Effect of Mobile Phones on Rural Economy *

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Abstract

Since the beginning of the twenty-first century, mobile telephony has witnessed unprecedented growth in developed nations. The adoption of mobile phones in developing countries was even faster. In this paper, we study the effects of access to mobile telephony on economic growth and inequality in the context of an emerging country. We use exogenous change in mobile coverage in rural India under the Shared Mobile Infrastructure Program between 2007–2009. Using village level nighttime lights between 2003-2013 as a proxy for income and a difference-in-difference estimation strategy we find that the villages covered under the program had a 12 percent additional growth compared to the uncovered villages. Our results on luminosity Gini suggests that for every additional percent of population brought under mobile phone connectivity reduces income inequality by 0.06 percent. These results are robust to alternate specifications and a smaller sample where the baseline difference between the villages covered under the program and control villages are minimum.

Key Words: Mobile telephony, Economic growth, Income inequality
JEL Codes:

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1 Introduction

Mobile telephony has witnessed unprecedented growth since the beginning of the twenty-first century.[1] Since 2002 mobile subscribers have exceeded the number of fixed lines globally. In developed countries usage in mobile telephony and data services has transformed the way people connect and work. Such rapid communication technologies have played a significant role in driving economic growth in the last few decades (Gruber and Koutroumpis, 2011). The adoption of mobile phones in developing countries was even faster. Currently, there are more than twice as many subscriptions in developing countries (3.2 billion) compared to the developed nations. (1.4 billion). The importance of the telecommunications sector also becomes evident by comparing the share of telecommunications revenues in GDP: telecommunications services accounted for on average 4.8% of the total GDP of sub-Saharan Africa compared to 3.1% in the European Union (Gruber and Koutroumpis, 2011).

This unparalleled catch-up, particularly for India with a meager 1.3 telephones per 100 population in 1996, is probably one of a kind technology adoption. Between 2001-2014, mobile subscription in India increased more than 100 fold, from about 0.62 to 74 mobile subscribers per 100 inhabitants.[2] In 2010, the growth rate of mobile penetration hovered at around 75 percentage per annum. Such high subscription growth rate was mainly due to the low initial base, declining tariff rates and handset prices, liberalization of the telecom market and subsequent expansion of mobile networks. The causal effect of rapid changes in mobile telephony on economic outcomes is poorly understood. Its proliferation is argued to be largely demand driven and therefore endogeneous to various confounding factors.

The rapid adoption of mobile phones in developing countries can have far-reaching impacts. Proliferation of mobile phones in developing countries has reduced information asymmetry (Jensen, 2007), increased employment (Klonner et al., 2010), and agricultural profitability (Beuermann, 2011). At the same time, there is a growing consensus that that technological advancement is one of the major factors behind rising income inequality (Acemoglu, 2002; Jaumotte et al., 2013). In this paper, we study the effects of access to mobile telephony on economic growth and inequality in the context of an emerging country.

A key methodological challenge in studying the effect of mobile telephony is the problem of reverse causality. Economic outcomes such as income and expected growth affect telecom service providers' decision to offer access. Unlike experiments on the effectiveness of microfinance or access to sanitation, for instance, it is costly if not plain infeasible to conduct randomized control trials (RCTs) under which mobile telephone towers are randomly constructed across locations.

We use the construction of mobile towers under the Shared Mobile Infrastructure Program in India as an exogeneous source of variation in mobile connectivity in rural areas to overcome

[1] See Figure **??**.

[2] The drop in the mobile subscribers in 2012 for India is partly due to operators no longer including inactive subscriptions in their reports.

the reverse causality problem. Despite the rapid growth in subscription, mobile penetration in India is heavily skewed in favor of urban areas.[3] . The capital cost of providing telecom services in rural and remote areas is much larger due to the lack of infrastructure and uneven terrain. Besides, sparse population density and limited commercial activities fail to attract private capital. However, given the importance of telecom connectivity, most countries have policies for Universal Access and Universal Service to ICT. In India, the Universal Service Obligation Fund (USOF) was set up in 2003 with the obligation to provide affordable telecommunication to unconnected villages. Under the Shared Mobile Infrastructure program of USOF, private infrastructure providers received a subsidy to build and operate mobile towers in pre-determined rural and remote areas without mobile connectivity. In Phase-I (2007–2010) of the program, 7,353 mobile towers, spread over 500 districts and 27 states, were installed in villages that did not have fixed wireless or mobile coverage. The increase in mobile coverage under the program was not demand driven and therefore, provides an exogenous variation in coverage to study its impact on economic growth and inequality.

Most of the micro-level analyses of ICT focus on a very narrow outcome, either geographically and by product-type. Jensen (2007) studies the effect of mobile telephony on the fishing industry in one Indian state. Goyal (2010) focuses on the implication of internet kiosks on the soybean industry in one Indian state. Aker (2010) studies the effect on the millet market in Niger and Muto and Yamano (2009) study the different implications for a perishable (banana) and a non-perishable (maize) products in Uganda. In addition, each of these papers emphasizes the market performance outcome in the form of prices or sales. We also want to move away from the narrower focus in the literature on the impact of new mobile technologies and applications (e.g., Jack and Suri (2009) for M-Pesa in Kenya, Stone et al (2009) for mobile banking in South Africa, Kahn et al (2008) for potential for m-health). Mobile coverage under SMIP was administered at the village level. However, information on economic activity at the village level is sparse. We use data on the luminosity of nighttime lights extracted at the village level for the period 2003-2013 as a proxy for the size of the economy and study the impact of mobile telephony on growth of luminosity and inequality.[4]

Using Census data, we find that villages covered under the SMIP were 20 percent more likely to have mobile coverage. Our difference-in-difference estimates using nighttime lights data show that villages covered under the program had 16 percent higher growth in luminosity. We do not find any effect on the growth rate of luminosity in the first year of construction of towers. However, the effects are positive and increasing for the subsequent years. Our results on first differences in log nighttime lights suggest that the growth rate of night lights in the post period was 9 percent higher in the covered villages. These results indicate that mobile

[3]Current urban teledensity is 4.4 times that of the rural density. In 1996, urban areas in India had 3.7 more telephones per 100 population compared to rural areas. This gap increased to 56.4 in 2008, driven primarily by the lack of adequate mobile infrastructure in the countryside (Figure **??**)

[4]Henderson et al. (2011) show that there is a strong relationship between economic growth and night light intensity at the sub-national level using a cross-section of countries for the world.

connectivity increases the levels as well as the growth rate of nighttime lights. Additionally, we find that that every additional percent of population brought under mobile phone connectivity brings down income inequality by 0.06 percent.

This study is organized as follows. Section 2 provides a survey of the relevant economic literature in the context of telecommunications infrastructure and presents the results from microeconomic case studies concerning the impact of mobile telecommunications in developing countries. Section 3 presents the background of the Shared Mobile Infrastructure program in India. Section 4 and 5 describes the data and the econometric specifications, in particular a difference-in-difference model used to estimate the impact of mobile coverage. econometric modelling approach, in particular and describes the dataset used. Section 6 and 7 presents and discusses the results and provides some evidence in robustness of the results. Section 8 draws conclusions from the results and discusses some policy implications.

2 Literature

Diffusion of information and communication technologies (ICTs) has played a significant role in driving economic growth in the last few decades. In a comparative study of nine OECD countries, Colecchia and Schreyer (2002) find a positive effect of capital investments in ICT on economic growth. Country-specific studies, in particular, Oliner et al. (1994) and Jorgenson and Stiroh (2000) for the United States, Cette et al. (2005) for France, Niininen (1998) for Finland, and Oulton (2002) for the United Kingdom, estimates the contribution of ICT to economic growth between —. However, a simple extrapolation of these estimates may not hold for developing countries, since the digital divide is wider than the income gap between the developed and developing world (Wong, 2002).

Most of the cross-country studies focus on the relationship between ICT and economic growth while the micro studies often explore various channels through which increased ICT coverage can lead to growth. First, access to mobile phones may reduce information asymmetry in the product market and improve welfare. Jensen (2007) shows that the adoption of mobile phones by fishermen and wholesalers in Kerala was associated with a dramatic reduction in price dispersion and a complete elimination of waste. Aker (2010) finds that the introduction of mobile telephony in Niger explains a significant decrease in grain price dispersion. A second channel through which network coverage can affect growth is by creating new jobs for mobile-related services and reducing search costs in the labor market. In South Africa, Klonner et al. (2010) find a correlation between network coverage and employment in a locality. Growth in ICTs can also lead to increased competition, which can result in increased market efficiency, and hence, higher income. In a study on the insurance sector, Brown and Goolsbee (2000) show that the growth of the Internet has reduced term life prices and increased consumer surplus. Finally, Cronin et al. (1993) suggest that investment in telecommunications infrastructure is causally related to the United States' total factor productivity.

The existing literature comes close to establishing a direct link between access to mobile telephones and agricultural income. Beuermann (2011) has documented an increase in agricultural profitability from the adoption of mobile phones. Beuermann et al. (2012) show that mobile phone expansion has increased household real consumption, reduced poverty incidence, and decreased extreme poverty in which country.

Using nighttime lights data, extracted at the village level as a proxy for economic activity we are able to establish an association between access to mobile telephony and increased income. Henderson et al. (2011) was first to suggest that satellite data on nighttime lights could be used to augment official income growth measures. Nordhaus and Chen (2014) conclude that lights data contain substantial cross-sectional information and may be useful for developing countries where statistical systems are often weak. Weidmann and Schutte (2016) also noted that light emissions are highly accurate predictors of economic wealth estimates even with simple statistical models. Mellander et al. (2015) use a combination of correlation analysis and geographically weighted regressions to examine the relationship between economic activity and luminosity. Elvidge et al. (2012) use nighttime lights to develop the Night Light Development Index(NLDI), a measure of regional development. Among others Kulkarni et al. (2011), Castell-Climent et al. (2015), and Guariso and Rogall (2016) also use nighttime lights as a proxy for GDP at a sub-national level. How many of these studies are at sub-nation level?

The empirical evidence on the effect of ICTs on inequality is inconclusive at best. Bandyopadhyay (2005) finds a negative association between the two, Sahoo (2012) observes that ICTs may end up aggravating inequalities, and Kahanec (2005) notes that decreasing desegregation of minorities and increasing minority-majority income inequality may be seen as two faces of the ICT revolution. Pepper and Garrity (2015) conclude that ICTs have different effects on the top and the bottom of the income distribution, and its effects on inequality depend on the relative effect. Income and development measures constructed using nightlights can also be used as a measure of economic inequality. Alesina et al. (2015) use nighttime lights to create measures of ethnic inequality. Mveyange (2015) estimates the Gini coefficient from district-level nighttime light data to assess regional inequality. Kuhn and Weidmann (2015) use variation in nighttime lights to calculate within-group wealth inequality. Xu et al. (2015) use NLDI to measure the regional inequality of public services in Mainland China. Huber and Mayoral (2013), however, caution that there have been no studies on the strengths and weaknesses of nighttime light-based inequality measures, and recommend care in using such measures.

3 Background

3.1 Universal Service Obligation Fund

The Universal Service Obligation Fund (USOF) was set up in India in 2003 with the obligation to provide affordable telecommunication to hitherto unconnected villages. **Proportion of**

villages uncovered at the start of the program, using WPC data on uncovered villages as 41% of total villages in India, and what proportion was proposed to be covered. The funds for the program were raised through a Universal Access Levy (UAL), a percentage of the revenue earned by operators under various licenses. Bids were invited from public and private infrastructure providers to construct towers. Under the program, private infrastructure providers received a subsidy to build and operate mobile towers in rural and remote areas without mobile connectivity.

In Phase-I of the program, 7,353 mobile towers were installed in villages that did not have fixed wireless or mobile coverage. These towers were built between 2007 and 2010 and are spread over 500 districts and 27 states in India. Figure 1 plots the spatial distribution of these towers. Besides remoteness and lack of mobile coverage, these villages were chosen from about 300,000 unconnected villages in India on the basis of their population. Villages with a population greater than 2000 were prioritized in Phase-1 of the program. The infrastructure providers (IPs) were responsible for setting up, operating, and maintaining these sites for a period of six and half years.[5]

4 Data

For analyzing the implications of mobile telephony at the village level, we use a number of datasets. We first describe the datasets with village level characteristics. Then, we discuss the list of villages that were covered or left uncovered under SMIP and the challenges of matching these villages to their characteristics data. We describe the data on luminosity, which is one of our outcome variables. Finally, we talk about the inequality measures constructed from the luminosity data.

