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Mobile Phones and Local Economic Development

A Global Evidence

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Abstract

This paper presents global evidence on the impact of expansion in mobile telephony and broadband Internet services on economic development at the subnational level. Leveraging two decades of satellite data on nightlights and the global expansion of 2G, 3G, and 4G mobile networks in over 34,000 subnational districts in 120 countries, it documents three main findings on the effects of mobile phones on local economic development (proxied by nightlights): I. The expansion of mobile coverage has a positive effect on economic activity. Using the GDP—nightlights elasticity from Henderson et al. (2012), the estimates suggest

a GDP growth—mobile phone penetration elasticity of 0.018–0.023; II. While mobile broadband (3G & 4G) Internet connectivity is associated with economic development across all countries, 2G connectivity boosts local economic growth mainly in developing countries; III. The economic effects of expansion in mobile network connectivity are more pronounced in countries that hitherto had limited access to fixed-line telephone infrastructure, thus highlighting the importance of mobile phones to developing countries in leapfrogging the technology ladder.

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Mobile Phones and Local Economic Development: A Global Evidence

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1 Introduction

*Mobile phones have changed the world,
for better or worse.*

Alex Clark

Mobile phones play an important role in modern life. Aside from the basic function of facilitating communication, mobile phones have become a tool for financial intermediation¹ and the source of broadband Internet to millions of people around the world. The significant increase in adoption of mobile phones across countries over the past two decades underscores the relevance of the technology to livelihoods.

The impact of mobile phones has become a topic of growing interest among researchers and policymakers (Aker and Mbiti, 2010; Manacorda and Tesei, 2020; Guriev et al., 2021). However, available studies have almost entirely focused on the microeconomic impacts of mobile phone uptake (Aker, 2010; Suri and Jack, 2016; Suri, 2017; Batista et al., 2018) and the effects on political economy (Manacorda and Tesei, 2020; Guriev et al., 2021; Gonzalez, 2021). Very little is known about the extent to which mobile phones stimulate economic development. While cross-country correlation between mobile phone penetration and GDP per capita as shown in Figure 1 suggests a positive relationship, evidence on the causal impact of mobile phones on economic development is scant.

In this paper, I present causal evidence on the extent to which mobile phone access spurs local economic growth. By linking a global dataset on the expansion in the second, third, and fourth generation (i.e., 2G, 3G, & 4G) mobile network coverage and nightlights (a proxy for economic activities) in over 34,000 subnational districts in 120 countries between 1998 and 2018, I provide new evidence on the development impact of mobile phones. The identification strategy of the paper is structured in two parts. First, I use a two-way fixed effects (TWFE) estimator that leverages the gradual expansion in mobile network connectivity across districts and time to estimate the effects of expansion in mobile connectivity on local economic growth. To minimize the bias associated with TWFE estimates resulting from heterogeneous treatment effects and the associated negative weighting, I complement the analysis with the De Chaisemartin and D’Haultfoeuille (2020a) TWFE estimator that is robust to heterogeneous treatment effects. In spite of this, the TWFE estimates are unlikely to generate causal impacts due to the plausibly endogenous nature of mobile network expansion.

¹Mobile money platforms—a financial technology (FinTech) application using mobile phones has revolutionized financial markets in Africa enabling previously unbanked population to access financial services. See for instance, Suri and Jack (2016), Suri (2017) and Batista et al. (2018).

Therefore, in the second part of the analysis, I use an instrumental variable regression (IV) strategy that leverages regional convergence in mobile network expansion induced by harmonization of telecom policies across countries in the region as an instrument. In essence, I use the predicted mobile network penetration in other countries in the same geographic region as instrument for the district level mobile network penetration. The instrument follows the approach of [Acemoglu et al. \(2019\)](#) and [Acemoglu et al. \(2021\)](#) who used regional waves in democratization as an instrument for democracy in studies on the effects of democracy on GDP and support for democratic institutions. The exclusion restriction assumption behind the instrument used in this paper is that conditional on controls including measures of trade and economic shocks at the regional level, district and year fixed effects, mobile network penetration in other countries in the same region affects economic growth at the district level only through its effect on mobile connectivity in the district. Further, to supplement the main IV analysis, I construct another instrument by interacting the predicted regional mobile coverage rates with quintiles of lightning intensity at the district level and estimate an additional IV regression, the results of which confirm the baseline IV results. The motivation behind the second instrument is that the effect of regional harmonization of telecom policies on mobile penetration at the local level should be high in places where mobile operators would otherwise not extend mobile coverage due to the effect of lightning strikes which causes destruction to digital infrastructure ([Andersen et al., 2012](#); [Manacorda and Tesei, 2020](#); [Guriev et al., 2021](#)),² relative to places with low lightning strikes and hence lower cost of mobile network extension. Thus, even if individually, lightning intensity and the predicted regional mobile penetration rate may not satisfy the exclusion restriction assumption, their interaction(s) may plausibly suffice.

Three main findings emerge from the paper. First, mobile phones exert a positive impact on economic growth at the subnational level. A 1 percentage point (pp) increase in mobile network penetration increases the growth rate in nightlight intensity by 0.0596 – 0.0777 pp. To understand how this translates into GDP growth, I rely on [Henderson et al. \(2012\)](#) who estimate a GDP-nightlights elasticity of 0.3. Combining these estimates, findings from the paper suggest a GDP growth – mobile penetration elasticity of 0.018 – 0.023. In other words, moving a district from no mobile network coverage to full coverage (100 pp) increases GDP growth by 1.8 pp – 2.3 pp. Secondly, while mobile broadband (3G/4G) penetration spurs economic activities in all income groups, the development effects of 2G penetration are largely present in developing countries. Finally, I find that the economic effects of expansion in mobile network connectivity are more pronounced in countries that hitherto had limited access to fixed line telephone in-

²Lightning strikes contain about a billion volts of electricity and have been known to cause severe destruction to electrical and digital infrastructure around the world, thereby increasing the cost associated with the diffusion of digital technologies ([Andersen et al., 2012](#); [Zeddham and Day, 2014](#); [Martin, 2016](#)).

frastructure. This evidence is perhaps suggestive of the effects of mobile phones for developing countries in leapfrogging the digital barriers associated with the costly expansion of fixed line telephone networks.

While this paper does not present evidence on the potential mechanisms, it is noteworthy to emphasize that the literature is replete with evidence on the socioeconomic impact of access to mobile phones and mobile broadband Internet that are generally consistent with the findings of this paper. For instance, [Aker \(2010\)](#) shows that expansion in mobile phone access reduces price dispersion in agricultural markets in developing countries by reducing search costs. Several pieces of evidence also suggest that mobile phone access has improved financial inclusion through mobile money with positive impacts on household welfare ([Aker and Mbiti, 2010](#); [Suri and Jack, 2016](#); [Suri, 2017](#); [Batista et al., 2018](#)). For instance, [Bahia et al. \(2020\)](#), using data from Nigeria show that access to mobile broadband Internet is associated with high household welfare via increasing labor market participation, particularly for women.³ Further, there is evidence that access to digital infrastructure like broadband Internet exerts positive impacts on labor market outcomes ([Akerman et al., 2015](#); [Hjort and Poulsen, 2019](#); [Zuo, 2020](#)), and firm performance ([DeStefano et al., 2018](#)). There is also evidence of mobile phones as technologies of change via political mobilization ([Manacorda and Tesei, 2020](#)), encouraging migration ([Adema et al., 2021](#)), reducing corruption ([Andersen et al., 2011](#); [Gonzalez, 2021](#)) and confidence in governments [Guriev et al. \(2021\)](#). These prior evidence highlight the numerous pathways through which the impact of mobile connectivity on economic growth, as shown in this paper, arises. Thus, this paper offers an important contribution to the literature by documenting the extent to which the various microeconomic impacts of mobile connectivity translate into aggregate economic outcomes.

This paper is closest with [Czernich et al. \(2011\)](#) and [Goldbeck and Lindlacher \(2021\)](#) who analyze the impact of broadband Internet on economic growth in the OECD and Sub-Saharan Africa respectively. [Czernich et al. \(2011\)](#) for instance using cross-country panel data for OECD countries between 1996 and 2007 found that a 1 pp increase in broadband penetration is associated with a 0.09 – 0.15 pp increase in economic growth. The paper however differs from [Czernich et al. \(2011\)](#) by analyzing the impact of a broader spectrum of digital infrastructure (voice communication (2G) and mobile broadband (3G and 4G)) using granular and recent data from about 120 countries. [Goldbeck and Lindlacher \(2021\)](#) also exploit the staggered arrival of the submarine fiber-optic cables to Africa and estimate that access to internet connectivity via the fiber cables is associated with a 2 pp increase in local economic growth. The estimates from [Goldbeck and Lindlacher \(2021\)](#) are similar in order of magnitude to the findings in this paper

³[Beuermann et al. \(2012\)](#), also finds similar evidence in Peru

which shows that mobile broadband connectivity (3G/4G) is associated with a 2.1 pp increase in local economic growth.

The paper proceeds as follows. In Section 2, I describe and present the data used in the analysis. The empirical strategy and results are presented in Section 3. In Section 4, I examine the effects of mobile connectivity across heterogeneous groups. Also in Section 5 I explore the robustness of the main results to alternative hypotheses. Section 6 concludes the paper with a summary of findings.

2 Data

This section presents an overview of the main datasets used in the analysis. The core datasets are mobile phone network coverage maps and nightlights data. The unit of analysis is the second administrative district in each country hereafter referred to as districts.

2.1 Global Mobile Phone Network Coverage

Data on the global mobile network coverage comes from the Global System for Mobile Communications Association (GSMA) in collaboration with Collins Bartholomew, a digital mapping provider.⁴ GSMA is an association of mobile network operators around the world. The data is compiled from network coverage submissions by mobile operators. In the recent past, additional coverage maps have been developed based on data from [opencellid.org](https://www.opencellid.org).⁵

The data provides spatial coverage maps for three main technologies: 2G, 3G, and 4G mobile networks. From a technical standpoint, the main difference between these network technologies is that 2G mainly supports voice calls, SMS text messaging, and multimedia messages (MMS). However, in addition to these, 3G and 4G networks enable mobile broadband Internet services allowing users to utilize the Internet at a faster speed.⁶ It is also important to emphasize that if a given location is covered by 3G, it is by definition covered by 2G, likewise 3G if covered by 4G. Therefore, in this paper, 3G and 4G coverage are hereafter referred to as 3G/4G: thus essentially focusing on mobile network coverage that supports broadband Internet (3G/4G) and those that only support voice and text messaging (2G). The data on 2G coverage used in the

⁴<https://www.collinsbartholomew.com/mobile-coverage-maps/>

⁵This is particularly important for countries without frequent updates from mobile operators

⁶Theoretically, the main differences between 3G and 4G is that the later is expected to be much faster than the former in theory, although in practice this is not always the case. See <https://www.pcmag.com/news/3g-vs-4g-whats-the-difference>

paper spans the period 1998 to 2018⁷ while data on 3G/4G coverage covers the period 2006 to 2018.

