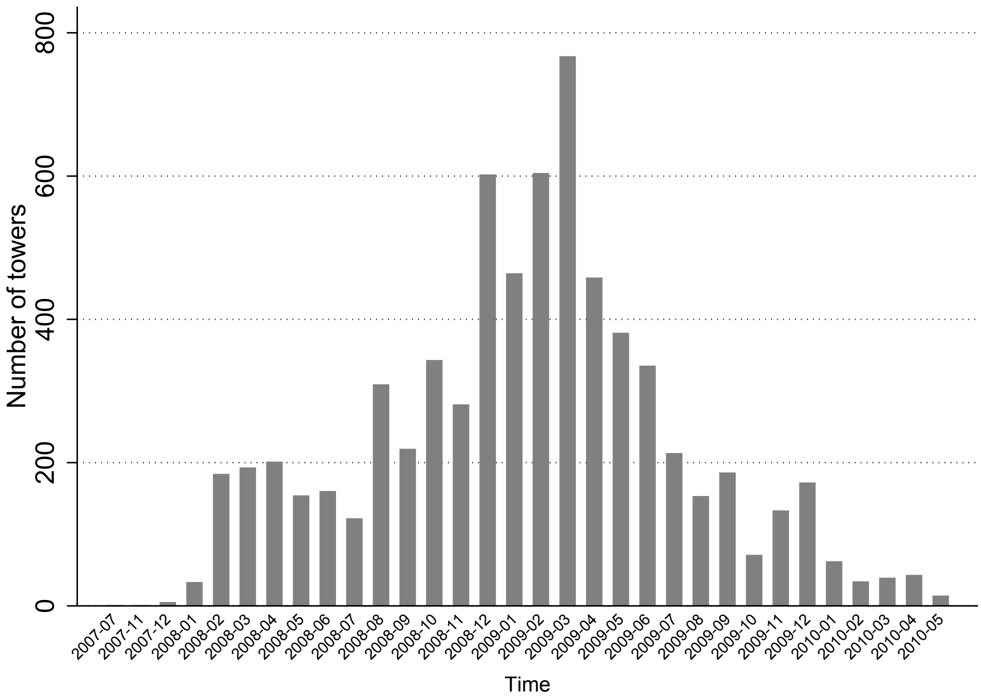
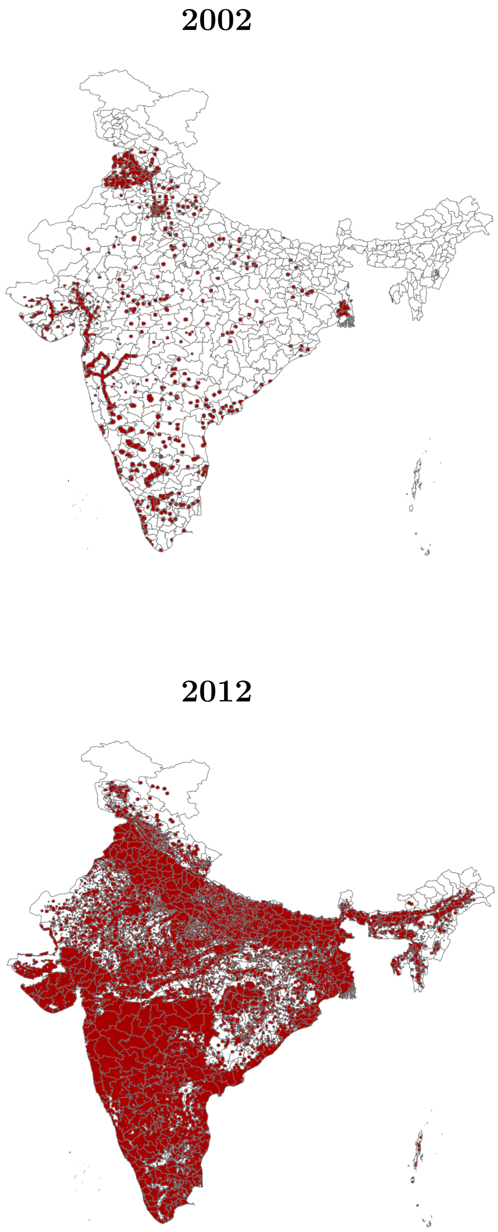
Figures

Figure 1: Timeline of tower construction under SMIS Phase I



Notes: Source: Department of Telecommunications, India

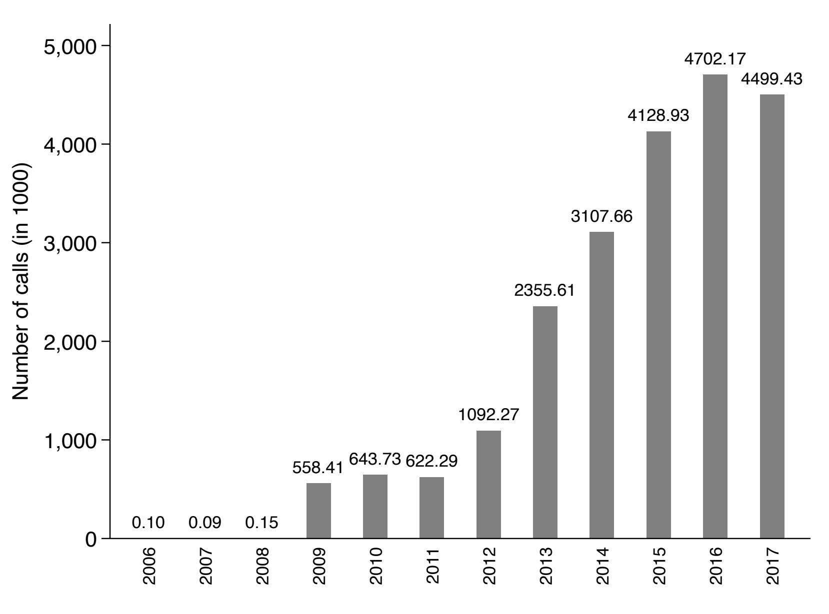
Figure 2: Mobile Phone Coverage Evolution, India 2002-2017