4.1 Census Data

The census of India, conducted decennially by the Office of the Registrar General & Census Commissioner, is the only source of village-level information on demographics, infrastructure, and household amenities. Given that the program of interest started in 2008–09, we use census data for the years 2001 and 2011. Besides a unique village identifier, the Primary Census Abstract (PCA) provides information on the distribution of village population over several categories of occupation such as cultivators, agricultural labor, household industry and others. These distributions are provided separately by gender and by main and marginal workers.[6]

There are 638,365 villages in the 2001 PCA. However, we have exact coordinates (longitudes and latitudes) for 592,490 villages. By 2011 the total number of villages stood at 600,497

[5]The IP was responsible for the land, tower, electrical connection, power backup, boundary wall, and security cabin.

[6]Those who did not work for more than six months in the preceding year of the census are defined as marginal workers and the remainder are called main workers.

villages in the 2011 PCA. However, village codes have changed between the two census. In order to link PCA 2001 and PCA 2011, we generate a crosswalk between the 2001 and 2011 village census codes. We obtain this information for each state from the Local Governance Directory (LGD) website and merge them to get a comprehensive dataset with census information for both 2001 and 2011.[7] Based on this crosswalk, we have 506,812 villages with both PCA 2001 and PCA 2011 codes along with the village coordinates.

The village level infrastructure dataset compiled as part of the census is referred to as the Village Directory (VD).[8] The dataset contains village location (state, district, and sub-district), demographics (such as population grouped by gender and caste), size and land use, and primary manufacturing and agricultural commodities produced in the village. It provides details of a variety of amenities available in each of the villages. These include educational, medical, drinking water, post and telegraph, banking, and recreational amenities, among others. There is also information on the availability and quality of infrastructure, such as transportation, telecommunication, and power supply. Under transportation, the dataset covers several alternative modes, including roads and national highways, and railways.

The 2011 Household Amenities (HA) dataset provides the average household characteristics in each village, such as the condition of the house, materials of construction, household size, the sources of drinking water and energy, and assets. This dataset also includes information on the fraction of households in a village with mobile phones. Of the 506,812 villages with 2001 and 2011 PCA codes, 463,353 villages have VD and HA data.

4.2 Coverage under Shared Mobile Infrastructure Program (SMIP)

4.2.1 Baseline Coverage Status

The Wireless Planning & Co-ordination (WPC) wing of the Department of Telecommunications (DoT) maintains records of the wireless coverage status in India. We obtained WPC's 2006 report and found that India had 236,240 uncovered villages as of 2006. It was based on this report that the Universal Service Obligation Fund (USOF) identified the set of villages to be considered for mobile connectivity under the Shared Mobile Infrastructure Program (SMIP).

4.2.2 Tower Locations and Covered Villages

For our purposes, we are interested in the set of covered and uncovered villages following SMIP. In order to identify the set of covered villages, we rely upon two information sources. We have the list of towers actually built, but it does not contain the set of villages that were

[7] Many of the villages with 2001 census code do not have a corresponding 2011 census code. One reason could be the change in status from village to town between 2001 and 2011.

[8] Village is a statutorily recognized unit having a definite boundary and separate land records. Data for villages that are considered as a "Census town" are not shown in the VD data set but in the Town Directory data set. Furthermore, villages that are no longer inhabited are present in the database but do not have any data on amenities.

covered by the towers. Separately, we have a list of proposed towers with the set of villages that were to be covered by each of the proposed towers. In this section, we discuss the process by which we match these two lists to get the villages actually covered under the program.

The USOF had the task of identifying locations to construct mobile towers under SMIP. It manually created village clusters using WPC coverage data and boundary maps from the Survey of India with an eye to maximize the population covered. Within each cluster, preliminary tower locations were then determined manually. Coverage radius of each tower was assumed to be about 5 km.[9] Subsequently, tower locations were optimised using digital elevation maps and radio frequency analysis.[10] Based on this process, the USOF prepared a list of 7,871 unique locations to construct mobile towers covering 256,234 villages.[11] However, the tower identifiers in the proposed list are noisy.

Separately, we obtained a list of 7,393 towers that were finally constructed.[12] In order to obtain the list of villages covered by these towers, we had to match the list of proposed towers to the list with the final towers based on the less-than-ideal tower identifiers. Through this process, we were able to match 4,849 actual towers to those in the proposed list. It is possible that at least some of the remaining 2,544 built towers that we could not match with the proposed list were relocated due to topographical limitations or inadequate electricity supply. For ease of reference, we will refer to the unmatched 2,544 towers as the relocated towers.

Besides the location of each of the built towers (i.e,. state, district, sub-district, and village codes based on the 2001 census), we also have information on the infrastructure provider, service providers, and date of commissioning of the base transceiver system set up by the service providers at each of the tower locations.[13]

For the 4,849 towers that were built at their proposed location, the USOF's proposed tower list provides the names of 140,777 covered villages. However, for the remaining 2,541 relocated towers,[14] the cluster of villages covered by them was not available with the DoT. To identify these villages, we follow a two-step process. First, we plot the precise location (latitude and longitude) of 234,836 of the 236,240 uncovered villages in WPC's 2006 report.[15] In the second step, using specialized GIS software, we superimpose the location of the 2,536

[9] There was some variation between the plains and hilly terrains.

[10] This information is based on numerous conversations with individuals closely associated with the project at the Centre for Development of Telematics, DoT.

[11] The number of villages in this proposed list exceeds the number of uncovered villages in the 2006 WPC report. This is because of overlap in the villages covered by multiple towers. Additionally, some of the villages may already have mobile coverage but fall within the proposed tower's coverage area.

[12] We were unable to get a satisfactory explanation for the shortfall of 478 towers. The reasons could be lack of interest among bidders, problems of insurgency, difficult terrain, etc.

[13] Each tower has a unique alpha-numeric identifier. The tower identifier contains information which allows us to extract 2001 census codes for the state, district, sub-district, and village where the tower is located. For example for a tower id, "28-01-0002-00004800-01-O-C", the 2001 Census codes for the state, district, sub-district and village would be 28, 01, 0002, 00004800 respectively. In addition, the dataset provides each tower's latitude and longitude.

[14] Longitude and latitude information are missing for 3 of the 2,544 relocated towers.

[15] Village co-ordinates were manually matched using the information made available by Mizushima Laboratory.

relocated towers on this map with a five kilometer buffer.[16] Through this process, we identify 30,044 villages that were most likely to be covered by the relocated towers.

4.3 Village Census Codes: Covered and Uncovered

We have three different sets of villages in our sample. The first is the list of 30,044 villages covered by relocated towers. The second is the set of 140,777 villages covered by towers built in the proposed location. Finally, the third set is one of 56,399 villages which remain uncovered after the implementation of SMIP. For the purposes of our analysis, we need village-level information both before and after the introduction of mobile telephony. So, we need to first determine each village's PCA 2001 code and then match it with that in the comprehensive census list based on the crosswalk.[17]

Since the WPC 2006 report of initially uncovered villages contains PCA 2001 code for each village, we apply fuzzy matching to match these village names to those in the list of covered villages. In many instances, we have multiple matches for a given village name. We then identify the best match between the two lists by ensuring that the remaining information – state, district, sub-district, population and number of households – are also the same. Through this process, we obtain PCA 2001 code for 84,131 villages covered by towers built in proposed locations and 28,824 villages covered by relocated towers. A closer looks reveals further discrepancies. Importantly, 33,772 of the 84,131 villages purported to be covered under the SMIP also appear in the WPC 2006 list of villages that were already covered prior to the SMIP. To avoid contamination of treated villages, we drop these villages from our sample of covered villages.

Separately, we obtained WPC's list of unconnected villages as of 2011. While this list contains names of 56,399 villages, we have 47,099 unique villages with PCA 2001 codes. Of these, 7,868 villages also appear in the WPC list of covered villages prior to 2006. We drop these villages from our list. We argue that the remaining villages must be a proper subset of uncovered villages in 2006 and 2011. We refer to these villages as "control" for the rest of the paper.

Once we merge all villages, both covered and uncovered, with the crosswalk data, we obtain matched 2001 and 2011 census codes for 79,183 covered villages (50,359 covered by towers in proposed locations and 24,671 covered by relocated towers) and 39,321 uncovered villages.

4.4 Night-time Lights Data

Mobile coverage under SMIP was administered at the village level. However information on economic activity at the village level is sparse. Henderson et al. (2011) show that there is a strong relationship between economic growth and night light intensity at the sub-national level

[16]The five kilometer buffer was suggested by the officials at the Centre for Development of Telematics, DoT.
[17]For any village, the 2001 census code is different from its 2011 census code.

using a cross-section of countries for the world. We use data on the luminosity of nighttime lights extracted at the village level for the period 1992-2013 as a proxy for the size of the economy.

The satellite raster images with nighttime lights were obtained from the National Aeronautics and Space Administrations (NASA) Defense Meteorological Satellite Programs Operational Linescan System (DMSPOLS), a set of military weather satellites orbiting and recording high resolution images of earth each night between 20:30 and 22:00 local time. The high resolution images captured at an altitude of 830 km above the earth record concentrations of outdoor lights, fires, and gas flares at a resolution of 0.56 km and a smoothed resolution of 2.7 km. These images are available from 1992 onwards and are used to produce annual composites during a calendar year after dropping cloud cover, aurora and solar glare (mainly near the poles), and fleeting lights such as forest fires and other noise. We use this series of the images from 1992–2013 after masking the raster data for the geographic boundary of India. These images are scaled onto a geo-referenced 30 arc-second grid (approximately 1 sq. km.). Each pixel is encoded with a measure of its annual average brightness on a 6-bit scale from 0 to 63. We use the data available on stable night lights that drop light values from pixels with unstable light signatures over time and village boundary maps to extract a time series of village level luminosity data.

The State Directorate of Census Operations publishes village boundary maps at the subdistrict level along with their census code. We obtain the digitized village level maps from a private vendor which scans and vector digitizes the boundaries of villages as polylines and the location of the village settlement as points from these maps. Figure 3 shows the nighttime lights data superimposed on the village boundary map for the state of Haryana in the year 2001. Figure 1 plots the location of the towers on the night-time satellite map of India for the year 2013. Note that almost none of the towers is located inside brightly lit areas. This confirms that the program provided coverage to rural India which is less likely to be brightly lit at night.

4.5 Inequality measures

Data on inequality measures at the village level is practically non-existent. It also proves difficult to use nightlights to construct an inequality measure at the village level because of the relatively small number of nightlight pixels in most given villages. We choose, therefore, to analyze inequality as a function of the intensity of treatment among the uncovered villages at the subdistrict-level.

We consider the villages that had no mobile coverage at the baseline, and group them by the subdistrict they belong in. Then, we use nightlights data for the period 2003-2013 to calculate the Gini coefficient, defined as half the relative mean absolute difference, for each group in each year, to be used as a measure of inequality. Further, for each such subdistrict group, we define intensity of treatment in a given year as the proportion of originally uncovered villages in the group that have been covered so far. In an alternate specification, we look at intensity of treatment as the proportion of the originally uncovered population of the group that has been covered so far. It is important to note that, under these definitions, the Gini coefficients and intensity of treatment do not refer to the subdistrict as a whole, but merely to that part of it which does not have mobile coverage at the baseline.

5 Estimation Strategy

As discussed in the previous section our sample is restricted to the period 2003–2013 covering 28 states and 118,510 villages. The Shared Mobile Infrastructure Programme provided mobile towers in hitherto uncovered villages and we exploit the variation in mobile coverage through the program to tease out the effects of mobile connectivity. As all towers were not built at the same time, we take advantage of the variation in timing to find the effects using a difference-in-difference framework. The following empirical model is standard for most of the outcomes

$$Y_{vst} = \beta_0 + \beta_1 \text{Treatment}_{vs} \times \text{Post}_t + \tau_t + \kappa_{vs} + \varsigma_s t + \varepsilon_{vst}. \tag{1}$$

where the indices v, s and t represent village, state and year respectively. Treatment_{vs} is a binary variable which takes the value one if the village v in state s received mobile tower connectivity under SMIP. Post_t is an indicator for years after the mobile connectivity was provided. The coefficient β_1 measuring the average effect of mobile connectivity is the parameter of interest. Our specification also include year (τ_t) and village (κ_{vs}) fixed effects, and state-specific time trends $(\varsigma_s t)$. Any unobserved secular changes in outcomes are controlled for under the standard difference-in-difference identifying assumption.