The mobile coverage maps provide granular data on spatial coverage of the mobile networks at a 1km × 1km grid-cell. However, it does not indicate the share of people in the respective grid-cells with access to the network. I, therefore, combine this data with 1km × 1km grid-cell population density⁸ data to calculate the share of population across subnational districts living in places covered by the mobile networks. Specifically, for a given subnational district J with underlying grid-cells, I calculate network coverage as:

$$\text{Mobile Coverage} = \frac{\sum_{j=1}^J \text{Population}_j \times \mathbb{1}\{\text{Covered by network}\}}{\sum_{j=1}^J \text{Population}_j} \quad (1)$$

where $\mathbb{1}\{\text{Covered by network}\}$ turns on if a grid-cell j is covered by mobile network and 0 otherwise. Mobile coverage, therefore, implies the share of the population in a given district living in areas covered by mobile networks. Three main coverage rates are computed and used in this paper: mobile coverage (all),⁹ 2G coverage, and 3G coverage.¹⁰

Figure 2 shows the global distribution of 2G and 3G mobile network coverage during 1999–2018 and 2007–2018 respectively. Figure 3 also shows the temporal growth in penetration of the respective mobile technologies. The figure shows a significant increase in coverage rates for 2G over the past two decades with the coverage rate for the average second administrative district increasing from 25% in 1999 to 91% in 2018, while 3G coverage also increased from 13% in 2007 to 74% in 2018.

2.2 Nightlights

Since the pioneering works of Henderson et al. (2011) and Henderson et al. (2012), satellite data on nighttime lights have gained popularity in the economics literature as a proxy for measuring economic activities, particularly, in districts where high frequency and disaggregated data on economic outcomes are scant. These nightlight data come from NASA’s Defense Meteorological Satellite Program/Operational Linescan System (OLS) covering the period 1992–2013 and the Visible Infrared Radiometer Suite (VIIRS)¹¹ from 2012 to present. However, due to incon-

⁷Data for 2005 and 2010 were not available due to a change in the company in charge of the data collection. Following Manacorda and Tesei (2020), I use linear interpolation across years to obtain estimates for the missing years.

⁸<https://sedac.ciesin.columbia.edu/data/set/popdynamics-1-km-downscaled-pop-base-year-projection-ssp-2000-2100-rev0>

⁹reflecting the maximum coverage for all available networks, i.e., 2G, 3G, 4G

¹⁰reflecting the maximum coverage for 3G or 4G networks

¹¹<https://ngdc.noaa.gov/eog/download.html>

sistencies in the measurement of light intensity between the DMSP and VIIRS satellites, the combination of nightlights data from these satellites is a challenge hence limiting the application of nightlights data over the long time horizon. To address this issue, Li et al. (2020) have derived consistent and integrated nightlights data from the two satellites by harmonizing the inter-calibrated nightlights data from the DMSP and a simulated DMSP-like nightlights data from the VIIRS satellite.¹² Using this data, I compute yearly average nightlights intensity for each subnational administrative district boundary as a proxy for the level of economic activity in each administrative boundary per year. I then compute the annual growth in nightlight intensity as the log-differences in the annual average nightlight intensity for each district. In the online Appendix, I conduct several robustness checks to ascertain the robustness of the baseline results using the harmonized data. First, Figure A1 in the online Appendix clearly shows a very high correlation between the harmonized and non-harmonized nightlights data for the period 1999-2013. Also, relying exclusively on DMSP nightlights data between 1998 and 2013, I show in Table A4 that the baseline results hold even if we restrict the data to the pre-VIIRS data.

2.3 Complementary data

I complement the analysis with data on indicators such as natural resource endowments from the IMF, quality of governance from the Polity IV database,¹³ distance to the coast,¹⁴ and average annual temperature and total precipitation obtained from the ERA5 Global Reanalysis Database by the Copernicus Climate Change Service.¹⁵ Data on fixed line telephone penetration and access to electricity are obtained from the World Bank's World Development Indicator database. Summary statistics of indicators used in the analysis are presented in Table A1 in the online appendix.

¹²See Li et al. (2020) for details and access to the dataset using https://figshare.com/articles/dataset/Harmonization_of_DMSP_and_VIIRS_nighttime_light_data_from_1992-2018_at_the_global_scale/9828827/2

¹³<https://www.systemicpeace.org/polityproject.html>. Also available for download here https://tcdata360.worldbank.org/indicators/h6906d31b?country=BRA&indicator=27470&viz=line_chart&years=1800,2018

¹⁴<https://oceancolor.gsfc.nasa.gov/docs/distfromcoast/>

¹⁵<https://cds.climate.copernicus.eu/cdsapp#!/home>

3 Empirical Strategy and Results

3.1 Two-way Fixed Effects

Starting with a naive regression, I estimate the following two-way fixed effect (TWFE) regression

$$\Delta \ln Y_{jct} = \beta \times \widehat{Mobile}_{jct} + \mathbf{Controls}'_{jct} \Gamma_0 + \theta_j + \delta_t + \epsilon_{jct} \quad (2)$$

where $\Delta \ln Y_{jct}$ denotes the growth (log differences) in nightlight luminosity as a proxy for local economic growth in district j , country c and year t . Due to the bias associated with taking logs of data with zeros, I use the inverse hyperbolic sine (ihs) transformation which provides a more robust transformation of data with zeros (Bellemare and Wichman, 2020). \widehat{Mobile}_{jct} is a measure of the mobile phone penetration rate. The main measure used in this paper is the share (%) of the population in a given district with mobile network coverage. In the appendix, I show that the results are robust to the measure of coverage, by using a dummy measure of mobile penetration set equal to 1 if the penetration rate is at least 10% and 0 otherwise.¹⁶ To absorb other determinants of local economic development, I control for an extensive list of district and country correlates represented by $\mathbf{Controls}'_{jct}$. District controls include average annual temperature and total precipitation, as well as linear time trends interacted with distance to the coast, latitude and longitude of district centroids. Country covariates include a time-varying measure of institutional quality based on Polity IV scores, a dummy variable for whether the country is natural resource rich interacted with linear time trends, and country's income classification at the baseline interacted with linear time trends. The baseline income classification interacted with time trends, for instance, is included to absorb cross-country differences in economic development, which is an important driver of both economic growth and diffusion of technologies such as mobile phones. In addition, I generate a dummy variable for equal 1 for countries without universal access to electricity at the baseline and interact it with time trends as an additional control to absorb trends in nightlight intensity largely associated with expansion in electrification rather than improvement in economic activities. I cluster standard errors at the level of subnational districts to account for correlation in standard errors over time.

Conditional on plausibly exogenous variation in the diffusion of mobile network coverage across districts and time, the TWFE estimate, $\hat{\beta}$, recovers the causal impact of mobile network penetration on local economic growth. However, recent advances in the literature suggest that even in the presence of plausibly exogenous variation in the treatment, the TWFE estimator

¹⁶The choice of this threshold is arbitrary, however, given that mobile network coverage can spill over across locations, coverage rates can be non-zero even if a district has no active mobile network provider, but neighboring districts have sufficiently high (geographic) coverage

is likely to be biased due to the possibility of heterogeneity in the treatment effects across groups (De Chaisemartin and D’Haultfoeuille, 2018, 2020a,b; Goodman-Bacon, 2021; Callaway and Sant’Anna, 2021). De Chaisemartin and D’Haultfoeuille (2020a) and De Chaisemartin and D’Haultfoeuille (2020b) for instance, show that in a staggered treatment design with multiple groups and treatment periods, the TWFE estimate is a weighted average of the average treatment effect (ATE) across the various groups and time periods. They show that these weights may even be negative. As a result, the overall ATE can be negative even though the ATE of all the groups is positive, thereby leading to biased estimates. To ensure the robustness of the TWFE estimates in this paper, I present additional estimates using the De Chaisemartin and D’Haultfoeuille (2020a) estimator for estimating robust treatment effect in the presence of heterogeneous treatment using a continuous measure of treatment as in the case of this paper where mobile network coverage rates vary between 0 and 1.

3.1.1 Results

Table 1 presents estimates from the TWFE regressions. Panel A presents estimates from the conventional TWFE estimator with continuous treatment. Panel B however, presents estimates from the De Chaisemartin and D’Haultfoeuille (2020a) TWFE estimator (hereafter referred to as D&G estimator) that is robust to heterogeneous treatment effects.

Starting with panel A, the results show a positive and statistically significant association between expansion in mobile network coverage and growth in nightlight intensity. In Column 1 for instance, the results suggest that a 10 pp increase in mobile network coverage is associated with a 0.18 pp increase in the growth rate of nightlight intensity. Accounting for country controls, the effect reduces slightly to 0.14 pp growth in nightlight intensity for every 10 pp increase in mobile penetration. To what extent does the effect of mobile coverage vary across the various technologies? As highlighted earlier, the 2G mobile technology only allows voice calls and SMS, while 3G and 4G technologies facilitate mobile broadband internet, in addition to the functionalities of the 2G. The results again show a positive association between the 2G and 3G/4G penetration and local economic growth. Specifically, a 10 pp increase in 2G and 3G/4G penetration are associated with a 0.2 pp (column 4) and 0.06 pp (column 6) growth in nightlight intensity respectively.

However as highlighted in Section 3, the TWFE estimates are likely to be biased even under a strict assumption of exogenous variation in mobile network coverage across districts and time, due to the possibility of heterogeneous effects across groups and time, and the associated negative weighting of some groups. To explore this, I first estimate the weights attached to the average treatment effects of the treated (ATT) associated with the TWFE estimates in panel A us-

ing the *twowayfweights* Stata package from De Chaisemartin and D’Haultfoeuille (2020b). The results show that 57% of the ATTs have positive weights, while 43% have negative weights. The negative weights sum up to -0.54. Also, the TWFE estimate has a standard deviation of 0.006, meaning that the TWFE estimate and ATTs may be of opposite sign if the standard deviation of the treatment effect across the district×year observations is equal to 0.006. Thus, the possibility of bias in the TWFE estimates in panel A cannot be overemphasized.

I, therefore, proceed to estimate the effects of mobile penetration on economic activities using the De Chaisemartin and D’Haultfoeuille (2020a) TWFE estimator that is robust to heterogeneous treatment effect.¹⁷ The results as shown in panel B of Table 1, are qualitatively similar to the estimates in panel A. Quantitatively, there are some differences in the parameter estimates, plausibly due to heterogeneity in the treatment effects across groups. Nonetheless, the C&D estimator confirms a positive association between mobile penetration and local economic growth. Further, in Table A2 in the online Appendix, I replicate the results in Table 1 using a binary of treatment defined as 1 for districts with at least 10% coverage rate and 0 otherwise. The TWFE estimates in both tables are largely consistent: an indication that the results in this paper are not sensitive to the measure of mobile network coverage.