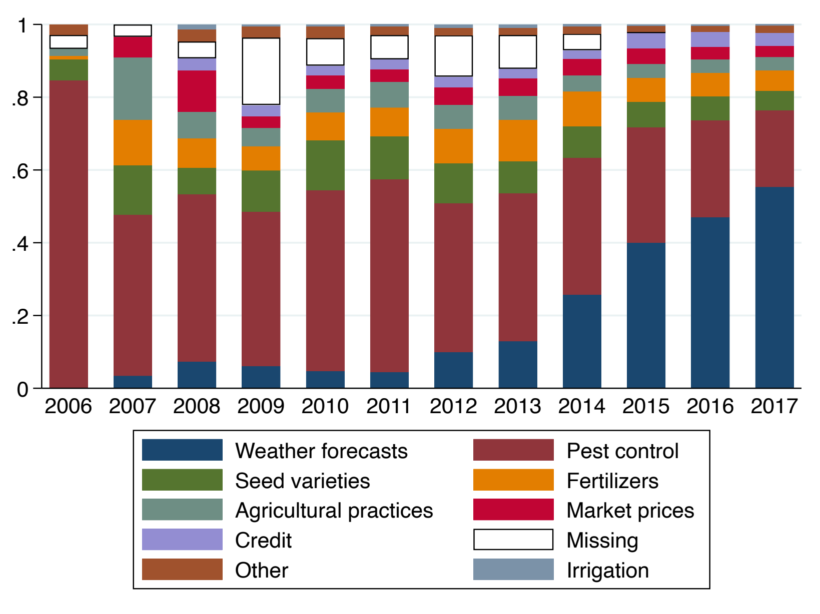
Notes: The figure reports geo-referenced data on mobile phone coverage for all of India at five-year intervals between 2002 and 2017. Source: GSMA.

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

(a) Number of calls by year



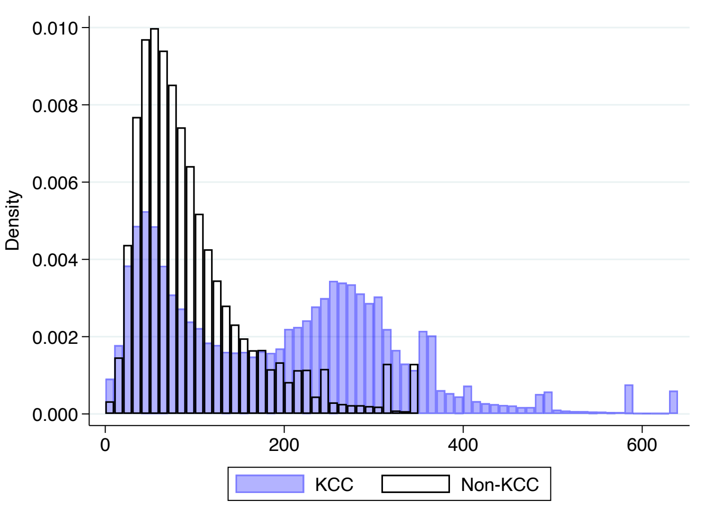
(b) Composition of calls by year



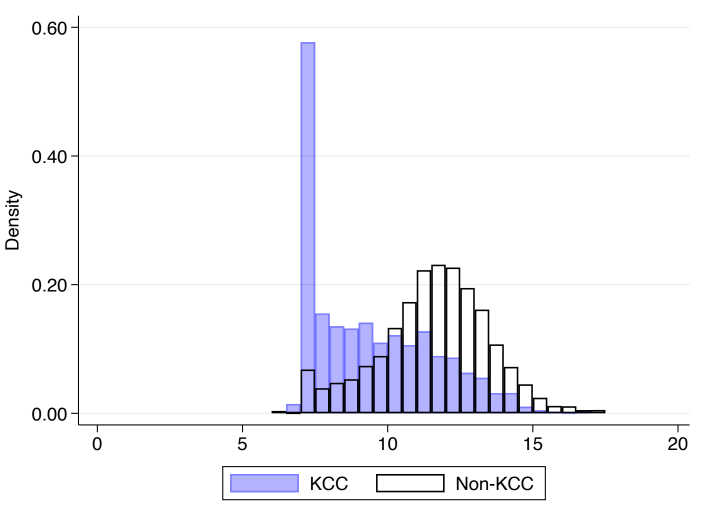
Notes: Source: Authors' calculations based on the data on calls to Kisan Call Centers made available on the Open Government Data (OGD) Platform of India `https://www.data.gov.in/` as of January 2024.