The estimation framework outlined in equation (1) assumes that a priori the group-specific trends were uncorrelated with treatment. However, it is possible that some unobserved factor was associated with both the trend of nighttime lights and mobile coverage under SMIP. For instance, it is possible that the program was implemented in villages which were more likely to get covered endogenously and consumption of electricity in such villages was increasing over time. To allow for differential pre-treatment trends, we estimate the following specification for the villages that were covered in 2008.

$$\begin{aligned} Y_{vst} = \beta_0 + \beta_1 \text{(t-2003)} + \beta_2 \text{Treatment}_{vs} \times \text{(t-2003)} + \beta_3 \text{Treatment} \times \text{Post}_t \times \text{(t-2008)} \\ + \beta_4 \text{Treatment}_{vs} \times \text{Post} + \tau_t + \kappa_{vs} + \varsigma_s t + \varepsilon_{vst}, \end{aligned} \tag{2}$$

The coefficient β_1 captures the time trend while β_2 captures the differential in linear time trend between the treatment and control villages. β_3 allows a trend-break between the groups after the construction of the towers in 2008 and β_4 captures difference in difference estimate of the outcome variable.

5.1 Descriptive Statistics

Starting with the sample of covered and uncovered villages with both 2001 and 2011 census codes, we merge these data with the Household Amenities (HA) data and finally with the Night Light data. Our final sample has 79,229 covered and 39,281 uncovered villages with the variables needed for our analysis. Table 2 provides some descriptive statistics for the sample villages. Columns (1) and (2) show the averages for the dependent and independent variables while column (3) reports the differences for the pre-SMIP period. The villages covered under SMIP show 19 percent less luminosity, had 586 additional residents and with higher literacy rate. These villages also have better infrastructural facilities in terms of availability of post offices, land line connections, banking and transportation services. These significant differences clearly point out that the covariates are not balanced for the treatment and control villages.[18]. Columns (4) and (5) report the averages for the post SMIP period. Except for the outcome variable, natural log of average luminosity, the differences in the averages for the other variables, reported in Column (6), continue to remain significantly positive. Column (7) shows the differences between column (6) and (3). The difference-in-differences estimate for log luminosity is significant at one percent level and is measured at 0.31. Except for banking services the difference-in-differences estimates for other observables are also significant.

6 Results

We show our main results using two sources of data. Census data from 2001 and 2011 are used to confirm that both mobile coverage and ownership improved for the villages covered under the Shared Mobile Infrastructure Program (SMIP). Second, we construct a time series of village level luminosity as a proxy for economic growth and inequality to gauge the impact of mobile coverage.

6.1 Mobile Coverage and Ownership

Village Directory data from the 2011 Census provides village level information on endline mobile connectivity, while we obtain baseline coverage status from the Wireless Planning & Co-ordination (WPC, 2006) reports.[19] According to the report in 2006, 340,170 villages were connected with mobile telephony while 236,240 villages remained uncovered.

In order to find the effects of the SMIP on mobile coverage we estimate a difference-in-difference model as specified in equation (1) after restricting the sample to villages that were not covered in 2006. Table 3 reports the results of the regressions. In column (1) the coefficient

[18] In one of the robustness checks we attempt to address this issue by carefully selecting a sub-sample of treatment and control villages that are more comparable.

[19] WPC reports also served as the basis of determining villages to be covered under the SMIP. Village Directory data from the 2001 Census does not have any information on mobile connectivity.

on the interaction between *Treatment* and *Post* after controlling for baseline village infrastructure facilities such as telephones, post offices, banking, etc. is estimated at 0.19.[20] The point estimate is statistically significant at 1 percent level. This suggests that treatment villages were 19 percent more likely to have mobile connectivity by 2011 compared to the control villages. Note that by 2011 the control villages may have access to mobile telephony driven by endogenous demand. In column (2) we report the D-i-D estimate after controlling for village fixed effects. This specification helps us to eliminate time invariant village characteristics that might have affected the likelihood of treatment. The interaction coefficient is marginally higher in magnitude at 19.9 percentage points and continues to be significant at 1 percent level.

We explore the effects of the program on mobile ownership in Table 5. Household amenities data in the Census 2011 collects information on the fraction of households in a village with mobile phone.[21] In column (1) we compare the fraction of households with mobile phones by SMIP coverage in 2011 after controlling for district fixed effects. The point estimate suggests that the fraction of households that own a mobile phone increased by 13.6 percentage points for villages that were covered under the SMIP and it is significant at 1 percent level. In column (2) we control for additional baseline village level characteristics along with district fixed effects and the coefficient on SMIP reduces to 10 and it continues to be significant at 1 percent. These results suggest that the program significantly increased mobile coverage and ownership in rural India.

6.2 Effects on Nighttime Lights

The Shared Mobile Infrastructure Program connected villages with mobile telephony. Access to mobile telephony can potentially affect village economies in a multitude of ways. The objective of this paper is to estimate the effects on rural income. However, village level per capita income data is not available for India. Henderson et al. (2011) have shown that nighttime lights visible from outer space reflect variation in per capita income. In the absence of income data, nighttime lights can be a very good proxy for economic growth.[22] In this section we describe the effects of mobile telephony on nighttime lights.

6.2.1 Difference-in-Difference Estimates

Our nighttime lights data spans a period of ten years from 2003 to 2013 and mobile towers under the SMIP were commissioned between 2008-2009. Table 7 reports the effects of mobile connectivity on natural log and log differences of average nighttime lights using a difference in

[20] *Treatment* takes the value one if a village was scheduled to be covered under the program and zero otherwise. *Post* is an indicator for the year 2011

[21] Household amenities data in the Census 2001 did not cover mobile ownership.

[22] See citations

difference estimation framework outlined in equation (1).[23] Column (1) of Table 7 presents the result on log nighttime lights. The coefficient on the interaction between *Treatment* and *Post* is estimated at 0.15 suggesting 16 percent brighter nighttime lights for the entire post period from the baseline average. The coefficient is highly significant at 1 percent level. In column (2) we report the results of the D-i-D framework on first differences of natural log nighttime lights. The interaction coefficient is measured at 0.08 and is significant at 1 percent level. This suggests that the growth rate of nighttime lights in the post period was 9 percent higher than the baseline average. These results indicate that mobile connectivity increases the levels as well as the growth rate of nighttime lights.

6.2.2 Time Varying Estimates

We present the time-varying effects of mobile coverage under the program on the same outcome variables in Table 9. Column (1) reports the effects on log nighttime lights. The coefficient estimate for the interaction between treatment and an indicator for the first year since a tower was built is 0.02, and it is significant at 10 percent level. This estimate suggests that average luminosity increased by 2 percent in the treated villages one year after the commissioning of a mobile tower. The coefficient estimates for later years are 0.07, 0.15, 0.35, and 0.45 respectively. These time-varying effects of mobile telephony are very precisely estimated at one percent level and indicate that the effects of mobile towers take some time to emerge but the effects increase over time. We plot the estimated coefficients over time in Panel A of Figure 4. The time-varying estimates for log differences, reported in Column (2) also shows similar effects. We do not find any effect on the growth rate of luminosity in the first year of construction of towers. However, the effects are positive and increasing for the subsequent years. Panel B of Figure 4 plots the estimated coefficients.

6.2.3 Trend-Break Estimates

One of the main empirical concerns for the results reported in Table 7 and 9 might be that luminosity of the village covered under SMIP is trending differently, and the results are confounded by these trends. We allay this concern by estimating a model that allows the treatment and control villages to evolve along different time trends before the implementation of SMIP. The estimation strategy with trend-break is outlined in equation 2.

We report the results separately for villages that were treated in the year 2008 and 2009 in Panel A and B, respectively in Table A.6. Column (1) in Panel A presents the result for log nighttime lights for the villages where mobile towers were commissioned in 2008. The coefficient on the interaction between *(Year-2003)* and *Treatment* is estimated at 0.04 and is

[23] We use log transformations and differences in logs instead of using levels of nighttime lights because it enables us to ally concerns about non-normality assumption and see the effect of mobile towers on growth rate of nighttime lights.

highly significant at 1 percent level. This suggests that even before the SMIP the nighttime lights for treatment villages were increasing over time at a higher rate than for the control villages. The coefficient on the interaction between *Year-2008*, *Treatment* and *Post* is estimated at 0.04 suggesting that even after controlling for the differential trend of nighttime lights for the two groups, the treatment villages on average had higher nighttime lights in the post period than the baseline average. The coefficient is highly significant at 1 percent level. The coefficient estimate for the interaction between treatment and post is negative at -.17 and it is highly statistically significant. In column (2) we report the results of the above specification on first differences of log nighttime lights. The coefficient on the interaction between *Year-2008*, *Treatment* and *Post* is estimated at 0.05 suggesting that even after controlling for the pre-existing differential trend, the treatment villages were on a significantly higher trajectory of growth of nighttime lights in the post period. For villages that were covered in 2009, the results show a similar pattern. However, the coefficient on the triple interaction between *Year-2009*, *Treatment* and *Post* is estimated at 0.11, is much larger than the villages that were covered earlier.

6.3 Complementarity with Village Amenities

Improved communication technology may be a necessary condition for growth, but it might not be sufficient. Physical infrastructures and socio-economic conditions along with improved connectivity may act as a catalyst that can enable growth. We use data from the Village Directory 2001 to obtain village infrastructure characteristics and use a triple difference model to explore which baseline amenities facilitate the effects of mobile coverage. Our triple difference model is specified below.

$$\begin{aligned} Y_{vst} = {} & \beta_0 + \beta_1 \text{Treatment}_{vs} \times \text{Post}_t \times \text{Infrastructure Dummy}_{2001} + \beta_2 \text{Treatment}_{vs} \times \text{Post}_t \\ & + \beta_3 \text{Treatment}_{vs} \times \text{Infrastructure Dummy}_{vs2001} + \beta_4 \text{Post}_t \times \text{Infrastructure Dummy}_{v,2001} \\ & + \tau_t + \kappa_{vs} + \varsigma_s t + \varepsilon_{vst}, \end{aligned} \tag{3}$$

where the indices v, s and t represent village, state and year respectively. Treatment_{vs} is an indicator which takes the value one if the village v in state s received mobile tower connectivity under SMIP. Post_t is an indicator for years after the mobile tower was built. $\text{Infrastructure Dummy}_{vs2001}$ is an indicator for the relevant infrastructure, taking the value one if the village v in state s in 2001 had access. The coefficient β_1 measuring the average effect of interaction of the infrastructure variable with mobile connectivity is the parameter of interest. Our specification also include year (τ_t) and village (κ_{vs}) fixed effects, and state-specific time trends $(\varsigma_s t)$.

Each row in Column (1) and (2) of Table 11 presents the result of a separate regression with different indicators for infrastructure. Results on log nighttime lights reported in column

(1) suggest that covered villages that had more literates, access to banking services, closer to a town, bus services, and better telephone connections at the baseline, had higher average nighttime lights for the entire post period. The results on first differences of nighttime lights presented in Column (2) are however not significant for most of the infrastructure variables. The coefficient on the interaction of *Treatment* and *Post* with literacy and bank facility continues to remain positive and significant at 1 percent level. These results provide suggestive evidence that mobile phone are more effective to improve economic outcomes in areas with high literacy rates and access to formal banking facilities. Literate mobile users can make the most use out of cellular phones and access to banking services may act as a catalyst for growth as it can facilitate access to loans and money transfer during distress.

6.4 Effects on Inequality

Many countries have experienced sharp increases in wage and income inequality over the past several decades. There is a growing consensus that technological advancement is one of the major factors behind rising income inequality (Acemoglu, 2002; Jaumotte et al., 2013; Krueger, 1993). The adoption rate for mobile phones had been one of fastest technology adoption. The effects of mobile phones on income inequality is theoretically ambiguous. For example, declining handset prices and tariff rates have made the technology affordable for the poor. Therefore, the benefits of using mobile phones are not limited to higher ends of the income distribution. At the same time, there are significant price and non-price entry barriers for adoption of mobile phones with internet connectivity. There is also considerable regional variation in mobile coverage. These factors may encourage income and regional inequality.