It is noteworthy to emphasize that both the De Chaisemartin and D’Haultfoeuille (2020a) and the conventional TWFE estimators rely on the common trends assumption. To assess the plausibility of this assumption, I provide three placebo estimates: $DID^{pl,1}$, $DID^{pl,2}$, and $DID^{pl,3}$ as shown in panel C. These estimates compare changes in the outcome variable of districts changing their treatment status and those not changing their status at the respective time periods before the change. For instance, $DID^{pl,1}$ compares the growth in nightlight intensity for districts changing their treatment (mobile connectivity) status and those not changing their status one year before the change. Similarly, $DID^{pl,2}$ and $DID^{pl,3}$ compare the growth in nightlight intensity for districts changing their treatment (mobile connectivity) status and those not changing their status two and three years, respectively, before the change. As shown in panel B, the placebo estimates are mostly negative and statistically significant in periods 2 and 3. That is, districts start experiencing differential negative pre-trend two and three years before connectivity. This provides suggestive evidence that even the De Chaisemartin and D’Haultfoeuille (2020a) estimates are likely to be biased and not represent the causal impact of mobile connectivity due to the presence of pre-trends.

It is possible that the pre-trends are likely to arise from the nature of expansion in mobile network connectivity, as the expansion is less likely to be randomly designed, motivated by market potential or policy requirements. To further explore the pre-trends assumption, I follow the

¹⁷Using the STATA package `did_multiplegt`.

approach of [Gurieva et al. \(2021\)](#) and focus on districts that experienced sharp increases in mobile coverage. Specifically, I consider the case where mobile coverage increased by more than 50 percentage points in a year. In principle, districts can only experience such an event only once, assuming that coverage doesn't fall substantially.¹⁸ About 15,303 districts in 99 countries in the sample experienced such a sharp increase in mobile coverage at some point during the study period. Focusing on this sample, I estimate an event study using the [De Chaisemartin and D'Haultfoeuille \(2020b\)](#) estimator that is robust to heterogeneous treatment.¹⁹ Results are plotted in Figure 4. Still, the results do not show the absence of pre-trends, as the growth in nightlight intensity in treated districts appears to be decreasing from periods 5 to 3 prior to the treatment. The post-treatment estimates, however, confirm the findings in Table 1 of a positive association between mobile connectivity and economic activities. Overall, the results from the TWFE estimator show a strong association between mobile connectivity and local economic growth. These effects are statistically and economically significant. In spite of this, the estimates are unlikely to be causal due to the plausibly endogenous rollout of the mobile network expansion: telecom companies are more likely to deploy network coverage to areas with high economic activity and potentially high demand relative to places with low potential demand. The absence of parallel trends as shown in the event study analysis confirms this assertion.

3.2 IV Regression

To address the issue of causality, I use an IV strategy that exploits plausibly exogenous variations in the diffusion of mobile network coverage in other countries in the same region induced by the harmonization of telecom policies within the region as an instrument. This instrument follows the approach of [Acemoglu et al. \(2019\)](#) and [Acemoglu et al. \(2021\)](#) who exploit regional waves in democratization as instrument for democracy in estimating the effect of democracy on economic growth and citizens' support for democratic institutions, respectively.

Two main factors motivate this instrument. The first relates to the regionalization of telecom policies. In many regions around the world, regional economic blocs (unions) have an association of national telecom regulators or regional telecom regulators that set guidelines on telecom policies in member countries. A good example is the European Union, where the European Commission through its Body of European Regulators for Electronic Communications

¹⁸Decline in coverage can occur when the rate of population increases at a faster rate than coverage.

¹⁹Notice that here, a district is considered treated in year t if the coverage rate increased by more the 50% and 0 otherwise. Hence, the [De Chaisemartin and D'Haultfoeuille \(2020b\)](#) estimator that is robust to heterogeneous treatment effect with a binary treatment variable is used.

(BEREC) sets directives on telecom policies in the union.²⁰ Specifically, the Commission sets targets on access and connectivity, pricing, competition, and investments in the telecom sector in member states.²¹ For instance, the EU's "European Gigabit Society" strategy seeks to ensure that by 2025, all households, schools, hospitals, and transport hubs should have access to high-speed broadband connectivity. In addition, all urban areas and major terrestrial transport paths should have 5G connectivity.²²

Outside the developed markets of Europe, regionalization of telecom policies also exists, albeit, in a slightly different manner. In Africa, given the relatively underdeveloped state of the telecom sector, many regional economic blocs have associations of national telecom regulators²³ to facilitate learning, coordination and policy harmonization across member states with the goal of increasing access to digital infrastructure such as mobile phones and internet to promote sustainable development (Kessides et al., 2009).²⁴ One of the main goals of these regional regulator unions is the harmonization of telecom policies toward improving connectivity at affordable rates. In addition, the presence of these regional regulator unions could trigger a wave of telecom reforms, particularly among member states with underdeveloped telecom sectors, and opening up the sector for increased competition. These activities have implications for access and pricing. For instance, ECOWAS (the (sub)regional economic bloc in West Africa)) and the Central African Economic and Monetary Community (CEMAC), announced the elimination of roaming charges within their respective blocs by 2021 and 2022 respectively.²⁵ The construction of submarine fiber-optic cables linking Africa and the rest of the world that brought high-speed internet to African countries was largely stimulated by regional telecom associations that worked with a consortium of private investors in the construction of the infrastructure. Similarly, in the Asia and Pacific regions, several telecom regulatory unions exist that work to ensure policy harmonization among member states. These include the South Asian Telecommuni-

²⁰The EU Electronic Communications Code (EECC) established by the European Commission is a directive for reforming and consolidating the regulatory framework on telecom services and networks among member states. (See: https://ec.europa.eu/commission/presscorner/detail/en/ip_20_2482)

²¹https://ec.europa.eu/commission/presscorner/detail/en/ip_20_2482

²²https://ec.europa.eu/commission/presscorner/detail/en/ip_20_2482

²³Examples include the West African Telecommunications Regulators Assembly (WATRA), Assembly of Telecommunication Regulators of Central Africa (ARTAC), Association of Regulators of Information and Communications for Eastern and Southern Africa (ARICEA), and Communication Regulators' Association of Southern Africa (CRASA).

²⁴For instance, WATRA and Economic Community of West African States (ECOWAS) have over the past decades been working towards harmonization of telecom policies as well as implementing cross-border connectivity projects in the region (Kessides et al., 2009).

²⁵see: <https://www.ghanaweb.com/GhanaHomePage/business/No-more-roaming-charges-ECOWAS-citizens-to-enjoy-local-r>
<https://itweb.africa/content/G98YdqLY3AZvX2PD>; <https://www.ecowas.int/ecowas-member-states-reaffirm-commitment-to-the>

cation Regulators' Council²⁶ (SATRC), Asia-Pacific Telecommunity²⁷ (PITA) and Pacific Island Telecommunication Association²⁸ (APT).

The second motivation behind the instrument is that the presence of regional associations of telecom operators and multinational telecom operators in multiple countries in the region can also facilitate learning and sharing of business ideas, and operational strategies that can stimulate convergence in telecom network expansion within the region.²⁹

These factors suggest that access to telecom services such as mobile phone networks is plausibly correlated within regions, as countries may anchor their access targets on current and projected access rates in other countries in the region. In other words, I argue that the average mobile phone penetration rate within a region is a strong predictor of the penetration rate in a given country. Leveraging this idea, I instrument mobile network coverage (of districts) in a given country using lagged (past) average mobile network coverage rates in other countries in the region.

To this end, I adopt the approach of [Acemoglu et al. \(2019\)](#) and [Acemoglu et al. \(2021\)](#), and define $I_c = \{c' : c' \neq c, R_{c'} = R_c\}$ as the set of countries whose mobile phone access (coverage) rates influence the penetration (coverage) rates in country c in the same region R . Using these sets, the instrument is constructed as follows:

$$Z_{ct} = \frac{1}{I_{ct}} \sum_{c' \in I} MobileCoverage_{c'(j)t} \quad (3)$$

where $MobileCoverage_{c'(j)t}$ represents the (district level) mobile penetration rate in other countries in the same region in year t . Essentially, Z_{ct} , represents the predicted mobile penetration that a district, j , in country c at time t would have faced if it was a different country in the same region in a given year. In simple terms, the Z_{ct} is a "leave-one-out" type instrument where the mobile penetration rate in a district in country c is instrumented with the average mobile penetration rate of all districts in other countries in the same region (i.e. excluding own country penetration rates).

Using lagged values of the predicted mobile coverage of all other countries in the region as instrument for mobile penetration, I estimate a two-stage least squares (2SLS) regression with the corresponding first stage and second stage equations specified as:

²⁶<https://www.apr.int/APTSATRC>

²⁷<http://www.pita.org.fj/>

²⁸<https://www.apr.int/>

²⁹Examples of such associations include the Asia Pacific Carriers' Coalition, European Telecommunications Network Operators' Association, Southern Africa Telecommunications Association (SATA), and the East African Communications Entities Organization (EACO).

First Stage:

$$Mobile_{jct} = \phi \times Z_{ct-1} + \mathbf{Controls}'_{jct} \Gamma_1 + \theta_j + \delta_t + \mu_{jct} \quad (4)$$

Second Stage:

$$\Delta \ln Y_{jct} = \beta \times \widehat{Mobile}_{jct} + \mathbf{Controls}'_{jct} \Gamma_2 + \theta_j + \delta_t + \epsilon_{jct} \quad (5)$$

where all variables remain as previously defined. The main assumption behind the 2SLS estimation is that conditional on the fixed effects and controls, past mobile coverage rates in other countries in the region affect the economic growth of a given district only through mobile network penetration in the district, i.e, the so-called exclusion restriction assumption. The main threats to this assumption are underlying regional economic or political shocks that influence mobile network expansion and local economic development. For instance, the assumption breaks down if economic shocks at the regional level influence local economic growth while at the same time influencing mobile network penetration. Similarly, channels such as regional trade can operate to violate our exclusion restriction assumption as it influences both economic growth and digital connectivity. To address these concerns, I construct spatially weighted GDP growth and Trade (% GDP) of neighboring countries in the region and include them as controls (Acemoglu et al., 2019). Specifically, following Acemoglu et al. (2019), I compute, for each country, the average real GDP growth and trade (export + import) (% GDP of other countries) in the region weighted by the inverse distance between the country and every other country (neighbors) in the region. Controlling for the spatially weighted regional GDP and trade indicators is useful to absorb the underlying factors that jointly influence the instrument and the outcome variable. Put differently, conditional on these controls, the exclusion restriction assumption is plausibly feasible.