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

(a) Credit per account

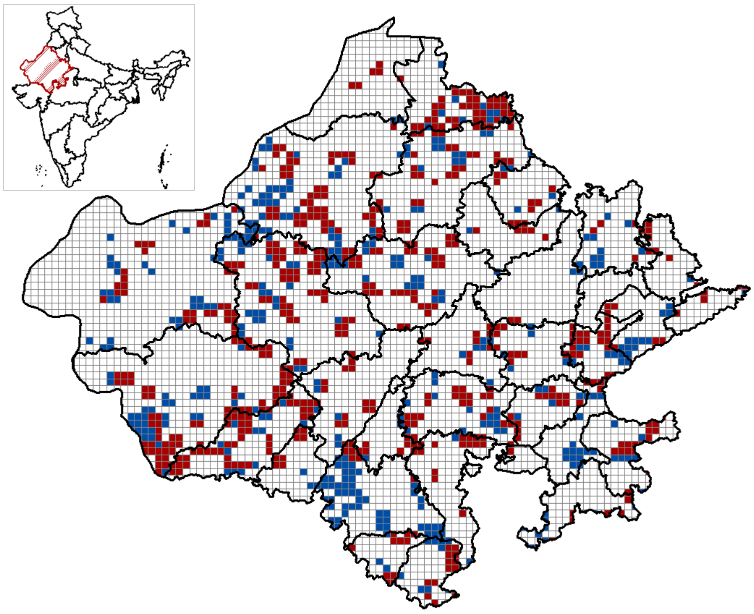


(b) Interest rates



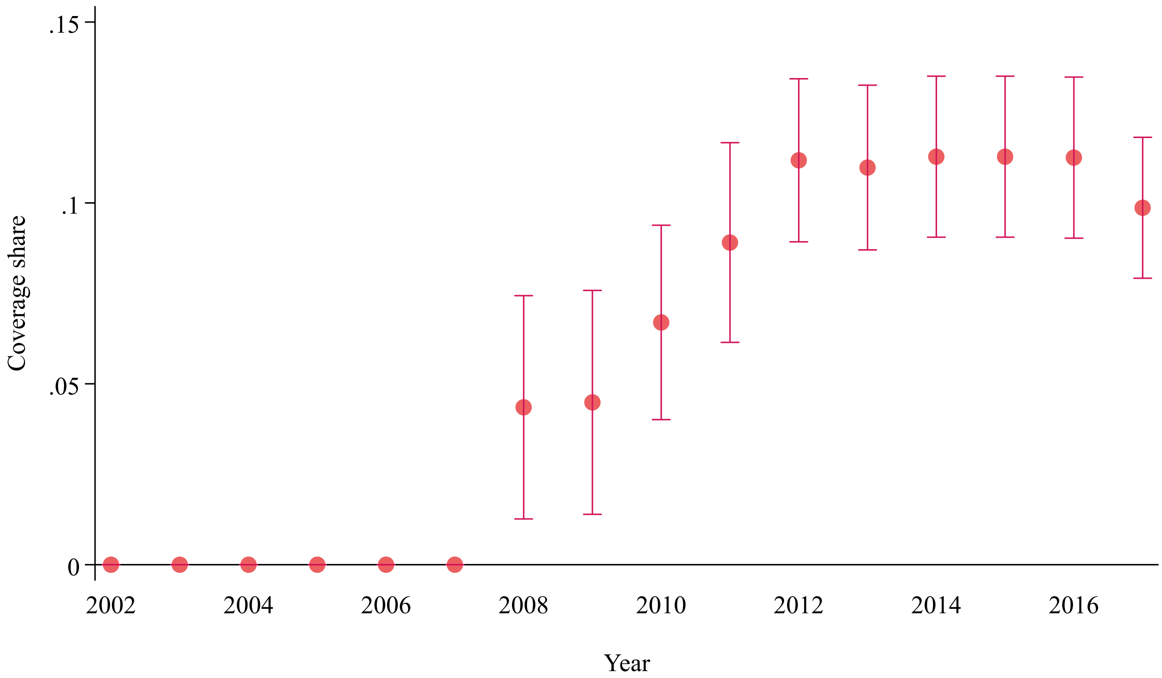
The graph plots the distribution of credit per account (panel a) and interest rates (panel b) separately for Kisan Credit Card (KCC) and non-Kisan Credit Card (non-KCC) credit as reported in the branch-level BSR data. Credit per account is in thousands and winsorized at the 95th percentile. Interest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

FIGURE 5: TREATMENT AND CONTROL CELLS
RAJASTHAN STATE



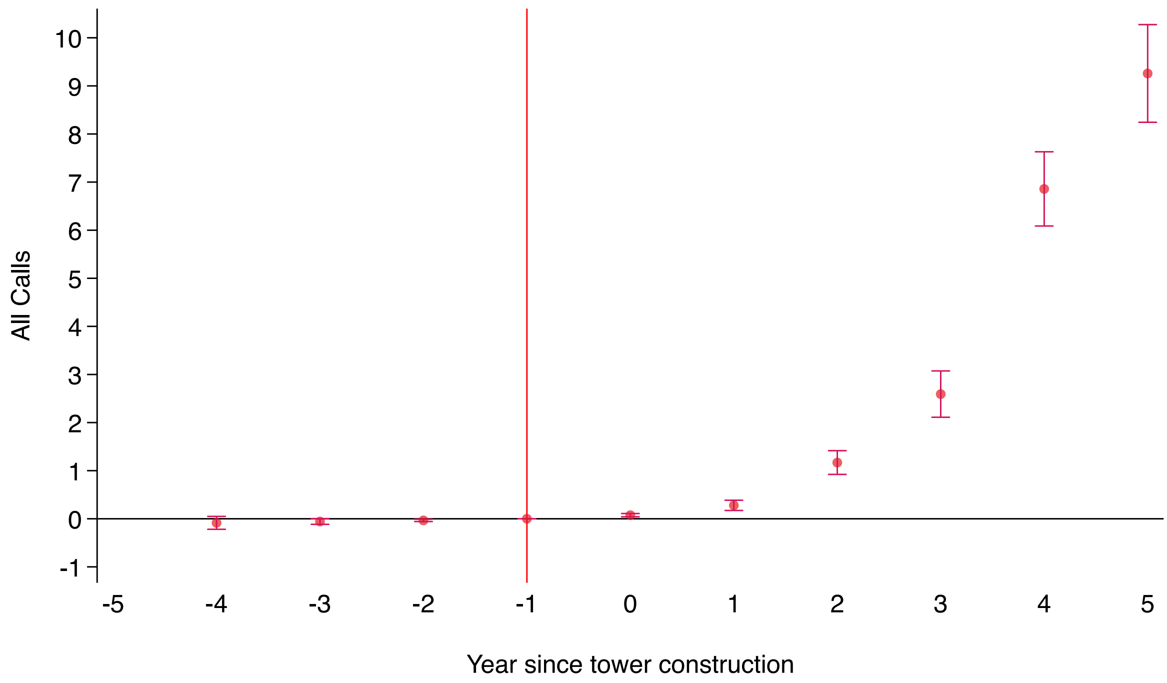
Notes: Treatment (red) and control (blue) cells for the state of Rajasthan. District boundaries are labeled in black. Treatment cells are those that are both proposed *and* covered by mobile tower under SMIS Phase I. Control cells are those that are proposed *and not* covered by mobile tower under SMIS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

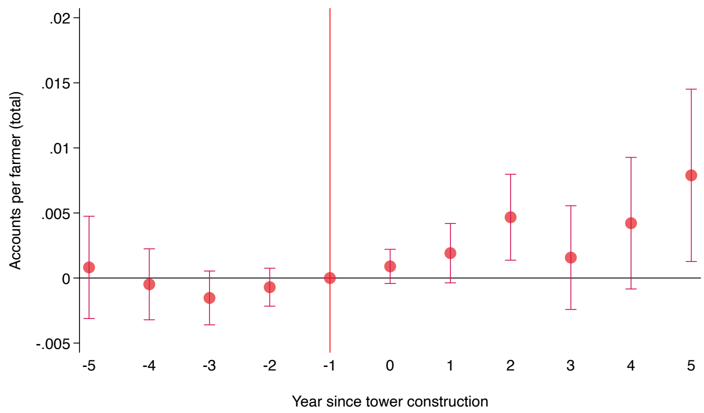
Figure 7: Reduced Form Effects of Tower Construction on Calls: Event Study



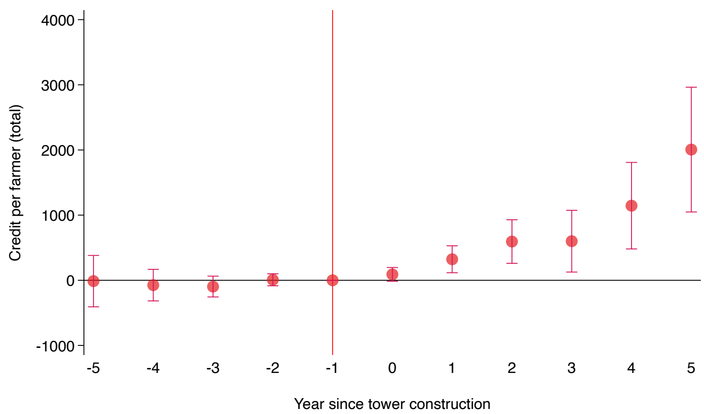
Notes: This figure presents the reduced-form estimates of the SMIS tower construction program on number of calls to Kisan Call Center per 1,000 farmers using specification (3). For treated cells, we assign calls to relative years around tower construction based on the month in which a given SMIS tower was constructed. For example, if a tower was constructed in June of 2009, the calls in relative year $t = 0$ for that cell will include all calls in the period between June 2009 and May 2010. We normalize the coefficients in the 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