In this section, we explore the effects of mobile coverage on income inequality. We construct a proxy for income inequality by calculating the Gini coefficient of luminosity at the subdistrict level. We collapse the village level mobile coverage under SMIP at the subdistrict level. As a result, our main explanatory variable is the fraction of villages covered under SMIP over time in a given sub-district. We report the results in Table 13. The variable *% of Villages Covered* measures the fraction of uncovered villages in a sub-district that were covered under SMIP while *% of Population Covered* measures the fraction of uncovered population that were covered. The coefficient estimate on *% of Villages Covered* in Column (1) suggests that for the villages without access to mobile telephony in 2006, a one percent increase in mobile coverage decreases luminosity Gini by 0.04 percentage points. The point estimate is highly statistically significant at one percent level. Given the baseline average Gini coefficient at 0.51, this translates as a 0.08 percent decrease in the measure of income inequality. Similarly, in Column (2) our estimate suggests that every additional percent of population brought under mobile phone connectivity reduces income inequality by 0.04 percentage points.

7 Conclusions

Since the beginning of the twenty-first century, mobile telephony has witnessed unprecedented growth in developed nations. The adoption of mobile phones in developing countries was even faster. In this paper, we study the effects of access to mobile telephony on economic growth and inequality in the context of an emerging country. We use exogenous change in mobile coverage in rural India under the Shared Mobile Infrastructure Program between 2007–2009. Using village level nighttime lights between 2003-2013 as a proxy for income and a difference-in-difference estimation strategy we find that the villages covered under the program had a 12 percent additional growth compared to the uncovered villages. Our results on luminosity Gini suggests that for every additional percent of population brought under mobile phone connectivity reduces income inequality by 0.06 percent. These results are robust to alternate specifications and a smaller sample where the baseline difference between the villages covered under the program and control villages are minimum.

References

Acemoglu, D. (2002). Technical Change, Inequality, and the Labor Market. *Journal of Economic Literature*, 40(1):7–72.

Aker, J. C. (2010). Information from Markets Near and Far: Mobile Phones and Agricultural Markets in Niger. *American Economic Journal: Applied Economics*, 2(3):46–59.

Alesina, A., Michalopoulos, S., and Papaioannou, E. (2015). Ethnic Inequality. *Journal of Political Economy*, 123(3):547–724.

Bandyopadhyay, S. (2005). *Are Mass Media and ICTs Associated with Inequality and Poverty?*, chapter 11, pages 185–216.

Beuermann, D. W. (2011). Telecommunications Technologies, Agricultural Profitability, and Child Labor in Rural Peru. *Central Bank of Peru, Working Paper Series*, 2.

Beuermann, D. W., McKelvey, C., and Vakis, R. (2012). Mobile Phones and Economic Development in Rural Peru. *The Journal of Development Studies*, 48(11):1617–1628.

Brown, J. R. and Goolsbee, A. (2000). Does the Internet Make Markets More Competitive? Technical report, National Bureau of Economic Research.

Castell-Climent, A., Chaudhary, L., and Mukhopadhyay, A. (2015). Tertiary Education and Prosperity: Catholic Missionaries to Luminosity in India. IZA Discussion Papers 9441, Institute for the Study of Labor (IZA).

Cette, G., Mairesse, J., and Kocoglu, Y. (2005). ICT Diffusion and Potential Output Growth. *Economics Letters*, 87(2):231–234.

Colecchia, A. and Schreyer, P. (2002). The Contribution of Information and Communication Technologies to Economic Growth in Nine OECD Countries. *OECD Economic Studies*, 2002(1):153–171.

Cronin, F. J., Colleran, E. K., Herbert, P. L., and Lewitzky, S. (1993). Telecommunications and Growth: The Contribution of Telecommunications Infrastructure Investment to Aggregate and Sectoral Productivity. *Telecommunications Policy*, 17(9):677–690.

Elvidge, C. D., Baugh, K. E., Anderson, S. J., Sutton, P. C., and Ghosh, T. (2012). The Night Light Development Index (NLDI): A Spatially Explicit Measure of Human Development from Satellite Data. *Social Geography*, 7(1):23–35.

Goyal, A. (2010). Information, Direct Access to Farmers, and Rural Market Performance in Central India. *World Bank Policy Research Working Paper Series, Vol.*

Gruber, H. and Koutroumpis, P. (2011). Mobile telecommunications and the impact on economic development. *Economic Policy*, 26(67):387–426.

Guariso, A. and Rogall, T. (2016). Rainfall Inequality, Political Power, and Ethnic Conflict in Africa.

Henderson, V., Storeygard, A., and Weil, D. N. (2011). A Bright Idea for Measuring Economic Growth. *American Economic Review*, 101(3):194–99.

Huber, J. D. and Mayoral, L. (2013). Inequality, Ethnicity and Civil Conflict. *Manuscript, Instituto de Análisis Económico, Barcelona*.

Jaumotte, F., Lall, S., and Papageorgiou, C. (2013). Rising Income Inequality: Technology, or Trade and Financial Globalization? *IMF Economic Review*, 61(2):271–309.

Jensen, R. (2007). The Digital Provide: Information (Technology), Market Performance, and Welfare in the South Indian Fisheries Sector. *The quarterly journal of economics*, pages 879–924.

Jorgenson, D. W. and Stiroh, K. J. (2000). Raising the Speed Limit: US Economic Growth in the Information Age. *Brookings papers on economic activity*, 2000(1):125–210.

Kahanec, M. (2005). Two Faces of the ICT Revolution: Desegregation and Minority-Majority Earnings Inequality. IZA Discussion Papers 1872, Institute for the Study of Labor (IZA).

Klonner, S., Nolen, P. J., et al. (2010). Cell Phones and Rural Labor Markets: Evidence from South Africa. In *Proceedings of the German Development Economics Conference, Hannover 2010*, number 56. Verein für Socialpolitik, Research Committee Development Economics.

Krueger, A. B. (1993). How Computers Have Changed the Wage Structure: Evidence from Microdata, 1984-1989. *The Quarterly Journal of Economics*, 108(1):33–60.

Kuhn, P. M. and Weidmann, N. B. (2015). Unequal We Fight: Between- and Within-Group Inequality and Ethnic Civil War. *Political Science Research and Methods*, 3:543–568.

Kulkarni, R., Haynes, K. E., Stough, R. R., and Riggle, J. D. (2011). Revisiting Night Lights as Proxy for Economic Growth: A Multi-Year Light Based Growth Indicator (LBGI) for China, India and the US. *GMU School of Public Policy Research Paper*, (2011-12).

Mellander, C., Lobo, J., Stolarick, K., and Matheson, Z. (2015). Night-Time Light Data: A Good Proxy Measure for Economic Activity? *PloS one*, 10(10):e0139779.

Muto, M. and Yamano, T. (2009). The Impact of Mobile Phone Coverage Expansion on Market Participation: Panel Data Evidence from Uganda. *World development*, 37(12):1887–1896.

Mveyange, A. (2015). Night Lights and Regional Income Inequality in Africa. *World Bank*.

Niininen, P. (1998). Computers and Economic Growth in Finland, UNU. Technical report, WIDER, Discussion Paper, 1998/148.

Nordhaus, W. and Chen, X. (2014). A Sharper Image? Estimates of the Precision of Nighttime Lights as a Proxy for Economic Statistics. *Journal of Economic Geography*.

Oliner, S. D., Sichel, D. E., Triplett, J. E., and Gordon, R. J. (1994). Computers and Output Growth Revisited: How Big is the Puzzle? *Brookings Papers on Economic Activity*, 1994(2):273–334.

Oulton, N. (2002). ICT and Productivity Growth in the United Kingdom. *Oxford Review of Economic Policy*, 18(3):363–379.

Pepper, R. and Garrity, J. (2015). ICTs, income inequality, and ensuring inclusive growth. *The Global Information Technology Report*.

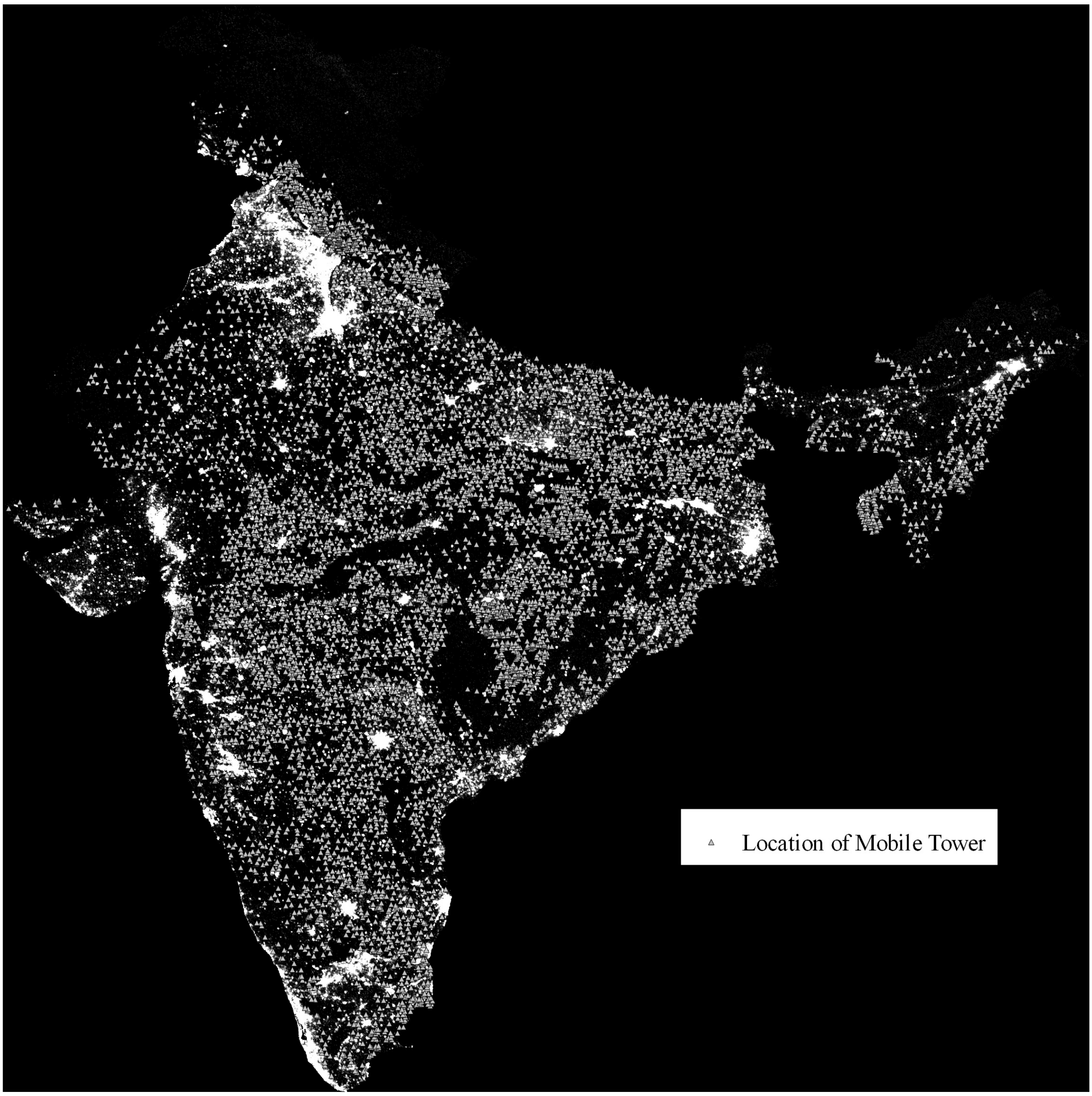
Sahoo, D. (2012). Role of ICT in Economic Growth and Regional Inequality in India. In *CPRafrica 2012/CPRsouth7 Conference, Port Louis, Mauritius*.

Weidmann, N. B. and Schutte, S. (2016). Using Night Light Emissions for the Prediction of Local Wealth. *Journal of Peace Research*.

Wong, P.-K. (2002). ICT Production and Diffusion in Asia: Digital Dividends or Digital Divide? *Information Economics and Policy*, 14(2):167–187.