Still there could be concerns that the instrument may be picking common economic shocks in the region thereby posing a risk to the validity of the IV estimates. In response to this, I estimate additional IV regressions by introducing adjustments to the instrument. A growing number of studies have shown that lightning intensity is an important factor influencing the diffusion of digital infrastructure (Andersen et al., 2011; Manacorda and Tesei, 2020; Guriev et al., 2021). Lightning strikes contain about a billion volts of electricity and have been known to cause severe destruction to electrical and digital infrastructure around the world, thereby increasing the cost associated with the diffusion of digital technologies (Andersen et al., 2012; Zeddiam and Day, 2014; Martin, 2016). Although the use of power surge protection technologies can alleviate the extent of the impact of lightning activities on digital infrastructure, it comes at a cost, thereby increasing the overall cost of deploying digital infrastructure in areas with high lightning intensity (Guriev et al., 2021). As a result, mobile penetration tends to be slower in

areas with a high incidence of lightning strikes, and vice versa. In spite of the seemingly strong correlation between lightning intensity and mobile network penetration, the destructive effect of lightning activities is not limited to mobile infrastructure. Indeed they affect the diffusion of general technologies such as electrification and computers (Andersen et al., 2012), thereby constraining their direct use as instrumental variables in studying the effect of mobile penetration on economic growth, as the exclusion restriction assumption is likely to be violated. However, the negative association between lightning and mobile penetration provides a sense check to our main instrument: mobile network operators are more likely to extend coverage to places with low lightning intensity due to the relatively low cost of deployment compared to places with high lightning intensity. This suggests that the role of policy instruments in improving connectivity is expected to be more salient in places where (private) mobile network operators are less motivated to expand coverage due to the lightning-induced cost of network expansion.

Therefore, I construct an additional instrument, by interacting the main instrument (predicted regional mobile coverage rate) with quintiles of lightning intensity at the district level. The intuition is that the effect of regional policy harmonization on mobile penetration at the local level should be high in places where mobile operators would otherwise not extend mobile coverage due to the effect of lightning strikes, relative to places with low lightning strikes and hence lower cost of mobile network extension. Thus, even if individually, lightning intensity and possibly the predicted regional mobile penetration rate may not satisfy the requirements of a good instrument, their interactions may plausibly suffice. The corresponding first-stage equation can be expressed as:

$$Mobile_{ict} = \phi_q \cdot \left(\sum_{q=1} \mathbb{1}(Lightning_q) \times Z_{ct-1} \right) + \mathbf{Controls}'_{ict} \Gamma_1 + \alpha \cdot (Lightning_i \times T) + \theta_i + \delta_t + \mu_{jct} \quad (6)$$

where $\mathbb{1}(Lightning_q)$ is an indicator variable equal to 1 if the lightning intensity in district j is in the q^{th} quintile and 0 otherwise. Again, to isolate the direct effect of lightning on economic development from confounding the relationship between the instrument and the outcome variable, I include the district-level lightning intensity interacted with time trends.³⁰ In this set-up, the main identifying assumption is that the differential effects of regional expansion in mobile network coverage across places with varying lightning intensity affect local economic development only through its effect on expansion in (local) mobile network coverage. Estimates are weighted by population. Robust standard errors are also clustered at the district level.

³⁰The interaction with time trends is necessitated by the fact that the lightning intensity data is cross-sectional.

3.2.1 Main IV Results

To estimate the causal impact of mobile penetration on local economic growth, I rely on the 2SLS estimation strategy using the (first lag) of the predicted regional mobile penetration rate described in section 3.2.

Before turning to the results of the 2SLS estimation, it is useful to explore the relationship between the endogenous variable (mobile penetration at the district level) and the proposed instrument (predicted mobile network penetration at the regional level). Figure 5 shows a strong positive association between district level mobile penetration rate and the instrument. The y-axis reports the (binned) residuals from a regression of mobile penetration rates on district and year fixed effects, while the x-axis reports (binned) residuals from a regression of the instrument on district and year fixed effects. The scatter plot shows a strong correlation between the instrument and mobile penetration: an indication that the instrument passes the relevance condition for an IV regression. Table 2 presents results from the first-stage estimation. For each measure of mobile penetration, I estimate two variant specifications, with and without the regional controls. Columns 2, 4 and 6 are the preferred specification as they include the full set of controls. Overall the results confirm the scatter plot in Figure 5, showing a positive association between (lagged) predicted regional mobile penetration rates and mobile penetration at the district level. In column (2) for instance, the results show that a 10 pp increase in the predicted regional mobile coverage is associated with a 5.9 pp increase in mobile penetration in a given district. Similarly, a 10 pp increase in predicted 2G (3G/4G) coverage at the regional level is associated with a 3.4 (2.9) pp increase in 2G (3G/4G) in a district. The F-statistics of the excluded instruments are also reasonably high ranging between 188 and 372: an indication of the relevance and strength of the instrument(s).

Turning to the second stage (2SLS) estimates in Table 3, the results show a positive effect of mobile phone penetration on local economic activities. In column 1, I find that a 10 pp increase in mobile phone coverage results in a 0.6 pp increase in the growth rate in nightlight intensity. The effect increases to 0.78 pp after accounting for the regional controls to absorb the potential effect of regional economic shocks that could confound the IV results. I also explore the individual effects of 2G mobile coverage which essentially supports voice calls, and the effects 3G/4G mobile technologies which support both voice call and mobile Internet on local economic activities in columns 3-4 and 5-6 respectively. The results suggest that a 10 pp increase in the 2G network coverage is associated with a 0.32 pp increase in the rate of growth in nightlight intensity (column 4). The effect of 3G/4G coverage however is about twice the effect of 2G coverage: a 10 pp increase in 3G/4G coverage generates a 0.7 pp growth in nightlight intensity (column 6). The mobile broadband Internet capabilities of 3G and 4G networks, and the associated eco-

conomic impact of Internet connectivity, plausibly explain the high impact of 3G/4G relative to the effects of 2G connectivity. Nonetheless, the results unanimously show that mobile phone penetration is a key driver of local economic development as the estimates are economically and statistically significant.

To what extent does the growth in nightlights induced by the expansion in mobile phone penetration translate into real growth in GDP? The seminal work of [Henderson et al. \(2012\)](#) shows an elasticity of GDP growth to nightlight of 0.3. The authors also show that the elasticity applies even in low and middle-income countries. Therefore using this elasticity, the results in [Table 3](#) (columns 1 and 2) suggest that a 1 pp expansion mobile network coverage leads to 0.018 – 0.023 pp increase in GDP growth respectively. Similarly, a 1 pp increase in the 2G and 3G coverage is associated with a 0.01 pp and 0.02 pp increase in GDP growth. To put this in perspective, between 2008 and 2018, the global mobile network coverage increased on average by 16 pp from 75% to 91%. Combining this with our estimated GDP-mobile coverage elasticity implies that the expansion in network coverage between 2008 and 2018 led to a 0.37 pp (16×0.023) increase in GDP growth.

3.2.2 Alternate IV Results

Next, I present additional 2SLS estimates leveraging the secondary instrument that relies on the interaction between the predicted regional mobile coverage rate and (quintiles of) lightning intensity in [Table 4](#). The associated first stage results shown in [Table A3](#) in the appendix confirm the a-priori expectations that the predicted regional mobile coverage rates are associated with higher mobile coverage rates in districts with relatively high cost of extending coverage (high lightning intensity). In other words, harmonization of telecom policies among countries in the region induces higher mobile penetration in areas where mobile operators would otherwise have less economic incentives to expand coverage due to the high damages to digital infrastructure associated with lightning strikes. The F-statistics of the excluded instruments are also sufficiently high.

The 2SLS estimates in [Table 4](#) are quantitatively and qualitatively similar to the baseline (main) 2SLS results in [Table 3](#), albeit the estimates in the former are relatively smaller compared to the latter. For instance, the IV regression results based on the new instrument suggest that a 10 pp increase in mobile network penetration is associated with a 0.46 pp increase in growth in nightlight intensity, compared with the 0.78 pp increase growth in nightlight intensity in [Table 3](#). Similar results are obtained for 2G and 3G/4G. Overall, the estimates herein provide support to the main IV regression on the causal impact of mobile network penetration on GDP growth.

4 Heterogeneity

Aside from evidence on the causal impact of mobile phone penetration on GDP growth, an important policy question is the distribution of the impacts across heterogeneous groups. For instance, how does the impact of mobile vary between developed and emerging markets. In addition, how did the arrival of mobile phones spur economic growth in countries that hitherto had low access to communication technologies such as the fixed line telephone network? In this section, I provide evidence on these questions by re-estimating the main IV regression while interacting measures of mobile penetration with measures of countries' income group and fixed telephone penetration at the baseline.

First, I explore the economic impact of mobile phones between developed and developing economies. Using the World Bank's income classification at the baseline, I split countries into two main groups: developing vs developed.³¹ I then interact the mobile penetration measures with a dummy variable equal to 1 for developing countries and 0 otherwise. Results are shown in Table 5. The results show that while mobile phones have a positive impact on local economic growth across all income groups, the effect is higher among developing countries. For instance, the results in column 2 suggest that a 10 pp increase in mobile penetration is associated with a 0.5 pp growth in nightlights in developed (high and upper middle income) countries, compared to a 0.9 pp increase in developing (low income and lower middle income) countries. The effect of 2G connectivity is however only present in developing markets (columns 3-4). These findings are plausibly indicative of the economic importance of mobile voice and SMS messaging which incidentally is the backbone of digital finance platforms like mobile money in most developing countries (Suri and Jack, 2016; Suri, 2017). However, the findings in relation to 3G/4G are interesting: in column 5, the results indicate that effects of 3G/4G connectivity are about 0.97 pp higher in developing markets relative to developed markets. However, the coefficient of the interaction loses statistical significance in column 6, where we include controls for economic shocks at the region level. Nonetheless, the results provide suggestive evidence that mobile broadband internet induce economic impacts in both developed and developing countries.

In addition, I explore how the relationship between mobile phone penetration and economic activities varies according to pre-existing access to digital communication, specifically fixed line telephony. For instance, in countries with relatively high fixed line telephony prior to the arrival of mobile phones, the additional impact of the mobile phone particularly 2G connectivity could be low compared to countries that hitherto had low access to any form of telephone

³¹Countries in the World Bank's low income (LIC) and lower middle income (LMIC) groups are classified as developing, while countries in the upper-middle income (UMIC) and high income (HIC) groups are classified as developed.

communication. To this end, I use data on fixed telephone network penetration and construct a dummy variable equal to 1 for countries where the penetration rate at the baseline is below the median and 0 for those above the median. I then interact the dummy with the various measures of mobile phone penetration to explore the differential effect of mobile penetration across these groups. Table 6 presents interesting findings. First, similar to the results on the interaction with the income grouping, the effect of 2G network expansion on economic growth is statistically significant only in countries with low fixed telephone penetration at the baseline. This finding suggests that access to 2G mobile networks is a plausible substitute to fixed line telephony, hence the expansion in 2G networks enabled countries that hitherto had no/low access to telephone services to reap the economic gains associated with digital connectivity. The effects of 3G/4G connectivity are however present in countries with low as well as high fixed line telephone penetration. However, once again the effect in locations with low prior fixed line telephone penetration is relatively higher. Overall, the results indicate that access to mobile phones induces greater economic footprints in countries with previously low digital communication capacity.