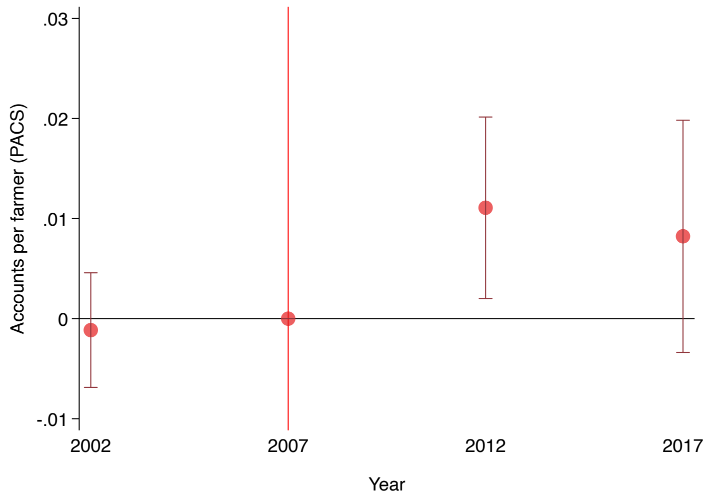
(b) Credit per farmer



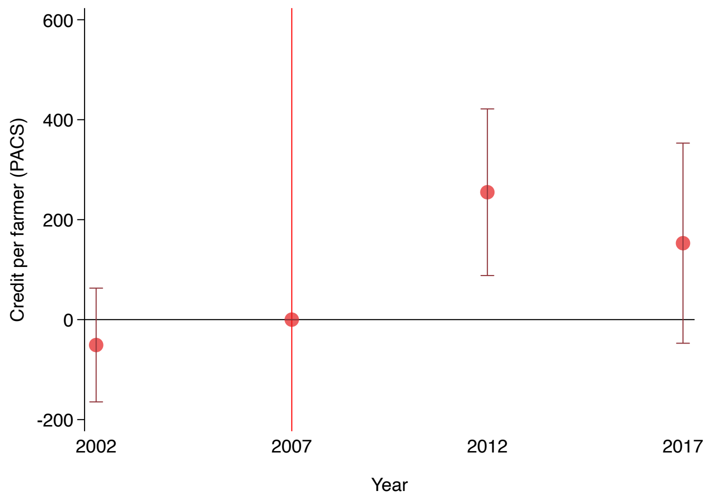
Notes: This figure presents the reduced-form estimates of the SMIS tower construction program on the credit accounts per farmers (panel a) and credit per farmer (panel b) as reported by the commercial and regional rural banks using specification (3). We normalize the coefficients in the year before tower 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)



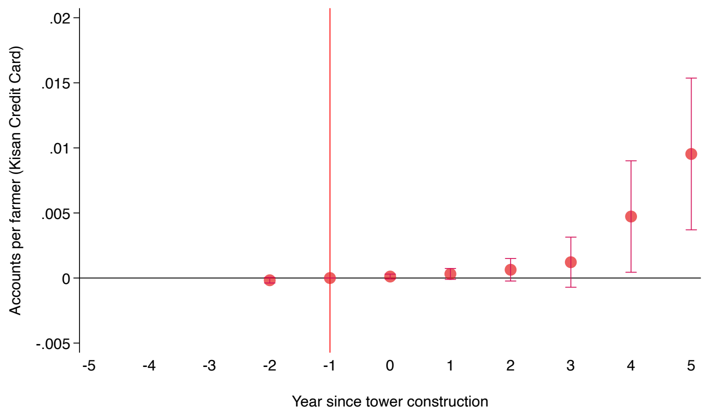
(b) Credit per farmer (PACS)



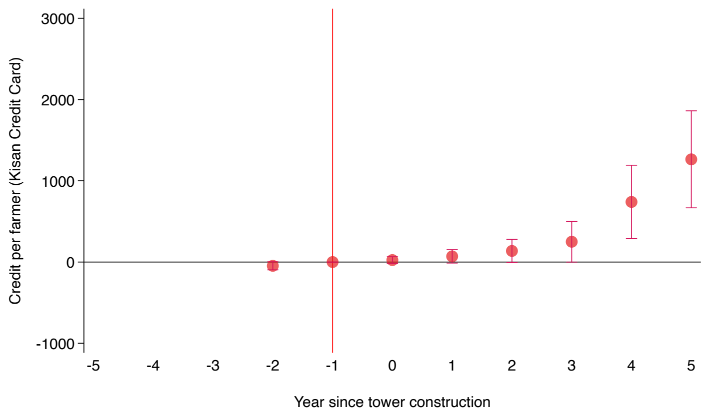
Notes: This figure presents the reduced-form estimates of the SMIS tower construction program on the share of farmers with credit (panel a) and credit per farmer (panel b) using specification (3). We normalize the coefficients in the year before tower construction to 0. We use data from the Agricultural 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



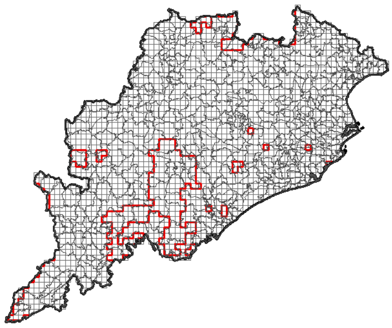
(b) Credit per farmer



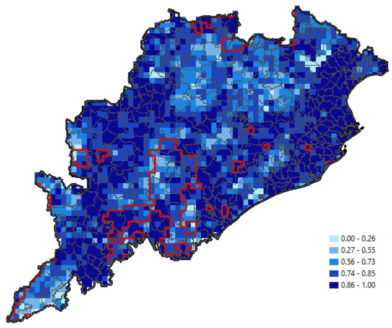
Notes: This figure presents the reduced-form estimates of the SMIS tower construction program on the account per farmers (panel a) and credit per farmer (panel b) as reported by the commercial and regional rural banks and classified under the category of Kisan Credit Cards loans using specification (3). 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

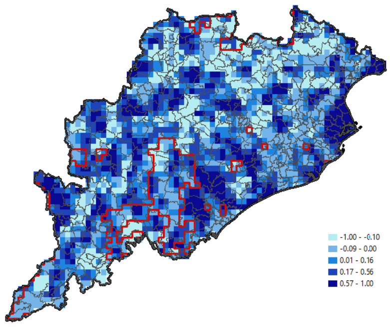
(a) Non-official language speakers



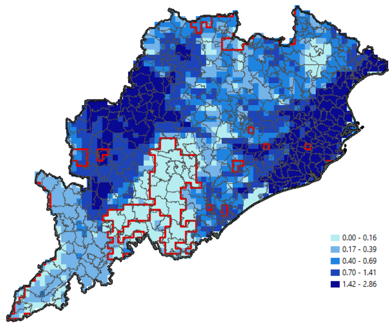
(b) Share of farmed land



(c) Change in mobile coverage



(d) Change in calls to Kisan Call Centers



Notes: Panel (a) shows 10×10 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. 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 (including share of farmers with credit, credit per farmer, interest rates, and NPA) come 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. The unit of observation in this table is a 10×10 km cell. See section 2.4 for a detailed description of the procedure to bring variables from the level of geographical aggregation at which they are reported in the original data sources to 10×10 km cells.