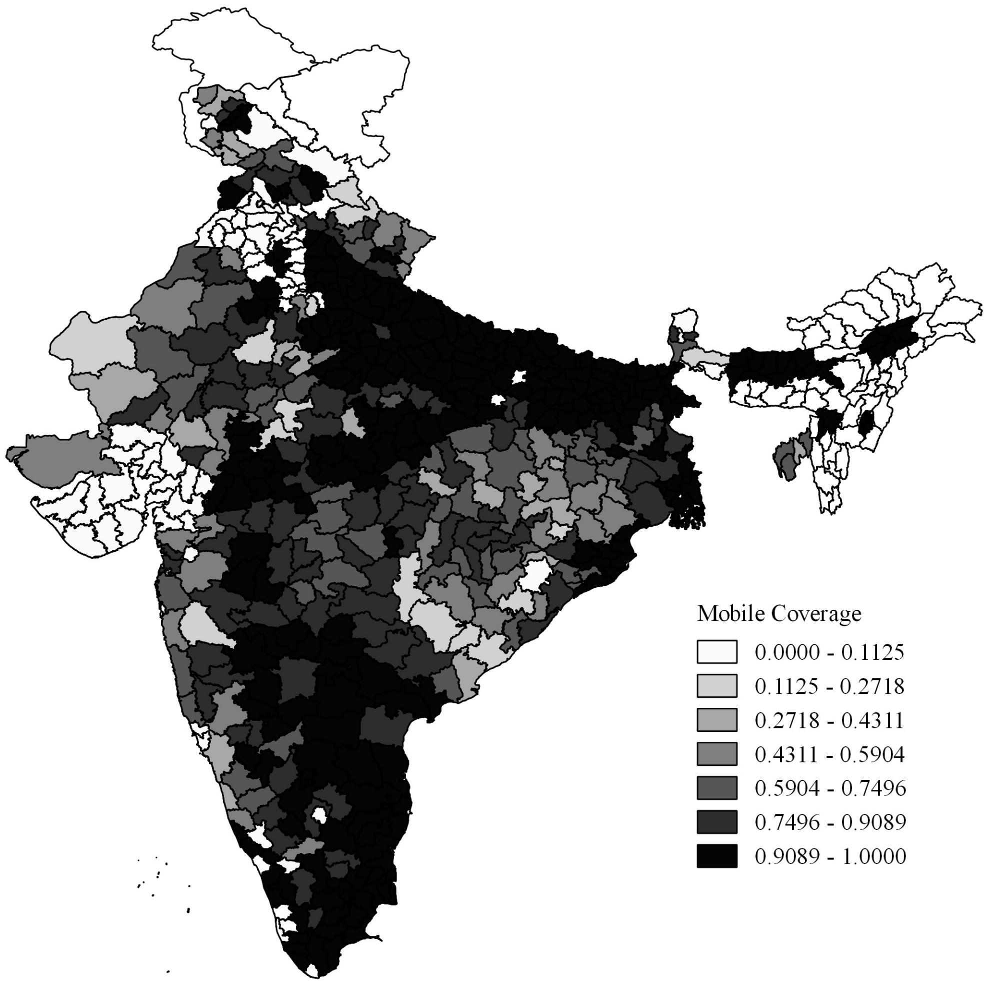
Xu, H., Yang, H., Li, X., Jin, H., and Li, D. (2015). Multi-Scale Measurement of Regional Inequality in Mainland China during 2005–2010: Using DMSP/OLS Night Light Imagery and Population Density Grid Data. *Sustainability*, 7(10):13469–13499.

FIGURE 1: Location of Mobile Towers Built under the Shared Mobile Infrastructure Program (SMIP).



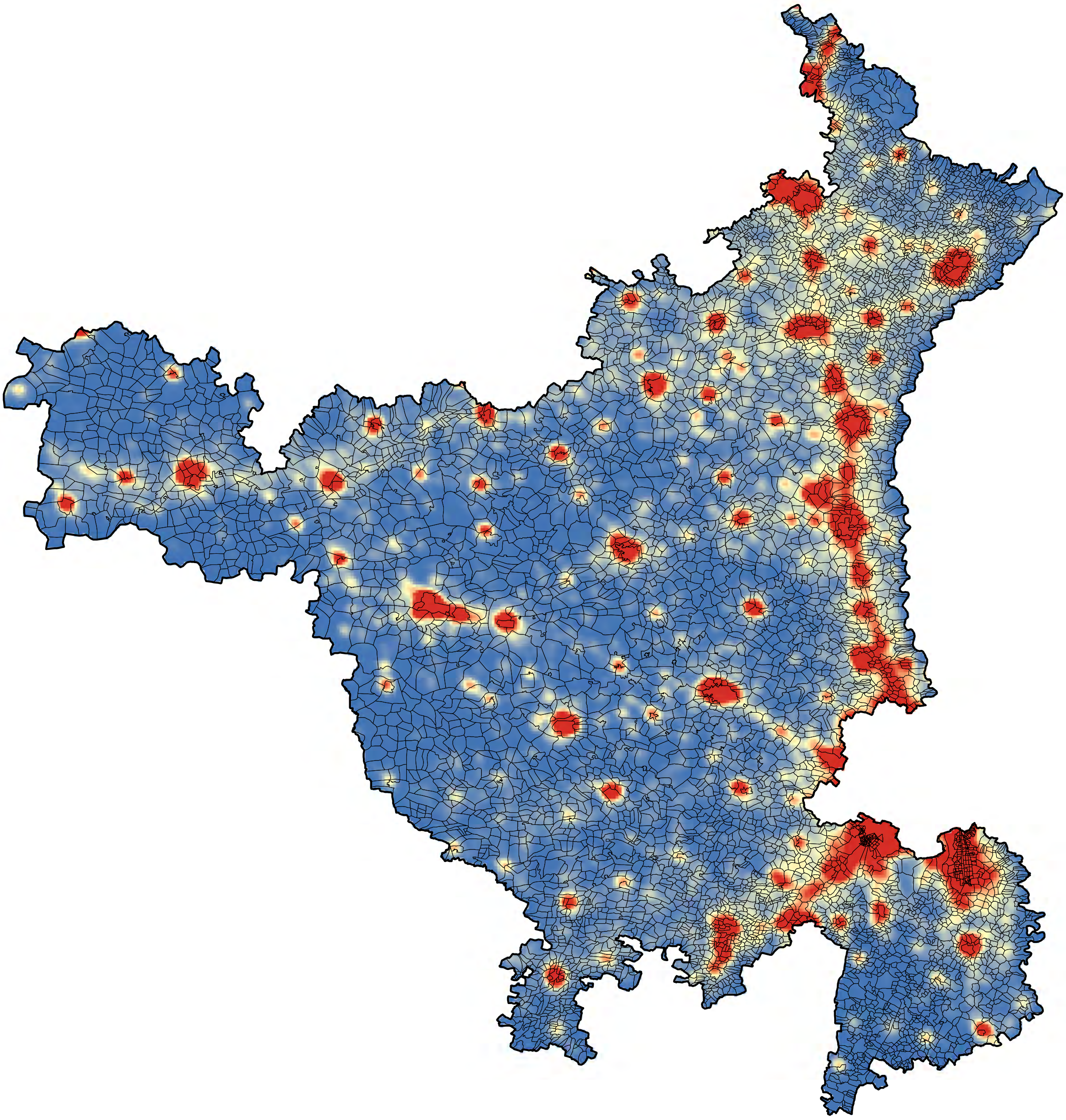
Notes: Locations of mobile towers built under the SMIP are shown by gray triangles. Tower locations are superimposed on the luminosity map of India. Tower locations are concentrated in the darker areas, in line with the intent of the SMIP to improve coverage in rural and remote areas. The satellite images come from the National Aeronautics and Space Administration's (NASA) Defense Meteorological Satellite Program's Operational Linescan System (DMSP-OLS). Exact location of towers are obtained from the Universal Service Obligation Fund (USOF).

FIGURE 2: District Level Mobile Coverage under the Shared Mobile Infrastructure Program (SMIP).



Notes: The map shows the district-wise mobile coverage under the SMIP (2008-09). Coverage is defined as the ratio of the number of villages that were covered under the SMIP to the number of villages that were uncovered at the baseline (2006). District-wise number of uncovered villages as of 2006 is obtained from the Wireless Planning & Co-ordination (WPC) wing of the Department of Telecommunications (DoT) and village-level mobile tower construction details were obtained from the Universal Service Obligation Fund (USOF).

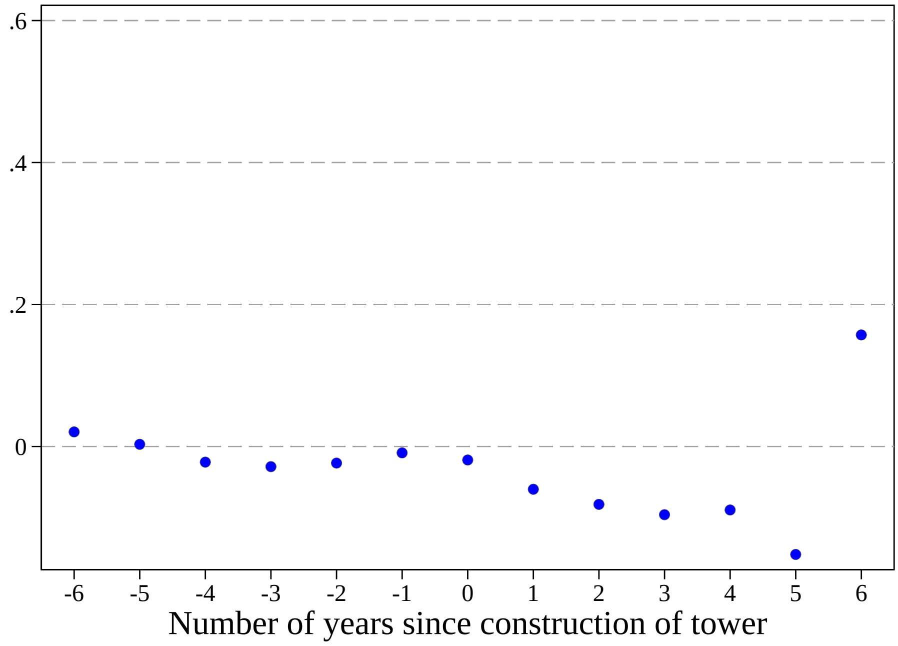
FIGURE 3: Nighttime Lights and Village Boundaries for the State of Haryana in 2001



Notes: The satellite image used was obtained from the National Aeronautics and Space Administration's (NASA) Defense Meteorological Satellite Program's Operational Linescan System (DMSP-OLS) and depicts the nighttime lights for the year 2001. The village boundary maps are obtained from the Registrar General of India.

FIGURE 4: Time-varying Effects of the SMIP on Nighttime Lights using Village-level Data

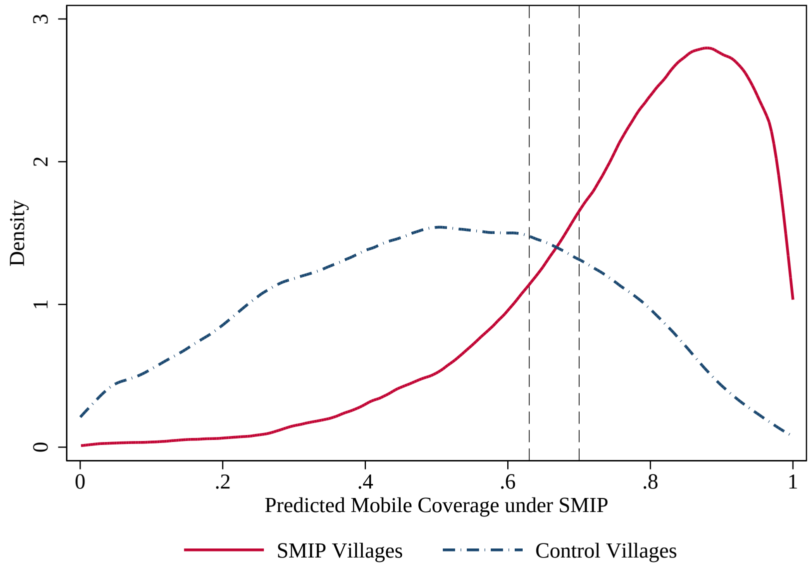
PANEL A: Natural Log of Average Nighttime Lights



PANEL B: Lagged Differences in Natural Log of Average Nighttime Lights

Notes: The graphs plot the coefficients (effects) of SMIP on the natural log and lagged differences of average nighttime lights over the years since construction of a mobile tower. Both specifications control for district- and year-fixed effects and state-specific time trends. Errors are robust and clustered at the district level.