5 Robustness Checks

To assess the robustness of the results, I perform several robustness checks: First, by restricting the data to the period between 1998 and 2013, I show that the results hold for both the harmonized and non-harmonized nightlights data. Specifically, Table A4 shows the results from estimating the main IV equations using the restricted data on harmonized and non-harmonized nightlights data. In fact, the results in Table A4 show that estimates based on the harmonized nightlights data are slightly lower than using the non-harmonized lights data. This gives assurance that using the harmonized nightlights data does not lead to an overestimation of the impact of mobile phone coverage on economic activities.

Secondly, I conduct sensitivity analysis by investigating whether the baseline results are driven by a particular group of countries, i.e. if the results are sensitive to the country composition in the dataset. To this end, I re-estimate the baseline IV regression, while dropping one country at a time. Once again the results in Figure A2 in the online appendix show that the results are robust to country composition in the dataset.

Finally, I show in Figure A3 that the results are not driven by locational factors as sequential trimming of subnational districts away from the equator does not alter the main findings of the paper.

6 Concluding Remarks

Mobile phones have become ubiquitous. It has revolutionized telecommunication and offers an array of services such as mobile banking, and access to social media. Mobile broadband Internet also offers millions of people access to the Internet for productive uses and leisure. In this paper, I present global evidence on the impact of mobile phone access on local economic development. To do this, I assemble a unique granular dataset on the global expansion in 2G, 3G and 4G mobile networks spatially matched with satellite data on nighttime lights.

The findings of the paper show that access to mobile phones is a significant driver of economic activities. The results provide suggestive evidence that the prior evidence in the literature on the effects of mobile phones and mobile broadband Internet on households and firms translates into meaningful impact on economic development. Moreover, the effects of mobile network penetration are more pronounced in developing countries as well as those that hitherto had low access to fixed-line telephone network infrastructure.

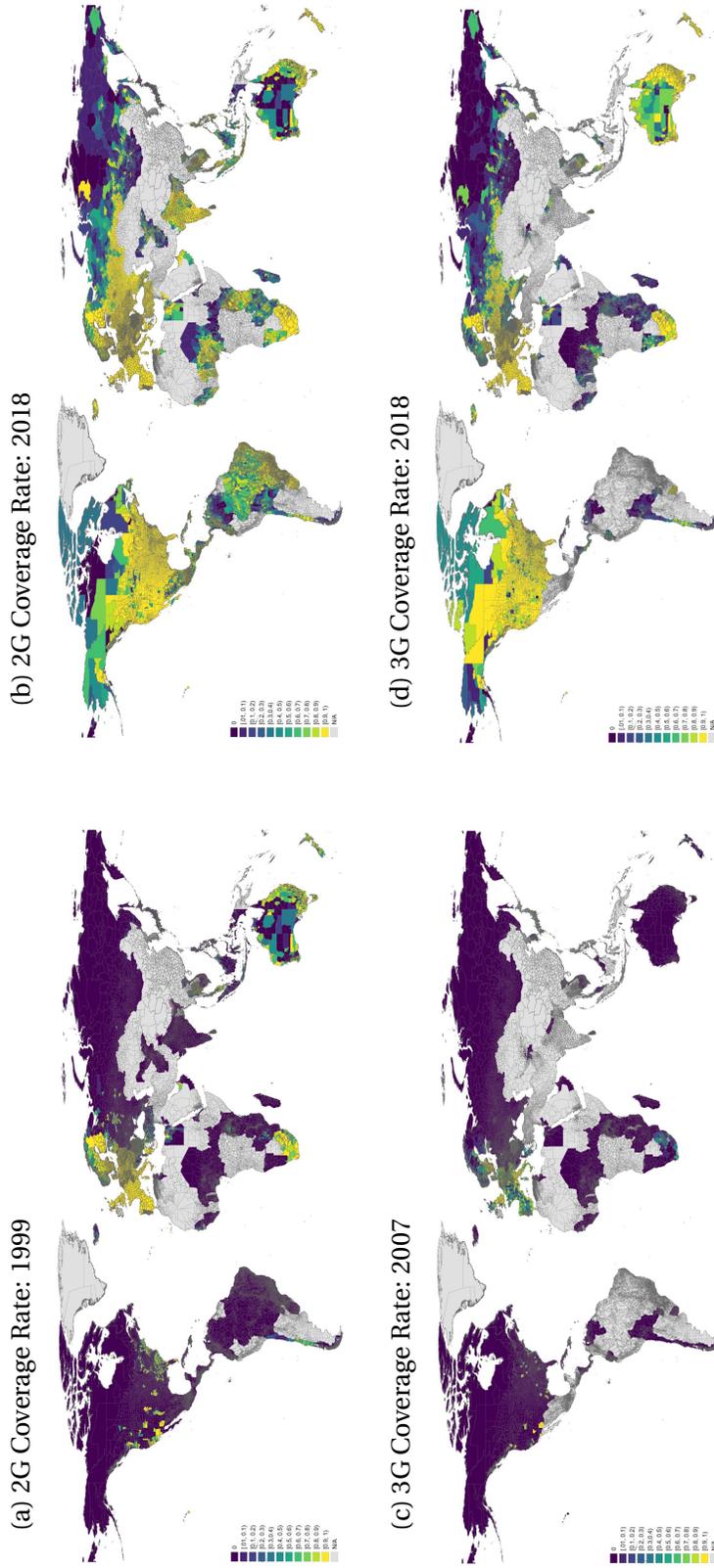
References

- Acemoglu, D., Ajzenman, N., Aksoy, C. G., Fiszbein, M., and Molina, C. A. (2021). (successful) democracies breed their own support. Technical report, National Bureau of Economic Research.
- Acemoglu, D., Naidu, S., Restrepo, P., and Robinson, J. A. (2019). Democracy does cause growth. *Journal of political economy*, 127(1):47–100.
- Adema, J., Aksoy, C. G., Poutvaara, P., et al. (2021). Mobile internet access and desire to migrate. Technical report, ifo Institute-Leibniz Institute for Economic Research at the University of . . .
- 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.
- Aker, J. C. and Mbiti, I. M. (2010). Mobile phones and economic development in Africa. *Journal of Economic Perspectives*, 24(3):207–32.
- Akerman, A., Gaarder, I., and Mogstad, M. (2015). The skill complementarity of broadband internet. *The Quarterly Journal of Economics*, 130(4):1781–1824.
- Andersen, T. B., Bentzen, J., Dalgaard, C.-J., and Selaya, P. (2011). Does the Internet reduce corruption? evidence from US states and across countries. *The World Bank Economic Review*, 25(3):387–417.
- Andersen, T. B., Bentzen, J., Dalgaard, C.-J., and Selaya, P. (2012). Lightning, IT diffusion, and economic growth across U.S. states. *The Review of Economics and Statistics*, 94(4):903–924.
- Bahia, K., Castells, P., Cruz, G., Masaki, T., Pedrós, X., Pfütze, T., Rodríguez-Castelán, C., and Winkler, H. (2020). The welfare effects of mobile broadband Internet: Evidence from Nigeria. Technical report.
- Batista, C., Vicente, P. C., et al. (2018). Is mobile money changing rural Africa? evidence from a field experiment. Technical report, Universidade Nova de Lisboa, Faculdade de Economia, NOVAFRICA.
- Bellemare, M. F. and Wichman, C. J. (2020). Elasticities and the inverse hyperbolic sine transformation. *Oxford Bulletin of Economics and Statistics*, 82(1):50–61.
- 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.
- Callaway, B. and Sant’Anna, P. H. (2021). Difference-in-differences with multiple time periods. *Journal of Econometrics*, 225(2):200–230.
- Czernich, N., Falck, O., Kretschmer, T., and Woessmann, L. (2011). Broadband infrastructure and economic growth. *The Economic Journal*, 121:505–532.
- De Chaisemartin, C. and D’Haultfoeuille, X. (2018). Fuzzy differences-in-differences. *The Review of Economic Studies*, 85(2):999–1028.

- De Chaisemartin, C. and D'Haultfoeuille, X. (2020a). Difference-in-differences estimators of intertemporal treatment effects. Technical report.
- De Chaisemartin, C. and D'Haultfoeuille, X. (2020b). Two-way fixed effects estimators with heterogeneous treatment effects. *American Economic Review*, 110(9):2964–96.
- DeStefano, T., Kneller, R., and Timmis, J. (2018). Broadband infrastructure, ICT use and firm performance: Evidence for UK firms. *Journal of Economic Behavior & Organization*, 155:110–139.
- Goldbeck, M. and Lindlacher, V. (2021). Digital infrastructure and local economic growth: Early internet in sub-saharan africa. Technical report, Working Paper.
- Gonzalez, R. M. (2021). Cell phone access and election fraud: Evidence from a spatial regression discontinuity design in Afghanistan. *American Economic Journal: Applied Economics (Forthcoming)*.
- Goodman-Bacon, A. (2021). Difference-in-differences with variation in treatment timing. *Journal of Econometrics*.
- Guriev, S., Melnikov, N., and Zhuravskaya, E. (2021). 3G Internet and confidence in government. *Quarterly Journal of Economics (Forthcoming)*.
- Henderson, J. V., Storeygard, A., and Weil, D. N. (2012). Measuring economic growth from outer space. *American Economic Review*, 102(2):994–1028.
- Henderson, V., Storeygard, A., and Weil, D. N. (2011). A bright idea for measuring economic growth. *American Economic Review*, 101(3):194–99.
- Hjort, J. and Poulsen, J. (2019). The arrival of fast internet and employment in Africa. *American Economic Review*, 109(3):1032–79.
- Kessides, I., Noll, R. G., and Benjamin, N. (2009). Regionalizing telecommunications reform in west africa. Technical Report 5126, World Bank Policy Research Working Paper.
- Li, X., Zhou, Y., Zhao, M., and Zhao, X. (2020). A harmonized global nighttime light dataset 1992–2018. *Scientific Data*, 7(1):1–9.
- Manacorda, M. and Tesei, A. (2020). Liberation technology: Mobile phones and political mobilization in Africa. *Econometrica*, 88(2):533–567.
- Martin, A. (2016). Effects of lightning on ICT circuits: Induction and GCR. *Compliance*, pages 36–46.
- Suri, T. (2017). Mobile money. *Annual Review of Economics*, 9(1):497–520.
- Suri, T. and Jack, W. (2016). The long-run poverty and gender impacts of mobile money. *Science*, 354(6317):1288–1292.
- Zeddani, A. and Day, P. (2014). Improving the protection of ICT equipment against lightning strikes. Technical report.