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)
p-value (joint F-test)			0.386
N		8,426	8,426
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 using the main 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 includes these three covariates along with all other covariates, using the sample of 7,139 cells for which this data is available. 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. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

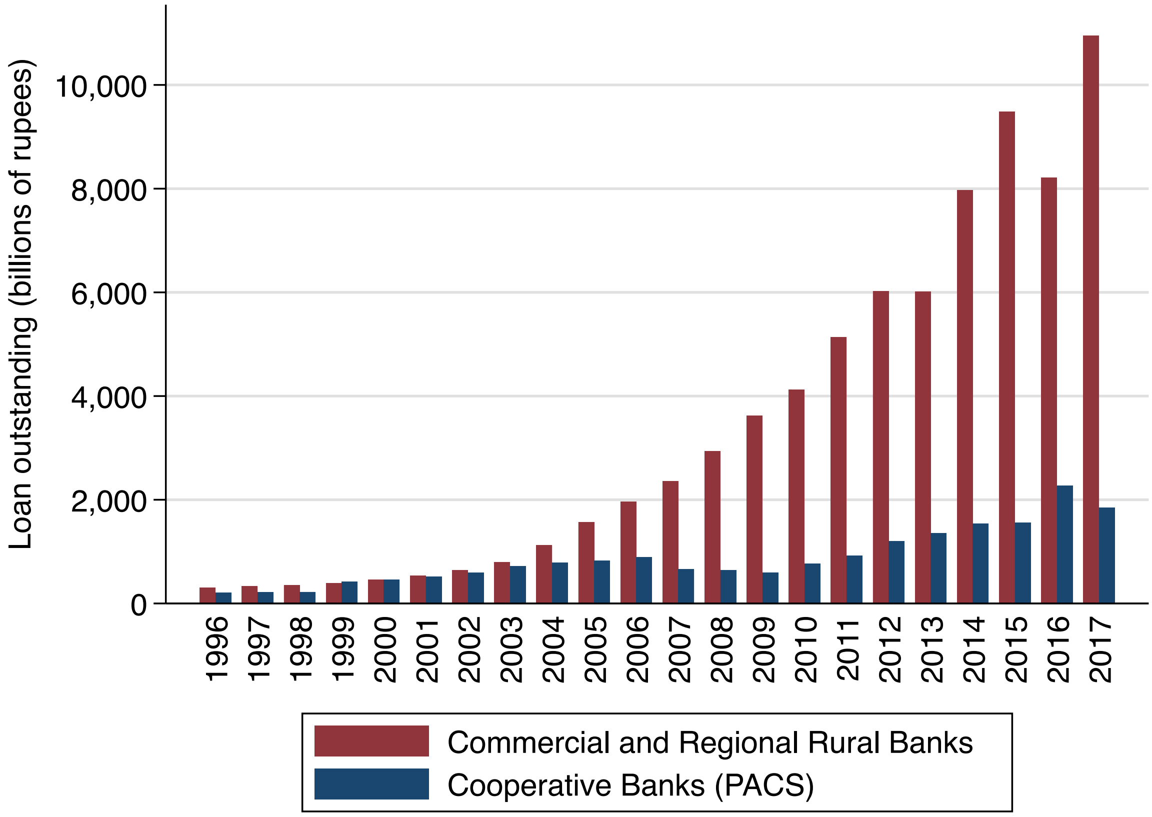
Table 9: Heterogeneous Effects by Language