FIGURE 5: Predicted Probabilities and the Common Support



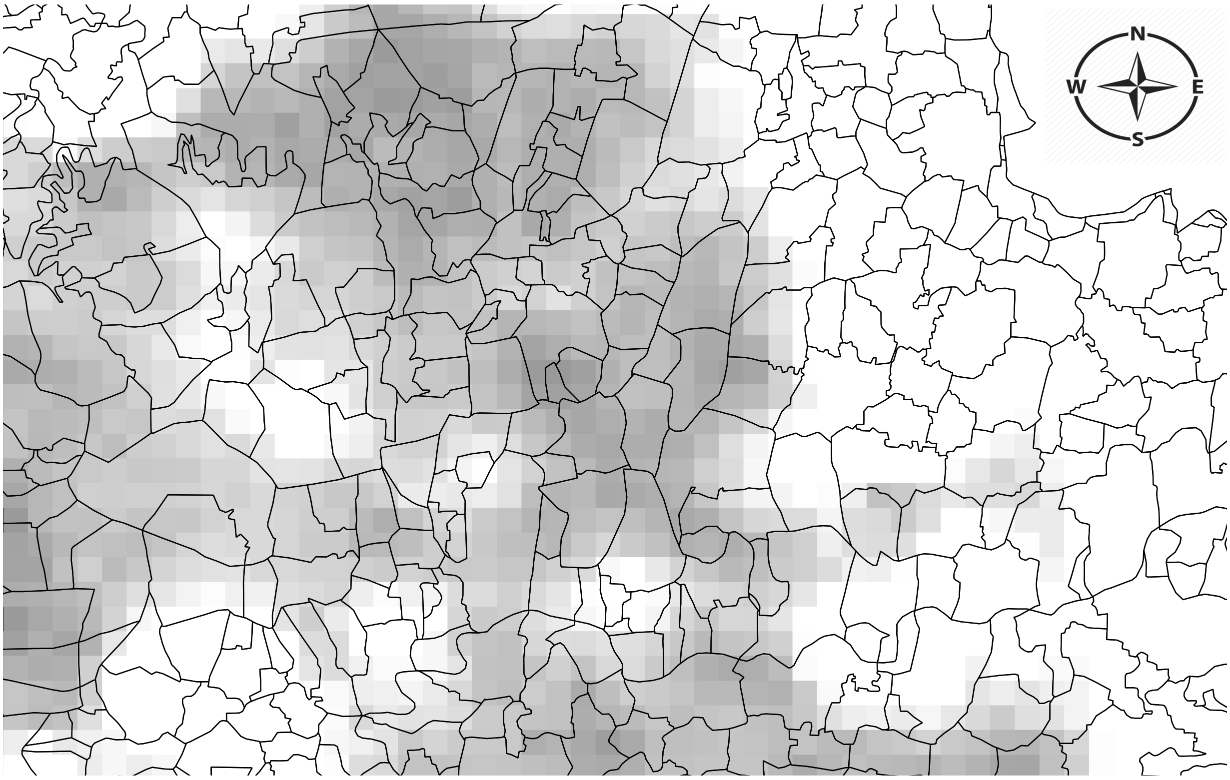
Notes: The solid line plots the predicted probability of mobile coverage under the SMIP for the villages that were actually covered under the program using a Linear Probability Model with baseline village characteristics as controls. The dashed line plots the predicted probability of mobile coverage under the SMIP for villages that were not covered under the program using the same model. The range of common support shown by the pair of dashed vertical lines $[0.63, 0.7]$ was selected on the basis of visual inspection of the predicted probability distributions.

TABLE 1: Summary Statistics for District-level Data

Variable	Pre-SMIP	Post-SMIP	Difference
	(1)	(2)	(2) – (1)
Nighttime Lights	0.80	1.36	0.56***
	(1.63)	(2.48)	
Population	288996.89	335017.68	46020.79**
	(258895.36)	(304222.35)	
Literacy	0.47	0.57	0.10***
	(0.12)	(0.10)	
Availability of Post Office	0.35	0.12	-0.23***
	(0.60)	(0.18)	
Number of Telephone Connections	521.18	105.54	-415.64***
	(930.94)	(117.56)	
Availability of Railway Services	0.01	0.02	0.01***
	(0.05)	(0.06)	
Availability of Domestic Power Supply	0.31	0.88	0.57***
	(0.27)	(0.22)	
Availability of Bank Facility	0.08	0.09	0.01
	(0.15)	(0.15)	
Availability of Bus Facility	0.42	0.51	0.09***
	(0.32)	(0.31)	

Notes: We use district-level characteristics for pre- and post-SMIP period from the Census of India 2001 and 2011, respectively. Luminosity data was extracted from the raster images for 2001 and 2011 obtained from the National Aeronautics and Space Administrations (NASA) military weather satellites.

FIGURE A.1: Village Boundaries for Mysore



Notes: The graph superimposes the nighttime lights data for the year 2013 on the map of village boundaries for the district of Mysore in Karnataka.

TABLE 2: Summary Statistics for Village-level Data

Variable	Pre-SMIP			Post-SMIP			
	Treatment	Control	(1)−(2)	Treatment	Control	(4)−(5)	(6)−(3)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Nighttime Lights	0.37	0.44	-0.07***	0.76	0.52	0.24***	0.31***
	(0.97)	(0.85)		(1.78)	(1.23)		
Total Population	1009.14	422.56	586.57***	1196.49	506.38	690.11***	103.54***
	(1174.96)	(499.32)		(1401.33)	(600.25)		
Literacy	0.44	0.33	0.11***	0.55	0.45	0.10***	-0.01***
	(0.17)	(0.20)		(0.15)	(0.19)		
Availability of Post Office	0.19	0.09	0.10***	0.11	0.06	0.05***	-0.05***
	(0.39)	(0.29)		(0.31)	(0.24)		
Availability of Telephone Connection	0.25	0.06	0.19***	0.38	0.21	0.17***	-0.01***
	(0.43)	(0.25)		(0.49)	(0.40)		
Availability of Railway Services	0.01	0.00	0.00***	0.02	0.01	0.01***	0.01***
	(0.08)	(0.04)		(0.13)	(0.07)		
Availability of Bank Facility	0.05	0.01	0.04***	0.06	0.02	0.04***	0.00
	(0.22)	(0.10)		(0.24)	(0.12)		
Availability of Bus Facility	0.28	0.17	0.11***	0.40	0.27	0.13***	0.03***
	(0.45)	(0.38)		(0.49)	(0.44)		

Notes: Treatment refers to the villages that were covered under the Shared Mobile Infrastructure Program (2008-09) and the villages that remained uncovered as of 2011 according to the Wireless Planning & Co-ordination wing are controls. We use village level characteristics for pre- and post-SMIP period from the Census of India 2001 and 2011, respectively. Luminosity data was extracted from the raster images obtained from the National Aeronautics and Space Administrations (NASA) military weather satellites.

TABLE 3: D-i-D Estimate of the Effect of SMIP on Mobile Coverage using Village-level Data.

	(1)	(2)
Treatment × Post	0.194***	0.199***
	(0.04)	(0.06)
Treatment	-0.023	
	(0.01)	
Post	0.507***	0.540***
	(0.04)	(0.06)
Total Population	0.000	
	(0.00)	
Total Literate Population	0.000**	
	(0.00)	
Availability of Telephone Connection	0.131***	
	(0.01)	
Availability of Post Office	-0.043***	
	(0.01)	
Availability of Bank Facility	-0.016*	
	(0.01)	
Availability of Bus Facility	0.059***	
	(0.01)	
R Squared	0.593	0.774
No. of Observations	209116	224809

Notes: Treatment refers to the villages that were covered under the Shared Mobile Infrastructure Program (2008-09) and the villages that remained uncovered as of 2011 are controls. Mobile coverage status at the endline are from the Village Directory 2011, while it is 0 for all villages at the baseline. The regression in column (1) controls for village characteristics and district fixed effects. The coefficients from a similar regression with village fixed effects are reported in column (2). Robust standard errors clustered at the district level are reported in parentheses. ***, **, and, * indicate statistical significance at the 1, 5, and, 10 percent levels respectively.

TABLE 4: Estimate of the Effect of SMIP on Mobile Coverage using District-level Data.

	(1)	(2)
Current Treatment Intensity	0.009***	0.009***
	(0.00)	(0.00)
Total Population	0.000	
	(0.00)	
Total Literate Population	-0.000***	
	(0.00)	
Availability of Telephone Connection	-0.000	
	(0.00)	
Availability of Post Office	0.005	
	(0.01)	
Availability of Domestic Power Supply	-0.001	
	(0.03)	
Availability of Bank Facility	-0.122	
	(0.08)	
Availability of Bus Facility	0.015	
	(0.05)	
R Squared	0.746	0.800
No. of Observations	974	988

Notes: Since our sample is restricted to the villages that did not have mobile coverage in 2006 as per the Wireless Planning & Co-ordination wing (WPC) of the Department of Telecommunications (DoT), mobile coverage status at the baseline (2006) is 0 for all districts. Coverage status at the endline (2011) is defined as the ratio of the number of villages that have received coverage as per the Village Directory 2011 to the number of villages that were uncovered in 2006. The coefficients in column (1) are from the regression of mobile coverage status on treatment intensity under SMIP, average village characteristics, and state fixed effects. The coefficients from a similar regression without average village characteristics but with district fixed effects are reported in column (2). Robust standard errors clustered at the district level are reported in parentheses. ***, **, and, * indicate statistical significance at the 1, 5, and, 10 percent levels respectively.

TABLE 5: Effect of SMIP on Mobile Ownership using Village-level Data.

Baseline Average	19.27	
	(1)	(2)
Treatment	13.572***	9.955***
	(1.27)	(0.99)
Total Population		-0.006***
		(0.00)
Total Literate Population		0.017***
		(0.00)
Distance from Town		-0.087***
		(0.01)
Availability of Telephone Connection		1.898**
		(0.72)
Availability of Post Office		-0.260
		(0.45)
Availability of Bank Facility		-2.161***
		(0.53)
Availability of Bus Facility		2.093***
		(0.70)
R Squared	0.420	0.438
No. of Observations	105372	96499

Notes: Treatment refers to the villages that were covered under the Shared Mobile Infrastructure Program (2008-09) and the villages that remained uncovered as of 2011 according to the Wireless Planning Commission are controls. The dependent variable, Mobile Ownership, is the fraction of households that own a mobile phone as of 2011. Both regressions control for district fixed effects. Robust standard errors clustered at the district level are reported in parentheses. ***, **, and, * indicate statistical significance at the 1, 5, and, 10 percent level respectively.

TABLE 6: Effect of SMIP on Mobile Ownership using District-level Data.

Average	0.50	
Treatment Intensity	0.002***	0.002***
	(0.00)	(0.00)
Total Population		-0.000***
		(0.00)
Total Literate Population		0.000***
		(0.00)
Distance from Town		-0.002***
		(0.00)
Availability of Telephone Connection		-0.000*
		(0.00)
Availability of Post Office		0.026*
		(0.01)
Availability of Domestic Power Supply		-0.010
		(0.03)
Availability of Bank Facility		0.008
		(0.06)
Availability of Bus Facility		0.142**
		(0.06)
R Squared	0.629	0.682
No. of Observations	480	474

Notes: The dependent variable, Mobile Ownership, is the fraction of households that own a mobile phone as of 2011. Both regressions control for state fixed effects. Robust standard errors clustered at the district level are reported in parentheses. ***, **, and, * indicate statistical significance at the 1, 5, and, 10 percent level respectively.

TABLE 7: D-i-D Estimate of the Effects of SMIP on Nighttime Lights using Village-level Data

Dependent Variable	Log	Log Difference
	(1)	(2)
Treatment × Post	0.12***	0.047***
	(0.01)	(0.01)
R Squared	0.588	0.135
No. of Observations	1013359	921230

Notes: Treatment refers to the villages that were covered under the Shared Mobile Infrastructure Program (2008-09) and the villages that remained uncovered as of 2011 according to the Wireless Planning & Co-ordination wing are controls. Post takes the value 1 after the SMIP and 0 otherwise. In columns (1) and (2), the dependent variables are nighttime lights in natural logs and lagged log differences, respectively. All specifications control for village and year fixed effects and state-specific time trends. Robust standard errors clustered at district level are reported in parentheses. ***, **, and, * indicate statistical significance at the 1, 5, and, 10 percent level, respectively.