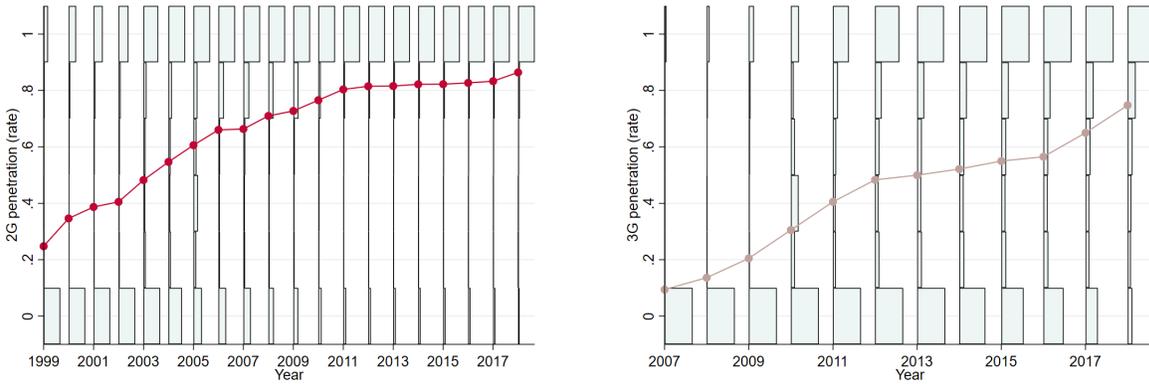
Zuo, G. (2020). Wired and hired: Employment effects of subsidized broadband Internet for low-income Americans. *American Economic Journal: Applied Economics* (Forthcoming).

Figure 2: Trends in Global Mobile Network Coverage



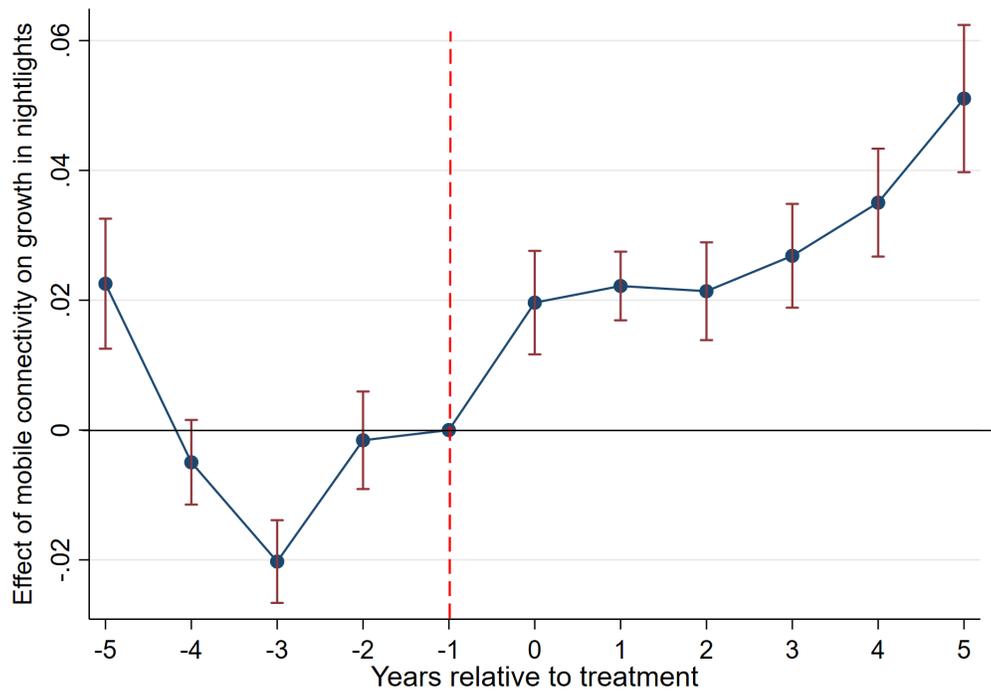
The panels show the coverage rate of the respective mobile phone technologies at the subnational level over time. Author's construct based on data from Collins Bartholomew Mobile Coverage Explorer

Figure 3: Mobile Network Coverage Across Districts and Time



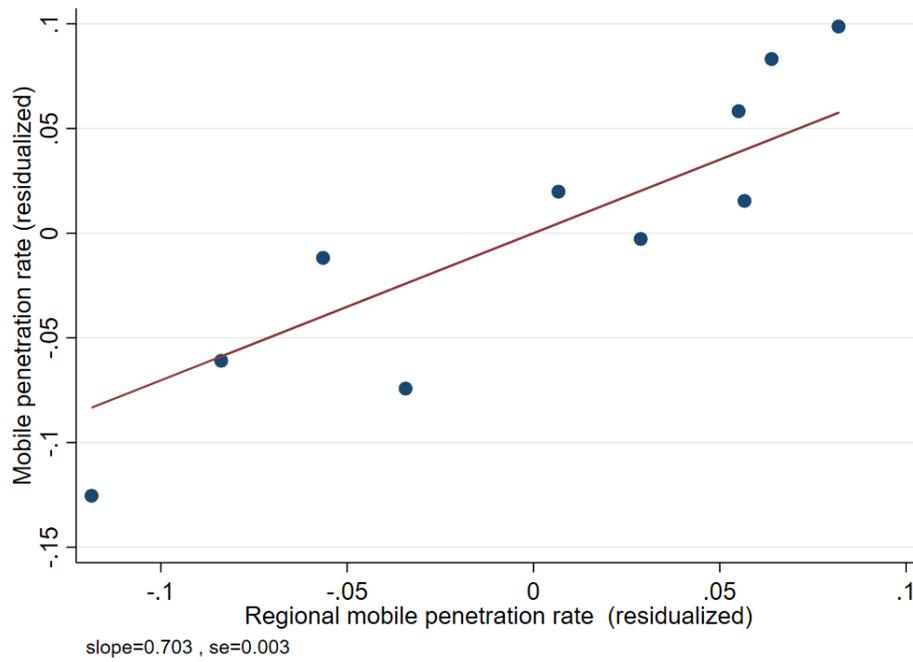
This figure shows the average penetration rates for 2G and 3G mobile networks across time.

Figure 4: Event Study Design: Mobile Network Connectivity and Growth in Nightlights



This figure shows the results from an event study design implemented using the [De Chaisemartin and D’Haultfoeuille \(2020b\)](#) estimator which ensures that the average treatment effect in each group and time period do not have negative weights

Figure 5: First Stage Relationship



This (binned) scatter plot shows the relationship between the average (residual) mobile network coverage at the district level, and the instrument, the average (residual) mobile network coverage of all districts in other countries in the same region.

Tables

Table 1: Mobile Phone Penetration and Economic Activity: Two-Way Fixed Effects Estimation Results

Dep. Var : Growth in Nightlight Intensity						
<i>Panel A:</i> TWFE						
	(1)	(2)	(3)	(4)	(5)	(6)
Mobile Coverage (all)	0.0179*** (0.0010)	0.0136*** (0.0010)				
2G Coverage			0.0273*** (0.0011)	0.0197*** (0.0011)		
3G/4G Coverage					-0.0008 (0.0021)	0.0059*** (0.0022)
<i>Panel C:</i> C&D TWFE with Heterogeneous Treatment Effect						
1 (Mobile Coverage (all))	0.0052** (0.0026)	0.0058** (0.0027)				
1(2G Coverage)			0.0093*** (0.0026)	0.009*** (0.0022)		
1(3G/4G Coverage)					0.0436*** (0.0039)	0.0411*** (0.0039)
DID ^{pl,1}	-0.0078*** (0.0027)	-0.0077*** (0.0022)	-0.0022 (0.0028)	-0.0018 (0.0024)	0.0032 (0.0030)	0.0046 (0.0033)
DID ^{pl,2}	-0.0095*** (0.0023)	-0.0085*** (0.0027)	-0.007*** (0.0022)	-0.006*** (0.0022)	0.0525*** (0.0044)	-0.0536*** (0.0047)
DID ^{pl,2}	-0.0091*** (0.0022)	-0.0106*** (0.0026)	-0.0004 (0.0025)	-0.0007 (0.0024)	0.0115*** (0.0048)	0.0082 (0.0064)
District Ctrl	Yes	Yes	Yes	Yes	Yes	Yes
Country Ctrl	No	Yes	No	Yes	No	Yes
District FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Mean dep. var	0.0492	0.0495	0.0494	0.0497	0.0613	0.0611
# of Countries	119	106	118	105	96	86
# of Districts	34387	33763	34205	33581	17746	17176
Observations	722067	702513	718245	698691	212952	205467

Notes: C&D TWFE with Heterogeneous Treatment Effect is estimated using the De Chaisemartin and D'Haultfoeuille (2020a) estimator. District Controls include, average annual temperature and total precipitation, and interaction between time trends and the following variables: distance to the coast, latitude and longitude of district centroid. Country controls also include Polity IV score, and interaction between time trends and the following variables: universal electricity access dummy, natural resource dependence, and the country's income classification, all measured at the baseline. of time trends with latitude, longitude. Robust standard errors clustered at district level in parenthesis.

* Significant at 10 percent level ** Significant at 5 percent level *** Significant at 1 percent level

Table 2: First Stage Regression: Mobile Phone Penetration and Economic Activity

	Mobile Coverage		2G Coverage		3G/4G Coverage	
	(1)	(2)	(3)	(4)	(5)	(6)
Regional Mobile Coverage (t-1)	0.7739*** (0.0402)	0.5946*** (0.0311)				
Regional 2G Coverage (t-1)			0.3411*** (0.0235)	0.3354*** (0.0224)		
Regional 3G/4G Coverage (t-1)					0.2834*** (0.0206)	0.2937*** (0.0212)
District Ctrl	Yes	Yes	Yes	Yes	Yes	Yes
Country Ctrl	Yes	Yes	Yes	Yes	Yes	Yes
Regional Ctrl	No	Yes	No	Yes	No	Yes
District FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Mean dep. var	0.0474	0.0474	0.0476	0.0476	0.0611	0.0611
First-stage F test	371.2771	365.8341	211.5158	224.8928	188.8642	191.8397
# of Countries	106	106	105	105	86	86
# of Districts	33759	33759	33577	33577	17176	17176
Observations	669375	669375	665735	665735	205467	205467

Notes: District Controls include, average annual temperature and total precipitation, and interaction between time trends and the following variables: distance to the coast, latitude and longitude of district centroid. Country controls also include Polity IV score, and interaction between time trends and the following variables: universal electricity access dummy, natural resource dependence, and the country's income classification, all measured at the baseline. Regional Ctrl include spatially weighted GDP and Trade % of GDP at the regional level. Robust standard errors clustered at district level in parenthesis.

* Significant at 10 percent level ** Significant at 5 percent level *** Significant at 1 percent level

Table 3: Mobile Phone Penetration and Economic Activity

	Dep. Var : Growth in Nightlight Intensity					
	(1)	(2)	(3)	(4)	(5)	(6)
	2SLS					
Mobile Coverage (all)	0.0596*** (0.0078)	0.0777*** (0.0098)				
2G Coverage			0.0351* (0.0181)	0.0321* (0.0183)		
3G/4G Coverage					0.0169 (0.0194)	0.0707*** (0.0217)
District Ctrl	Yes	Yes	Yes	Yes	Yes	Yes
Country Ctrl	Yes	Yes	Yes	Yes	Yes	Yes
Regional Ctrl	No	Yes	No	Yes	No	Yes
District FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Mean dep. var	0.0474	0.0474	0.0476	0.0476	0.0611	0.0611
First-stage F test	371.2771	365.8341	211.5158	224.8928	188.8642	191.8397
# of Countries	106	106	105	105	86	86
# of Districts	33759	33759	33577	33577	17176	17176
Observations	669375	669375	665735	665735	205467	205467

Notes: District Controls include, average annual temperature and total precipitation, and interaction between time trends and the following variables: distance to the coast, latitude and longitude of district centroid. Country controls also include Polity IV score, and interaction between time trends and the following variables: universal electricity access dummy, natural resource dependence, and the country's income classification, all measured at the baseline. Regional Ctrl include spatially weighted GDP and Trade % of GDP at the regional level. Robust standard errors clustered at district level in parenthesis.