	# 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

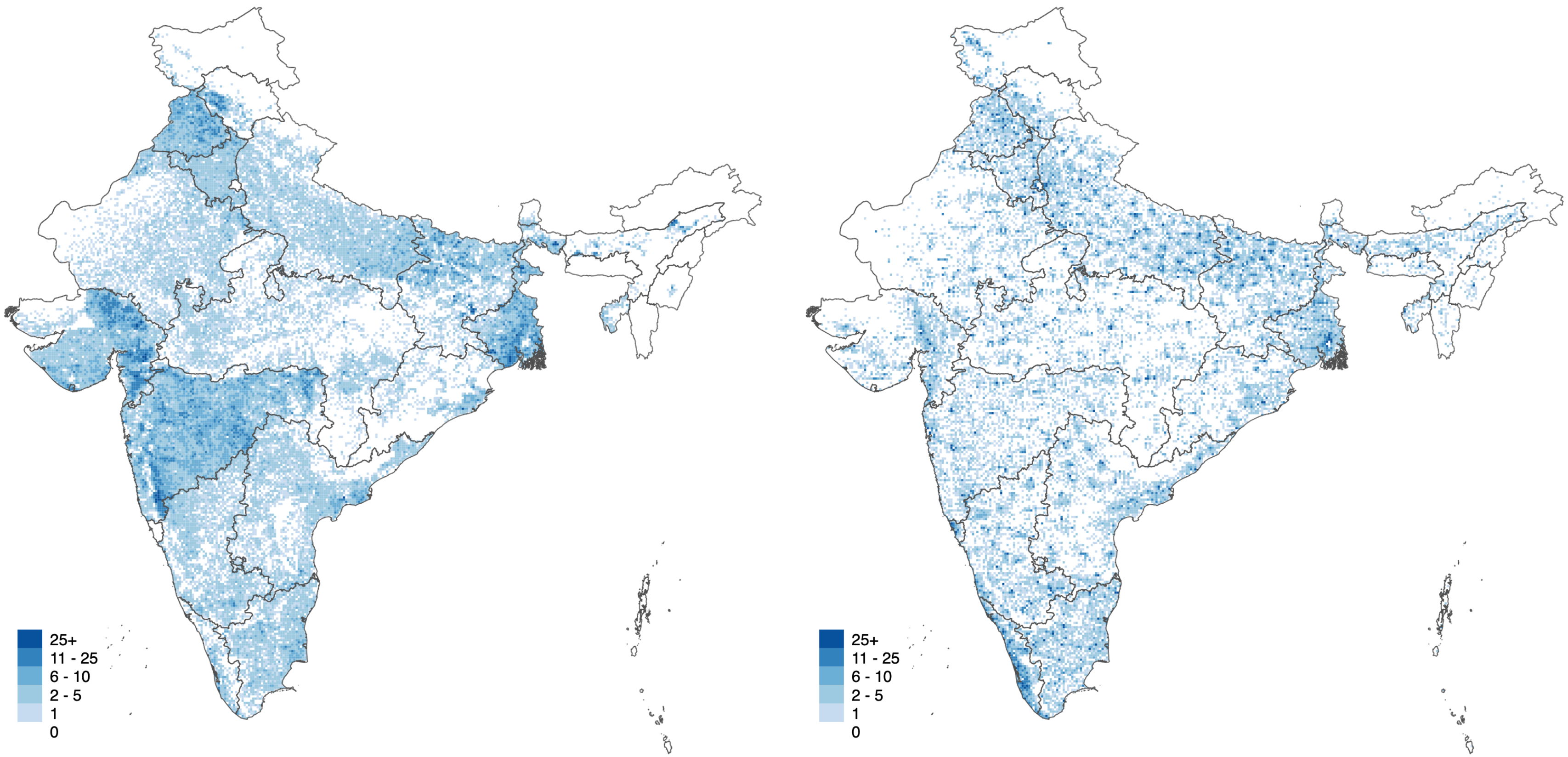


Notes: This figure shows aggregate agricultural credit by commercial and regional rural banks, and Primary Agricultural Credit Societies (PACS). Data is sourced from the Reserve Bank of India and the National Bank for Agriculture and Rural Development (NABARD).

Figure A2: Distribution of bank branches across India

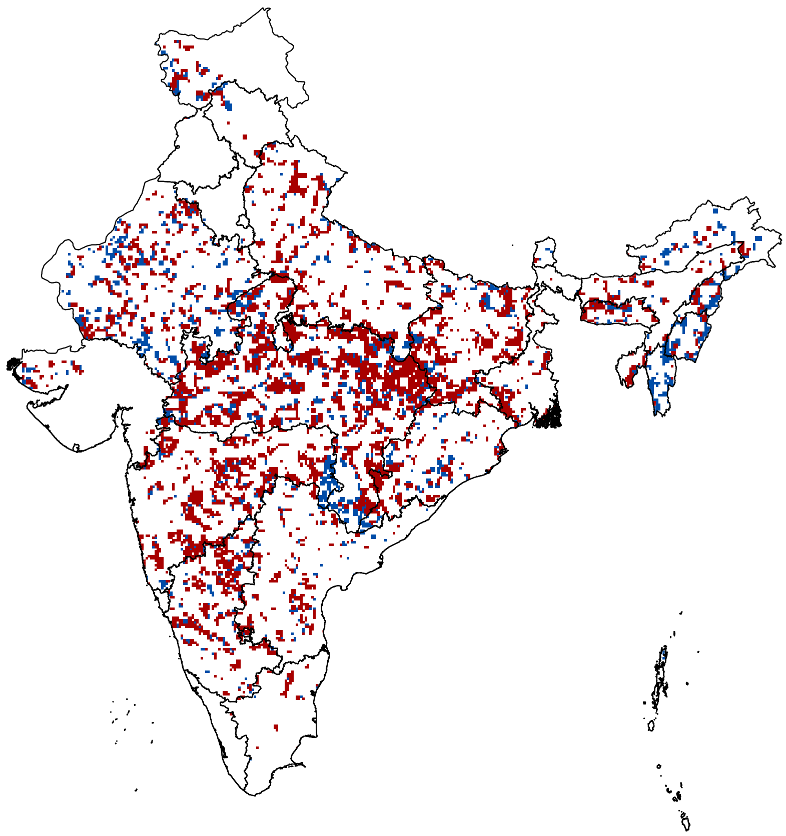
(a) PACS

(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

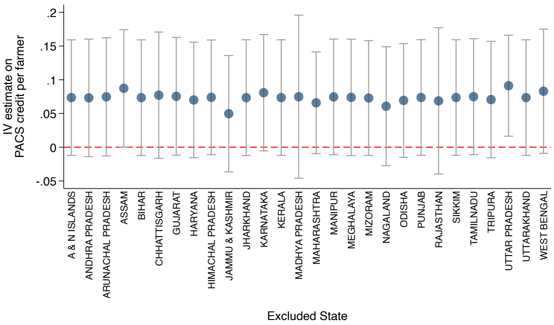


Notes: The figure shows the 8,426 cells used in the empirical analysis distributed across treatment (red) and control (blue). State borders are marked in black. Treatment cells are those that are both proposed *and* covered by mobile tower under SMIS. Control cells are those that are proposed *and not* covered by mobile towers under SMIS.

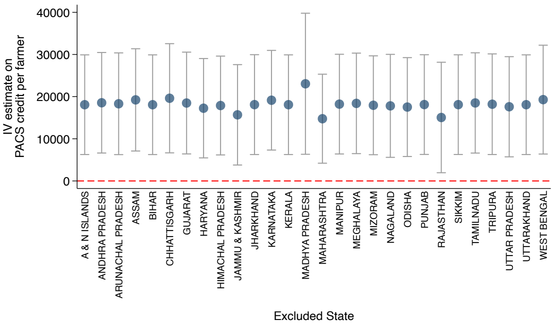
Figure A4: Robustness: Leave out one state at a time

A. Bank Credit (from BSR)

i. Share of farmers with bank credit

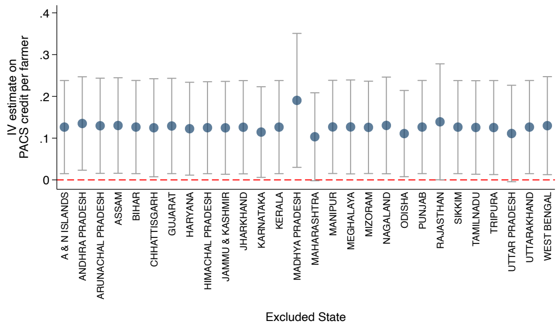


ii. Bank credit per farmer

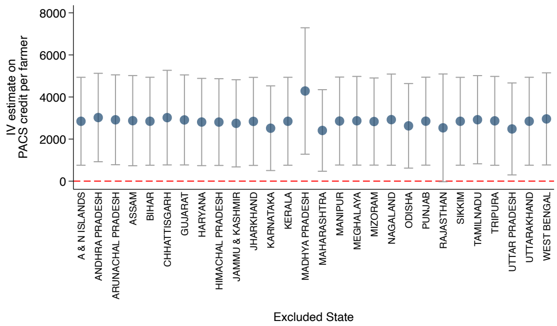


A. PACS Credit (from AIS)

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 (1)	Medium (2)	Long (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 (1)	Medium (2)	Large (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 in BSR	Credit per farmer in BSR	Share of farmers with PACS credit in AIS	PACS credit per farmer in AIS
	All calls	Credit calls	Gov credit calls				
	(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. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