TABLE 8: Effects of SMIP on Nighttime Lights using District-level Data

Dependent Variable	Log	Log Difference
	(1)	(2)
Intensity of Treatment	0.0037***	0.00035***
	(0.00)	(0.00)
R Squared	0.504	0.385
No. of Observations	10868	10374

Notes: In columns (1) and (2), the dependent variables are nighttime lights in natural logs and lagged log differences, respectively. Intensity of Treatment refers to the ratio of the number of villages covered under the SMIP in a district by the year corresponding to the observation to the number of villages in the district without mobile coverage as of 2006 as per the Wireless Planning & Co-ordination wing. All specifications control for state and year fixed effects and state-specific time trends. Robust standard errors clustered at district level are reported in parentheses. ***, **, and, * indicate statistical significance at the 1, 5, and, 10 percent level, respectively.

TABLE 9: Time-Varying D-i-D Estimate of SMIP on Nighttime Lights using Village-level Data.

Panel A: Effect on Log Nighttime Lights						
Dependent Variable	Log Nighttime Lights					
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment × 0 Years	0.074***					
	(0.01)					
Treatment × 1 Years		0.079***				
		(0.01)				
Treatment × 2 Years			0.077***			
			(0.01)			
Treatment × 3 Years				0.23***		
				(0.02)		
Treatment × 4 Years					0.29***	
					(0.02)	
Treatment × 5 Years						0.37***
						(0.03)
R Squared	0.690	0.681	0.684	0.590	0.584	0.580
No. of Observations	736992	736992	736992	736987	644863	552739
Panel B: Effect on Log Differences						
Dependent Variable	Log Differences					
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment × 0 Years	-0.015					
	(0.01)					
Treatment × 1 Years		-0.019***				
		(0.01)				
Treatment × 2 Years			-0.028***			
			(0.01)			
Treatment × 3 Years				0.13***		
				(0.01)		
Treatment × 4 Years					0.17***	
					(0.02)	
Treatment × 5 Years						0.24***
						(0.02)
R Squared	0.122	0.131	0.135	0.191	0.215	0.236
No. of Observations	644868	644868	644868	644858	552734	460610

Notes:

TABLE 10: Time-Varying Estimate of SMIP on Nighttime Lights using District-level Data.

Dependent Variable	Log	Log Difference
	(1)	(2)
Overall effect	0.0013***	-0.00041***
	(0.00)	(0.00)
Treatment Intensity $\times$ 1 Year after Coverage	0.0018*	-0.000099
	(0.00)	(0.00)
Treatment Intensity $\times$ 2 Years after Coverage	0.0037***	0.0026***
	(0.00)	(0.00)
Treatment Intensity $\times$ 3 Years after Coverage	0.0027***	-0.00018
	(0.00)	(0.00)
Treatment Intensity $\times$ 4 Years after Coverage	0.0057***	0.0039***
	(0.00)	(0.00)
Treatment Intensity $\times$ 5 Years after Coverage	0.0073***	0.0057***
	(0.00)	(0.00)
R Squared	0.482	0.164
No. of Observations	10868	10374

Notes: Years since coverage is the number of years since the construction of the majority of mobile towers being built in that district. Intensity of Treatment refers to the ratio of the number of villages covered under the SMIP in a district by the year corresponding to the observation to the number of villages in the district without mobile coverage as of 2006 as per the Wireless Planning & Co-ordination wing. In columns (1) and (2), the dependent variables are nighttime lights in natural logs and lagged log differences, respectively. All specifications control for state and year fixed effects and state-specific time trends. Robust standard errors clustered at district level are reported in parentheses. ***, **, and, * indicate statistical significance at the 1, 5, and, 10 percent level, respectively.

TABLE 11: Heterogeneity by Pre-Program Amenities using Village-level Data.

Dependent Variable	Log	Log Difference
	(1)	(2)
Treatment × Post × Literacy greater than Median	0.094***	0.048***
	(0.01)	(0.01)
Treatment × Post × Bank Facility	0.075***	0.022***
	(0.01)	(0.01)
Treatment × Post × Distance to Town greater than Median	-0.075***	-0.015*
	(0.01)	(0.01)
Treatment × Post × Bus Services	0.052***	0.015
	(0.01)	(0.01)
Treatment × Post × Telephone Connections	0.060***	-0.0024
	(0.01)	(0.01)
Treatment × Post × Power for Domestic Users	-0.012	0.0010
	(0.01)	(0.01)

Notes: Treatment refers to the villages that were covered under the Shared Mobile Infrastructure Program (2008-09) and the villages that remained uncovered as of 2011 according to the Wireless Planning Commission are controls. Post takes the value 1 after the SMIP and 0 otherwise. In columns (1) and (2), the dependent variables are nighttime lights in natural logs and lagged log differences, respectively. Each row reports results from a triple difference regression with village and year fixed effects and state specific time trends. Robust standard errors clustered at the district level are reported in the parenthesis. ***, **, and, * indicate statistical significance at the 1, 5, and, 10 percent level respectively.

TABLE 12: Heterogeneity by Pre-Program Amenities using District-level Data.

Dependent Variable	Log	Log Difference
	(1)	(2)
Intensity of Treatment × Literacy greater than Median	0.00074**	0.00051***
	(0.00)	(0.00)
Intensity of Treatment × Bank Facility	-0.00034	0.00029**
	(0.00)	(0.00)
Intensity of Treatment × Distance to Town greater than Median	-0.000060	0.00010
	(0.00)	(0.00)
Intensity of Treatment × Bus Services	0.000048	0.00039***
	(0.00)	(0.00)
Intensity of Treatment × Telephone Connections	0.00056	0.00038
	(0.00)	(0.00)
Intensity of Treatment × Power for Domestic Users	0.00074**	0.00023**
	(0.00)	(0.00)

Notes: Intensity of Treatment refers to the ratio of the number of villages covered under the SMIP in a district by the year corresponding to the observation to the number of villages in the district without mobile coverage as of 2006 as per the Wireless Planning & Co-ordination wing. In columns (1) and (2), the dependent variables are nighttime lights in natural logs and lagged log differences, respectively. Each row reports results from a regression with state and year fixed effects and state specific time trends. Robust standard errors clustered at the district level are reported in the parenthesis. ***, **, and, * indicate statistical significance at the 1, 5, and, 10 percent level respectively.

TABLE 13: Estimate of the Effects of SMIP on Inequality.

Panel A: Subdistrict-level Analysis		
Baseline Average	0.50	0.50
% Villages Covered	-0.00035***	
	(0.00)	
% Population Covered		-0.00034***
		(0.00)
R Squared	0.709	0.709
No. of Observations	43629	43629
Panel B: District-level Analysis		
Baseline Average	0.67	0.67
% Villages Covered	-0.00054***	
	(0.00)	
% Population Covered		-0.00048***
		(0.00)
R Squared	0.469	0.470
No. of Observations	10572	10573

Notes: Proportion of treatment by number of villages refers to the ratio of the number of villages covered under the SMIP in a subdistrict or district by the year corresponding to the observation to the number of villages in the subdistrict or district without mobile coverage as of 2006 as per the Wireless Planning & Co-ordination wing whereas, proportion of treatment by population refers to the ratio of the number of people covered under the SMIP in a subdistrict or district by the year corresponding to the observation to the number of people in the subdistrict or district without mobile coverage as of 2006 as per the Wireless Planning & Co-ordination wing. The Gini coefficients are calculated using night-time lights data. Robust standard errors clustered at the district level are reported in the parenthesis. ***, **, and, * indicate statistical significance at the 1, 5, and, 10 percent level respectively.

FIGURE A.2: Evolution of Coverage using Village-level Data.

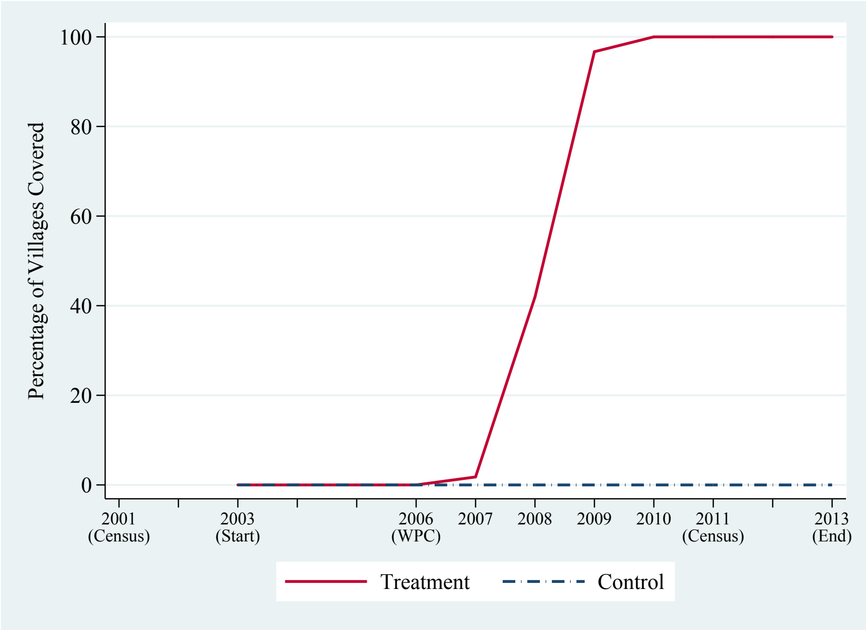


FIGURE A.3: Evolution of Coverage using District-level Data.

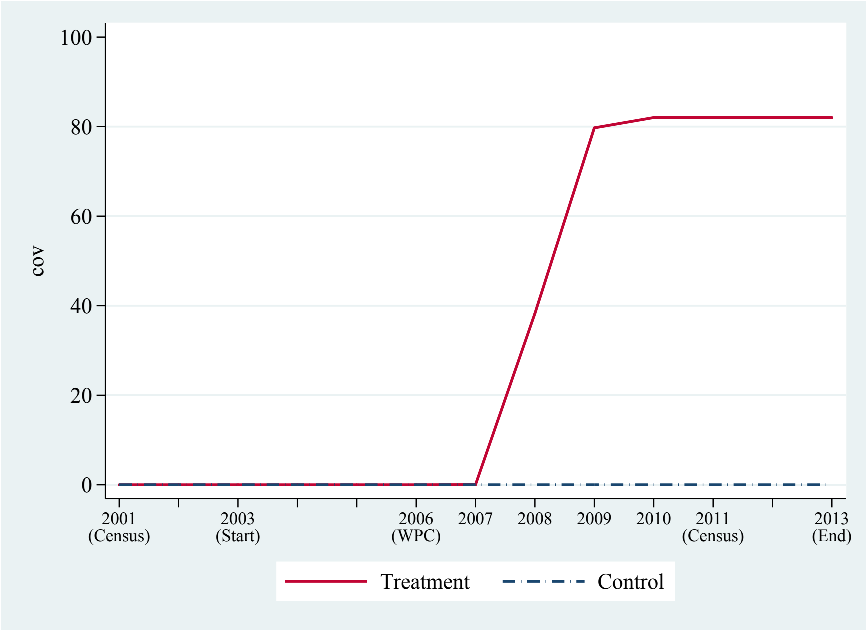


TABLE A.1: Covariate Balance for the Restricted Sample using Village-level Data.

	Full Sample			Common Support		
	Treatment	Control	(1)−(2)	Treatment	Control	(4)−(5)
	(1)	(2)	(3)	(4)	(5)	(6)
Nighttime Lights	0.37	0.44	-0.07*	0.25	0.34	-0.08***
	(0.97)	(0.85)		(0.60)	(0.51)	
Total Population	1009.14	422.56	586.57***	598.91	548.53	50.38*
	(1174.96)	(499.32)		(718.11)	(540.92)	
Literacy	0.44	0.33	0.11***	0.40	0.39	0.00
	(0.17)	(0.20)		(0.18)	(0.18)	
Availibility of Post Office	0.19	0.09	0.10***	0.13	0.13	-0.00
	(0.39)	(0.29)		(0.34)	(0.34)	
Availibility of Telephone Connection	0.25	0.06	0.19***	0.11	0.09	0.02*
	(0.43)	(0.25)		(0.32)	(0.29)	
Availibility of Railway Services	0.01	0.00	0.00***	0.00	0.00	-0.00
	(0.08)	(0.04)		(0.06)	(0.06)	
Availibility of Bank Facility	0.05	0.01	0.04***	0.02	0.01	0.01**
	(0.22)	(0.10)		(0.15)	(0.12)	
Availibility of Bus Facility	0.28	0.17	0.11***	0.26	0.24	0.02
	(0.45)	(0.38)		(0.44)	(0.43)	

Notes: Data used from the Village Directory, Census 2001. Common support refers to villages that had similar probability (between 0.63–0.7) of getting mobile towers under the SMIP as predicted by the 2001 village characteristics.