* Significant at 10 percent level ** Significant at 5 percent level *** Significant at 1 percent level

Table 4: Mobile Phone Penetration and Economic Activity: Results from Alternative instrument

Dep. Var : Growth in Nightlight Intensity						
2SLS						
	(1)	(2)	(3)	(4)	(5)	(6)
Mobile Coverage (all)	0.0447*** (0.0063)	0.0464*** (0.0077)				
2G Coverage			0.0315*** (0.0111)	0.0265** (0.0114)		
3G/4G Coverage					0.0338*** (0.0126)	0.0561*** (0.0136)
District Ctrl	Yes	Yes	Yes	Yes	Yes	Yes
Country Ctrl	Yes	Yes	Yes	Yes	Yes	Yes
Regional Ctrl	No	Yes	No	Yes	No	Yes
District FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Mean dep. var	0.0474	0.0474	0.0476	0.0476	0.0611	0.0611
First-stage F test	137.6473	124.8156	113.8053	111.4008	100.7374	95.4457
# of Countries	106	106	105	105	86	86
# of Districts	33721	33721	33539	33539	17138	17138
Observations	668615	668615	664975	664975	205011	205011

Notes: Results are based on IV regressions using the first lag of subregional mobile penetration rates of the respective technologies interacted with lightning intensity quintiles. District Controls include, average annual temperature and total precipitation, lightning intensity, and interaction between time trends and the following variables: distance to the coast, lightning intensity interacted with time trends, latitude and longitude of district centroid. Country controls also include Polity IV score, and interaction between time trends and the following variables: universal electricity access dummy, natural resource dependence, and the country's income classification, all measured at the baseline. Regional Ctrl include spatially weighted GDP and Trade % of GDP at the regional level. Robust standard errors clustered at district level in parenthesis.

* Significant at 10 percent level ** Significant at 5 percent level *** Significant at 1 percent level

Table 5: Mobile Phone Penetration and Economic Activity: Role of Existing Telephone Capacity

	Dep. Var : Growth in Nightlight Intensity					
	2SLS					
	(1)	(2)	(3)	(4)	(5)	(6)
Mobile Coverage (all)	0.0443*** (0.0067)	0.0510*** (0.0083)				
× 1(Developing countries)	0.0387*** (0.0087)	0.0395*** (0.0091)				
2G Coverage			0.0106 (0.0208)	0.0015 (0.0221)		
× 1(Developing countries)			0.0255*** (0.0079)	0.0265*** (0.0082)		
3G/4G Coverage					0.0382*** (0.0146)	0.0868*** (0.0187)
× 1(Developing countries)					0.0969** (0.0428)	0.0577 (0.0495)
District Ctrl	Yes	Yes	Yes	Yes	Yes	Yes
Country Ctrl	Yes	Yes	Yes	Yes	Yes	Yes
Subregional Ctrl	No	Yes	No	Yes	No	Yes
District FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Mean dep. var	0.0474	0.0474	0.0476	0.0476	0.0611	0.0611
First-stage F test	142.5237	144.6022	107.5526	109.4582	106.4979	96.3653
# of Countries	106	106	105	105	86	86
# of Districts	33759	33759	33577	33577	17176	17176
Observations	669375	669375	665735	665735	205467	205467

Notes: Low Fixed Telephone Penetration is a dummy equal to 1 for districts in countries whose fixed telephone penetration rate at the baseline is below median. District Controls include, average annual temperature and total precipitation, and interaction between time trends and the following variables: distance to the coast, latitude and longitude of district centroid. Country controls also include Polity IV score, and interaction between time trends and the following variables: universal electricity access dummy, and natural resource dependence, all measured at the baseline. of time trends with latitude, longitude SubRegional Ctrl include spatially weighted GDP and Trade % of GDP at the subregional level. Robust standard errors clustered at district level in parenthesis.

* Significant at 10 percent level ** Significant at 5 percent level *** Significant at 1 percent level

Table 6: Mobile Phone Penetration and Economic Activity: Role of Existing Telephone Capacity

	Dep. Var : Growth in Nightlight Intensity					
	2SLS					
	(1)	(2)	(3)	(4)	(5)	(6)
Mobile Coverage (all)	0.0396***	0.0539***				
	(0.0062)	(0.0081)				
× 1(Low Fixed Line Telephone Penetration)	0.0352***	0.0332***				
	(0.0059)	(0.0061)				
2G Coverage			-0.0269	-0.0256		
			(0.0257)	(0.0258)		
× 1(Low Fixed Line Telephone Penetration)			0.0469***	0.0439***		
			(0.0085)	(0.0085)		
3G/4G Coverage					0.0701***	0.1169***
					(0.0247)	(0.0267)
× 1(Low Fixed Line Telephone Penetration)					0.2412***	0.2019***
					(0.0647)	(0.0694)
District Ctrl	Yes	Yes	Yes	Yes	Yes	Yes
Country Ctrl	Yes	Yes	Yes	Yes	Yes	Yes
Subregional Ctrl	No	Yes	No	Yes	No	Yes
District FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Mean dep. var	0.0473	0.0473	0.0475	0.0475	0.0610	0.0610
First-stage F test	204.5590	204.0620	100.3583	110.741	49.9899	53.5871
# of Countries	104	104	103	103	85	85
# of Districts	33551	33551	33369	33369	17021	17021
Observations	665215	665215	661575	661575	203607	203607

Notes: Low Fixed Telephone Penetration is a dummy equal to 1 for districts in countries whose fixed telephone penetration rate at the baseline is below median. District Controls include, average annual temperature and total precipitation, and interaction between time trends and the following variables: distance to the coast, latitude and longitude of district centroid. Country controls also include Polity IV score, and interaction between time trends and the following variables: universal electricity access dummy, natural resource dependence, and the country's income classification, all measured at the baseline. of time trends with latitude, longitude SubRegional Ctrl

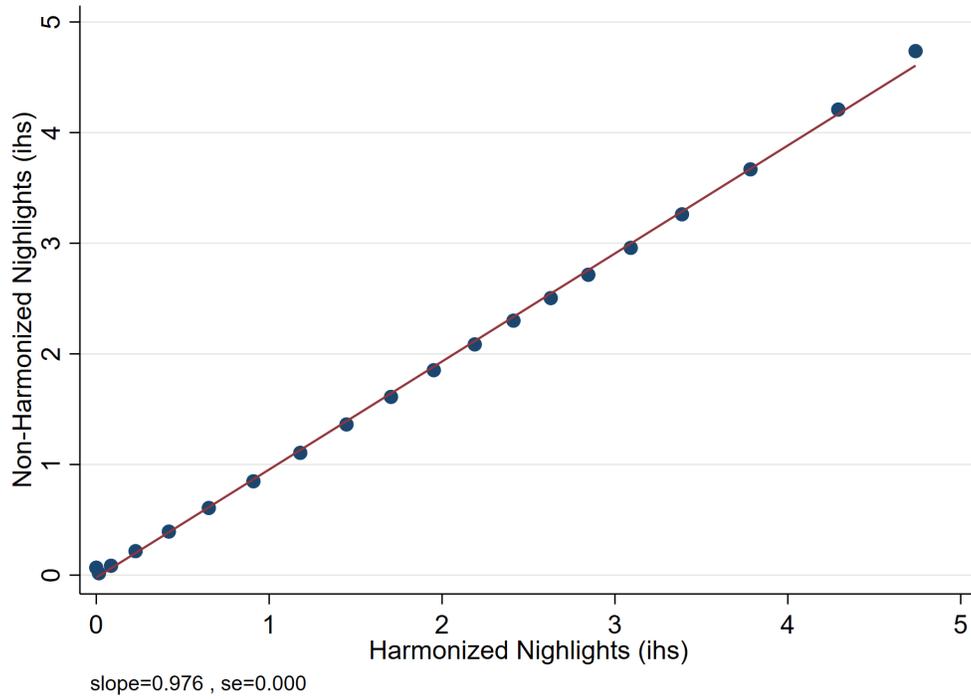
Robust standard errors clustered at district level in parenthesis.

* Significant at 10 percent level ** Significant at 5 percent level *** Significant at 1 percent level