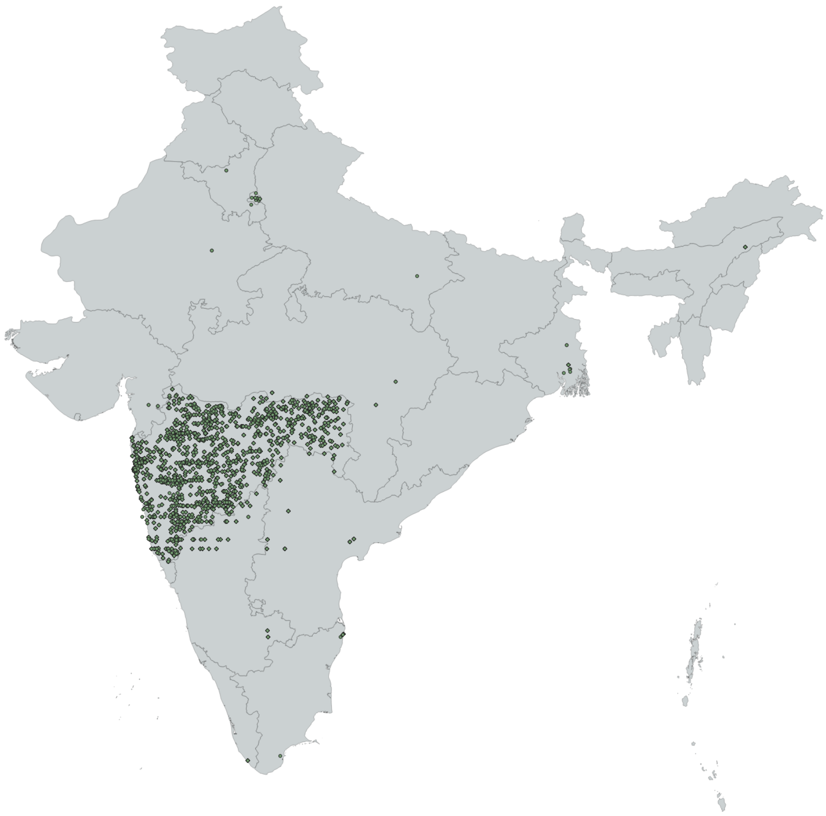
B Appendix: Bank Branch Location and Credit Allocation

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.

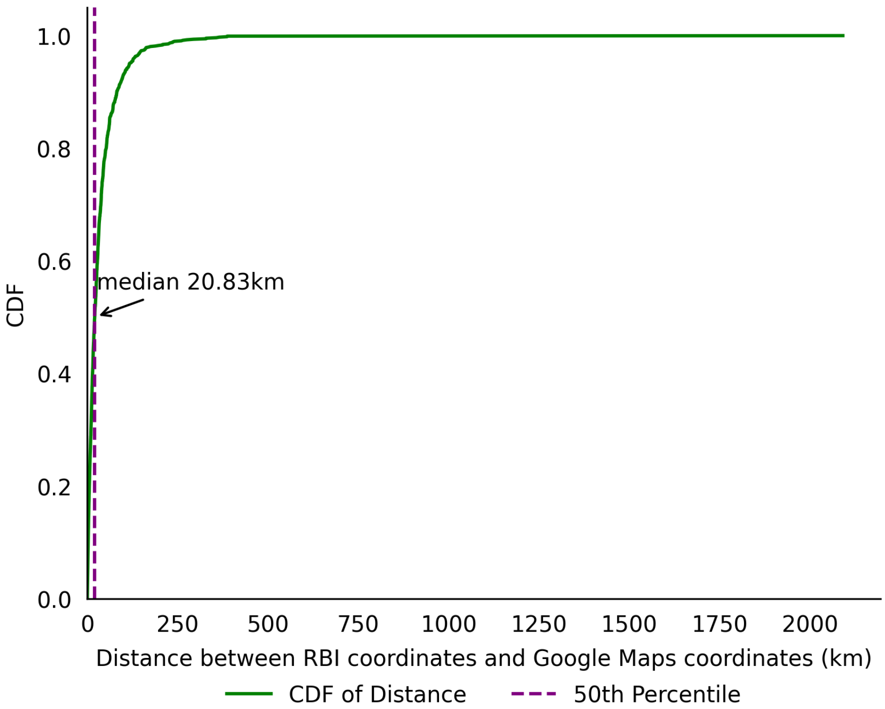
Figure B1: Bank branches with addresses in Maharashtra



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".[27]

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[28]. 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.[29].

[27] 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.

[28] 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.

[29] 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

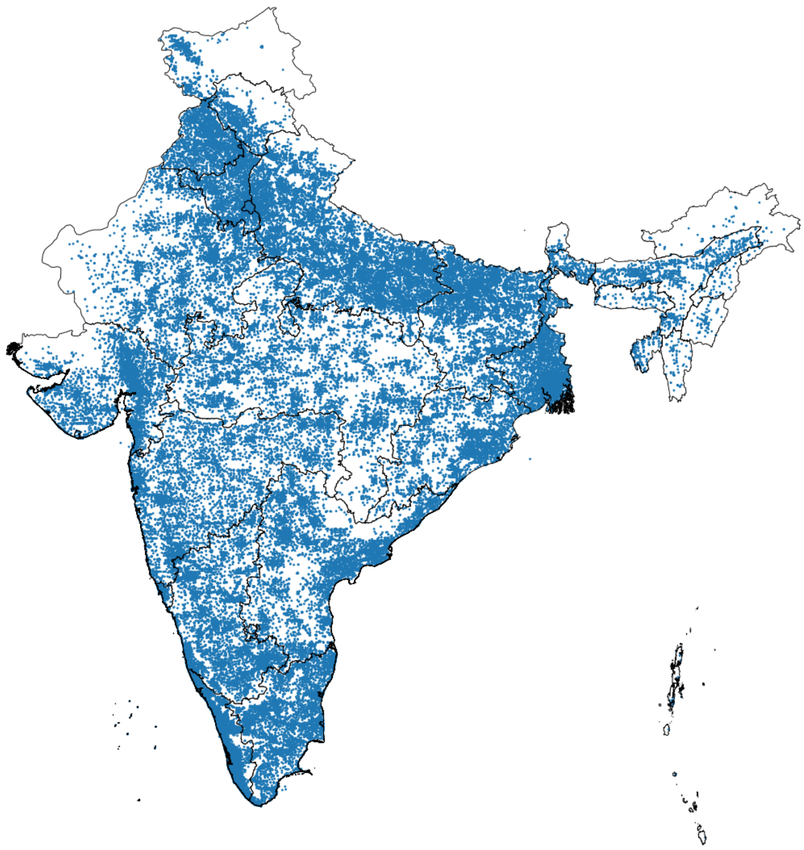
	(1) N inputs	(2) N found	(3) % GMaps inputs	(4) % total branches
Concatenation + Pincode	104,334	92,187	67.9	56.2
Concatenation + Address	37,417	23,387	17.2	14.2
Concatenation	20,116	19,612	14.5	11.9
Subtotal		135,186		82.3
N not in GMaps & in bank-branch location dataset		400		0.2
N not in GMaps & *not* 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[30]. Figure B3 plots the distribution of a universe of 164,088 bank branches in India after applying the Google Maps correction.