TABLE A.2: D-i-D Estimate of the Effects of SMIP on Nighttime Lights on Common Support using Village-level Data.

Dependent Variable	Log (1)	Log Difference (2)
Treatment × Post	0.092*** (0.02)	0.061*** (0.01)
R Squared	0.521	0.154
No. of Observations	77942	70385

Notes: Treatment refers to the villages that were covered under the Shared Mobile Infrastructure Program (2008-09) and the villages that remained uncovered as of 2011 according to the Wireless Planning Commission are controls. Post takes the value 1 after the SMIP and 0 otherwise. In columns (1) and (2), the dependent variables are nighttime lights in natural logs and lagged log differences, respectively. Common support refers to villages that had similar probability (between 0.63–0.7) of getting mobile towers under the SMIP as predicted by the 2001 village characteristics. All specifications control for village and year fixed effects and state-specific time trends. Robust standard errors clustered at district level are reported in parentheses. ***, **, and, * indicate statistical significance at the 1, 5, and, 10 percent level, respectively.

TABLE A.3: Time-Varying D-i-D Estimate of SMIP on Nighttime Lights on Common Support using Village-level Data.

Dependent Variable	Log	Log Difference
	(1)	(2)
Treatment × 1 Year after Coverage	0.0062	-0.0063
	(0.01)	(0.02)
Treatment × 2 Years after Coverage	0.040**	0.040***
	(0.02)	(0.02)
Treatment × 3 Years after Coverage	0.096***	0.079***
	(0.02)	(0.01)
Treatment × 4 Years after Coverage	0.20***	0.16***
	(0.03)	(0.03)
Treatment × 5 Years after Coverage	0.36***	0.33***
	(0.06)	(0.05)
R Squared	0.526	0.148
No. of Observations	82499	74999

Notes: The sample includes only villages covered under SMIP. Coverage takes the value 1 if a village was covered at time *t* and 0 otherwise. Years since coverage is the number of years since the construction of the mobile tower. In columns (1) and (2), the dependent variables are nighttime lights in natural logs and lagged log differences, respectively. Common support refers to villages that had similar probability (between 0.63–0.7) of getting mobile towers under the SMIP as predicted by the 2001 village characteristics. All specifications control for village and year fixed effects and state-specific time trends. Robust standard errors clustered at district level are reported in parentheses. ***, **, and, * indicate statistical significance at the 1, 5, and, 10 percent level, respectively.

TABLE A.4: NL, Energy Consumption, and Agri. GDP at 2004 prices

Panel A: Agricultural GDP at 2004 Prices				
Ln(NL per sq. km)	0.16**	0.17***		0.18**
	(0.06)	(0.06)		(0.07)
Ln(Square of NL per sq. km)		-0.018		
		(0.02)		
Ln(Energy Consumption)			0.055	0.041
			(0.05)	(0.04)
R Squared	0.997	0.997	0.997	0.997
No. of Observations	220	220	198	198
Panel B: Agricultural GDP at Current Prices				
Ln(NL per sq. km)	0.15***	0.14**		0.18***
	(0.05)	(0.06)		(0.05)
Ln(Square of NL per sq. km)		0.026		
		(0.02)		
Ln(Energy Consumption)			0.053*	0.038
			(0.03)	(0.03)
R Squared	0.997	0.997	0.997	0.997
No. of Observations	220	220	198	198

Notes: All estimates include state- and time fixed effects. Robust standard errors clustered at the state level are reported in the parenthesis. ***, **, and, * indicate statistical significance at the 1, 5, and, 10 percent level respectively.

TABLE A.5: Effect of SMIP on Nighttime Lights by Bins.

Dependent Variable	Log Avg. Lum.				
	1^{st} Quintile	2^{nd} Quintile	3^{rd} Quintile	4^{th} Quintile	5^{th} Quintile
	Panel A: Village-level Data				
Treatment × Post	0.044***	0.079***	0.11***	0.14***	0.15***
	(0.01)	(0.01)	(0.01)	(0.02)	(0.04)
R Squared	0.291	0.351	0.375	0.357	0.569
No. of Observations	200825	200812	200815	200813	200816
	Panel B: Subdistrict-level Data				
% Villages Covered	0.0012*	0.0033***	0.0045***	0.0060***	0.0087
	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)
R Squared	0.344	0.477	0.436	0.491	0.420
No. of Observations	7821	7821	7821	7810	7821
	Panel C: District-level Data				
Treatment Progress	0.0015**	0.0027	0.00070	0.0067***	0.0066***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
R Squared	0.520	0.522	0.519	0.641	0.528
No. of Observations	2178	2178	2178	2156	2178

Notes: Treatment refers to the villages that were covered under the Shared Mobile Infrastructure Program (2008-09) and the villages that remained uncovered as of 2011 according to the Wireless Planning & Co-ordination wing are controls. Post takes the value 1 after the SMIP and 0 otherwise. In all panels, quintiles are defined on the basis of average luminosity at the specified level over the period 2003-07. All specifications control for state- and time fixed effects and state-specific time trends. Robust standard errors clustered at district level are reported in parentheses. ***, **, and, * indicate statistical significance at the 1, 5, and, 10 percent level, respectively.

TABLE A.6: Effects of SMIP on Nighttime Lights with Differential Trends.

Dependent Variable	Log	Log Difference
	(1)	(2)
Panel A: Villages Covered in 2008		
Year-2003	0.02***	-0.01***
	(0.01)	(0.00)
(Year-2003)× Treatment	0.04***	0.03***
	(0.01)	(0.01)
(Year-2008) × Treatment × Post	0.04***	0.05***
	(0.01)	(0.01)
Treatment × Post	-0.17***	-0.23***
	(0.02)	(0.03)
R Squared	0.585	0.134
No. of Observations	574163	521961
Panel B: Villages Covered in 2009		
Year-2003	0.01	-0.02***
	(0.01)	(0.00)
(Year-2003)× Treatment	0.03***	0.01***
	(0.00)	(0.00)
(Year-2009) × Treatment × Post	0.09***	0.11***
	(0.01)	(0.01)
Treatment × Post	-0.18***	-0.17***
	(0.02)	(0.03)
R Squared	0.577	0.141
No. of Observations	675971	614518

Notes: The estimation sample is confined to villages that were covered in 2008 and 2009 in Panel A and B, respectively and the villages that remained uncovered. Treatment refer to the villages that were covered under SMIP and villages without mobile telephony in 2011 are controls. *Post* is an indicator taking value 1 for all years after the village was covered under SMIP and 0 otherwise. All specifications control for village and year fixed effects and state-specific time trends. Robust standard errors clustered at district level are reported in parentheses. ***, **, and, * indicate statistical significance at the 1, 5, and, 10 percent level, respectively.

TABLE A.7: Effects of SMIP on Nighttime Lights with Differential Trends using District-level Data.

Dependent Variable	Log	Log Difference
	(1)	(2)
Panel A: Districts Covered in 2008		
Overall effect	0.00***	0.00*
	(0.00)	(0.00)
Treatment Intensity × 1 Year after Coverage	-0.00	-0.00
	(0.00)	(0.00)
Treatment Intensity × 2 Years after Coverage	-0.00	0.00
	(0.00)	(0.00)
Treatment Intensity × 3 Years after Coverage	-0.00	-0.00
	(0.00)	(0.00)
Treatment Intensity × 4 Years after Coverage	-0.00	-0.00
	(0.00)	(0.00)
Treatment Intensity × 5 Years after Coverage	0.00*	0.00***
	(0.00)	(0.00)
R Squared	0.563	0.411
No. of Observations	5324	5082
Panel B: Districts Covered in 2009		
Overall effect	0.00***	-0.00
	(0.00)	(0.00)
Treatment Intensity × 1 Year after Coverage	0.00*	0.00
	(0.00)	(0.00)
Treatment Intensity × 2 Years after Coverage	0.00*	0.00
	(0.00)	(0.00)
Treatment Intensity × 3 Years after Coverage	0.00	0.00
	(0.00)	(0.00)
Treatment Intensity × 4 Years after Coverage	0.01***	0.01***
	(0.00)	(0.00)
R Squared	0.557	0.397
No. of Observations	6292	6006

Notes: The estimation sample is confined to districts that were primarily (more than half) covered in 2008 and 2009 in Panels A and B respectively, and the districts that remained uncovered under the scheme. All specifications control for state and year fixed effects and state-specific time trends. Robust standard errors clustered at district level are reported in parentheses. ***, **, and, * indicate statistical significance at the 1, 5, and, 10 percent level, respectively.

TABLE A.8: Effects of SMIP on Nighttime Lights with Differential Trends on Common Support using Village-level Data.

Dependent Variable	Log	Log Difference
	(1)	(2)
Panel A: Villages Covered in 2008		
Year-2003	0.03**	0.00
	(0.01)	(0.01)
(Year-2003)× Treatment	0.03***	0.02***
	(0.01)	(0.01)
(Year-2008) × Treatment × Post	0.03***	0.04***
	(0.01)	(0.01)
Treatment × Post	-0.16***	-0.18***
	(0.02)	(0.03)
R Squared	0.528	0.147
No. of Observations	48058	43689
Panel B: Villages Covered in 2009		
Year-2003	0.02***	-0.00
	(0.01)	(0.01)
(Year-2003)× Treatment	0.02***	0.01**
	(0.00)	(0.00)
(Year-2009) × Treatment × Post	0.05***	0.06***
	(0.01)	(0.01)
Treatment × Post	-0.12***	-0.11***
	(0.03)	(0.03)
R Squared	0.490	0.131
No. of Observations	58267	52970

Notes: The estimation sample consists of the villages that remained uncovered along with confined to villages that were covered in 2008 and 2009 in Panel A and B, respectively, and are part of the sample in both panels. Treatment refer to the villages that were covered under SMIP and villages without mobile telephony in 2011 are controls. *Post* is an indicator taking value 1 for all years after the village was covered under SMIP and 0 otherwise. Common support refers to villages that had similar probability (between 0.63–0.7) of getting mobile towers under the SMIP as predicted by the 2001 village characteristics. All specifications control for village and year fixed effects and state-specific time trends. Robust standard errors clustered at district level are reported in parentheses. ***, **, and, * indicate statistical significance at the 1, 5, and, 10 percent level, respectively.

TABLE A.9: Heterogeneity by Pre-Program Amenities on Common Support using Village-level Data.

Dependent Variable	Log	Log Difference
	(1)	(2)
Treatment × Post × Literacy greater than Median	0.034**	0.021**
	(0.02)	(0.01)
Treatment × Post × Bank Facility	0.015	-0.017
	(0.03)	(0.02)
Treatment × Post × Distance to Town greater than Median	0.0072	0.016*
	(0.02)	(0.01)
Treatment × Post × Bus Services	0.016	-0.0098
	(0.02)	(0.01)
Treatment × Post × Telephone Connections	-0.019	-0.022*
	(0.02)	(0.01)
Treatment × Post × Power for Domestic Users	-0.016	-0.0062
	(0.02)	(0.01)

Notes: Treatment refers to the villages that were covered under the Shared Mobile Infrastructure Program (2008-09) and the villages that remained uncovered as of 2011 according to the Wireless Planning & Co-ordination wing are controls. Post takes the value 1 after the SMIP and 0 otherwise. In columns (1) and (2), the dependent variables are nighttime lights in natural logs and lagged log differences, respectively. Common support refers to villages that had similar probability (between 0.63–0.7) of getting mobile towers under the SMIP as predicted by the 2001 village characteristics. Each row reports results from a triple difference regression with village and year fixed effects and state specific time trends. Robust standard errors clustered at the district level are reported in the parenthesis. ***, **, and, * indicate statistical significance at the 1, 5, and, 10 percent level respectively.