[30] 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

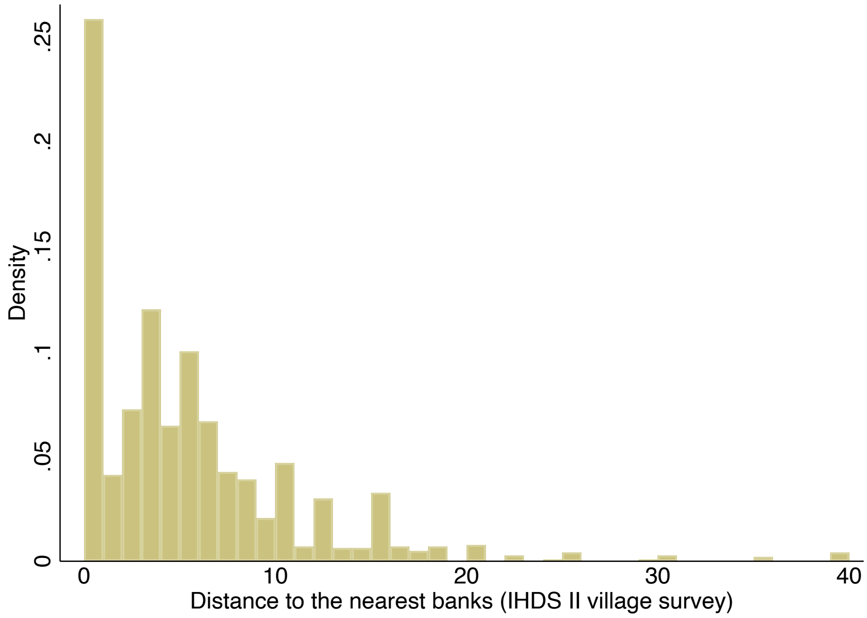


Notes: The figure plots the corrected bank branch locations after using the Google Maps Places API methodology described in Appendix B. The total number of branches is 164,088. The data covers branches of commercial banks and regional rural banks.

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)[31], 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

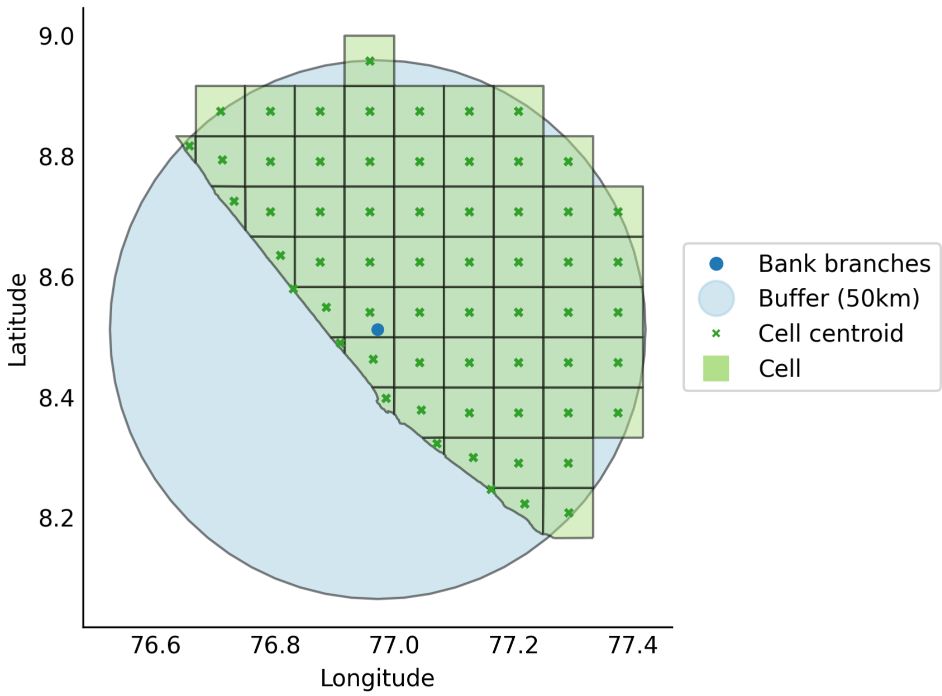


Notes: The figure shows the distribution of distance to the nearest bank branch in the Village Survey of IHDS II. The number of observations is 1,408.

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.

[31] 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:

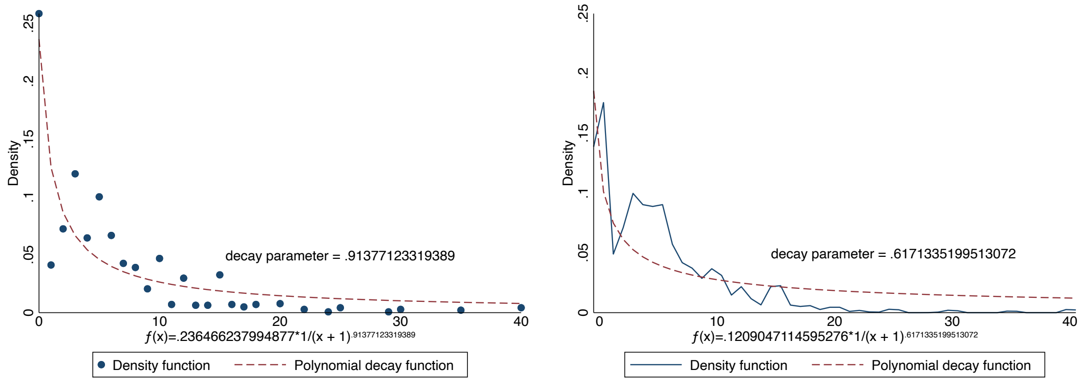
$$f(x) = \alpha \frac{1}{(x+1)^{\gamma}}, \quad \gamma > 0 \tag{7}$$

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.