A ONLINE APPENDIX

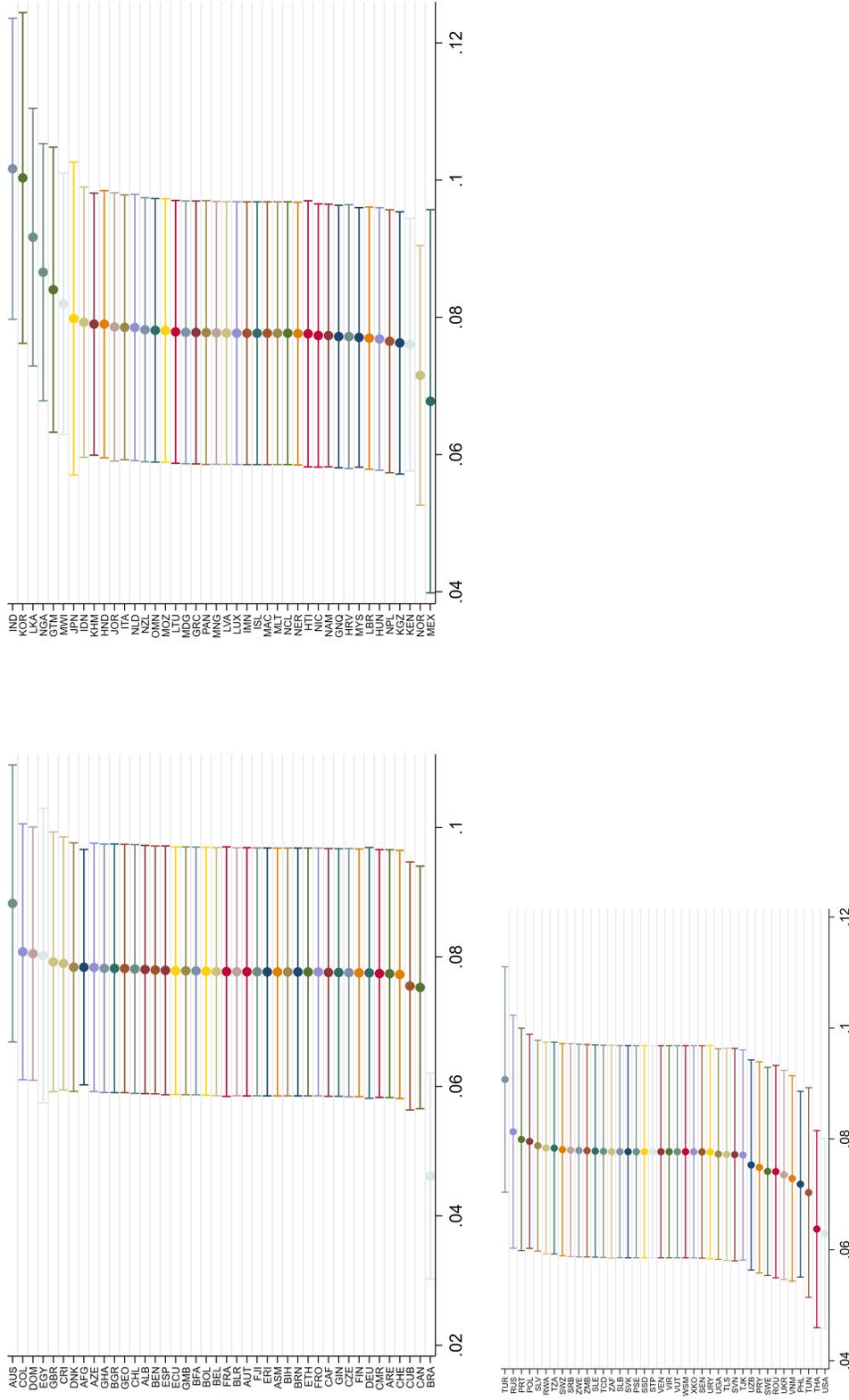
A.1 Figures

Figure A1: Harmonized vs Non-harmonized Nightlights Data



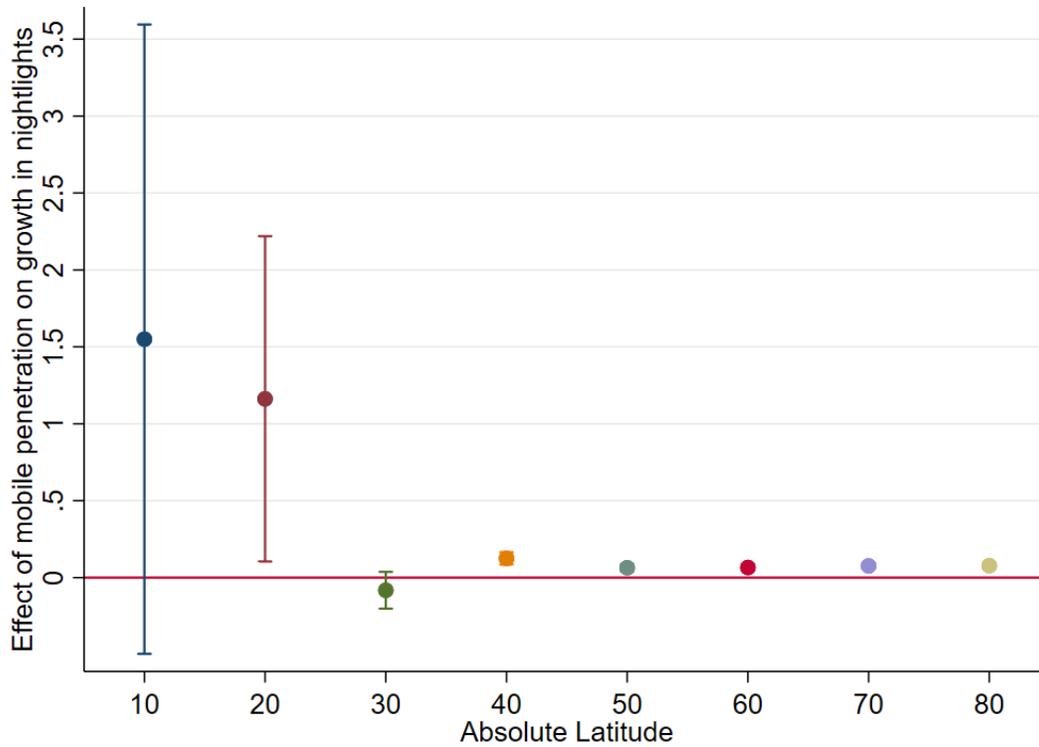
This binned scatter shows the correlation between the harmonized and non-harmonized nightlights (binned) data between 1998 and 2013.

Figure A2: Sensitivity Analysis: Dropping countries alternatively



The figures present point estimates and their 95% confidence intervals of the effects of mobile phone penetration on economic activities using the baseline equation without country and subnational characteristics. Estimates are derived from separate regressions and reflect the point estimates and confidence intervals from excluding the respective countries on the y-axis. All estimations control for district and year fixed effects. Standard errors at the level of district are applied.

Figure A3: Sensitivity Analysis: Locations based on Latitudes



The figure present point estimates and their 95% confidence intervals of the effects of mobile phone penetration on economic activities using the baseline equation without country and subnational characteristics. Estimates are derived from separate regressions and reflect the point estimates from excluding subnational districts with (absolute) latitude greater or equal to the thresholds on the x-axis. All estimations control for district and year fixed effects. Standard errors are clustered at the district level.

A.2 Tables

Table A1: Summary statistics

Variable	Mean	Std. Dev.	Min.	Max.	N
Growth in Nightlight Intensity	0.046	0.317	-4.82	4.82	841155
Mobile Coverage (all)	0.661	0.421	0	1	838644
2G Coverage	0.637	0.432	0	1	833835
3G/4G Coverage	0.437	0.442	0	1	275483
Non-universal Access to Electricity (0/1)	0.42	0.494	0	1	841428
Polity Score ≥ 8	0.669	0.471	0	1	823642
Natural Resource Dependent (0/1)	0.2	0.4	0	1	840798
Distance to the Coast (km)	302.121	371.629	0.001	2319.44	841428
Regional Mobile Coverage (t-1)	0.647	0.287	0	0.995	801360
Regional 2G Coverage (t-1)	0.623	0.281	0	0.995	801360
Regional 3G/4G Coverage (t-1)	0.399	0.291	0	0.96	480816
Regional Trade % GDP spatially weighted (t-1)	1.819	1.662	0.01	8.351	840315
Regional GDP Growth spatially weighted (t-1)	0.002	0.002	-0.006	0.016	840315

Table A2: Mobile Phone Penetration and Economic Activity: Two-Way Fixed Effects Estimation with dummy Treatment Results

Dep. Var : Growth in Nightlight Intensity						
<i>Panel A:</i> TWFE						
	(1)	(2)	(3)	(4)	(5)	(6)
1(Mobile Coverage (all))	0.0167*** (0.0009)	0.0132*** (0.0009)				
1(2G Coverage)			0.0246*** (0.0009)	0.0187*** (0.0009)		
1(3G/4G Coverage)					0.0052*** (0.0019)	0.0080*** (0.0019)
<i>Panel C:</i> C&D TWFE with Heterogeneous Treatment Effect						
1 (Mobile Coverage (all))	0.0057** (0.0027)	0.0067*** (0.0025)				
1(2G Coverage)			0.0115*** (0.0024)	0.0126*** (0.0021)		
1(3G/4G Coverage)					0.0312*** (0.0042)	0.0293*** (0.0044)
DID ^{pl,1}	0.0059*** (0.0022)	0.0063*** (0.0021)	-0.0023 (0.0024)	-0.0025 (0.0020)	0.0016 (0.0040)	-0.0006 (0.0028)
DID ^{pl,2}	-0.0076*** (0.0023)	-0.0079*** (0.0026)	-0.0087*** (0.0024)	-0.0087*** (0.0022)	-0.016*** (0.0045)	-0.0133*** (0.0039)
DID ^{pl,3}	-0.0183*** (0.0035)	-0.0183*** (0.0029)	-0.0351*** (0.0028)	-0.0344*** (0.0035)	0.0626*** (0.0074)	0.0556*** (0.0063)
District Ctrl	Yes	Yes	Yes	Yes	Yes	Yes
Country Ctrl	No	Yes	No	Yes	No	Yes
District FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Mean dep. var	0.0492	0.0495	0.0494	0.0497	0.0613	0.0611
# of Countries	119	106	118	105	96	86
# of Districts	34387	33763	34205	33581	17746	17176
Observations	722067	702513	718245	698691	212952	205467

Notes: C&D TWFE with Heterogeneous Treatment Effect is estimated using the De Chaisemartin and D'Haultfoeuille (2020b) estimator. District Controls include, average annual temperature and total precipitation, and interaction between time trends and the following variables: distance to the coast, latitude and longitude of district centroid. Country controls also include Polity IV score, and interaction between time trends and the following variables: universal electricity access dummy, natural resource dependence, and the country's income classification, all measured at the baseline. of time trends with latitude, longitude. Robust standard errors clustered at district level in parenthesis.
* Significant at 10 percent level ** Significant at 5 percent level *** Significant at 1 percent level

Table A3: First Stage Regression of Alternative IV regression: Mobile Phone Penetration and Economic Activity

	Mobile Coverage		2G Coverage		3G/4G Coverage	
	(1)	(2)	(3)	(4)	(5)	(6)
Regional Mobile Coverage (t-1) × Lightning quintile						
1	0.3819***	0.1862***				
	(0.0712)	(0.0596)				
2	0.9214***	0.6918***				
	(0.0755)	(0.0696)				
3	0.6758***	0.5131***				
	(0.0517)	(0.0483)				
4	0.9074***	0.7381***				
	(0.0400)	(0.0342)				
5	0.8676***	0.7344***				
	(0.0400)	(0.0344)				
Regional 2G Coverage (t-1) × Lightning quintile						
1			-0.0915**	-0.0955***		
			(0.0380)	(0.0371)		
2			-0.0520*	-0.0606**		
			(0.0281)	(0.0280)		
3			0.3062***	0.2991***		
			(0.0374)	(0.0366)		
4			0.5615***	0.5506***		
			(0.0291)	(0.0286)		
5			0.5231***	0.5130***		
			(0.0274)	(0.0270)		
Regional 3G/4G Coverage (t-1) × Lightning quintile						
1					0.0922***	0.1005***
					(0.0331)	(0.0327)
2					0.2604***	0.2725***
					(0.0376)	(0.0369)
3					0.3007***	0.3093***
					(0.0363)	(0.0363)
4					0.5443***	0.5524***
					(0.0320)	(0.0327)
5					0.6608***	0.6657***
					(0.0391)	(0.0399)
District Ctrl	Yes	Yes	Yes	Yes	Yes	Yes
Country Ctrl	Yes	Yes	Yes	Yes	Yes	Yes
Regional Ctrl	No	Yes	No	Yes	No	Yes
District FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Mean dep. var	0.0474	0.0474	0.0476	0.0476	0.0611	0.0611
First-stage F test	137.6473	124.8156	113.8053	111.4008	100.7374	95.4457
# of Countries	106	106	105	105	86	86
# of Districts	33721	33721	33539	33539	17138	17138
Observations	668615	668615	664975	664975	205011	205011

Notes: District Controls include, average annual temperature and total precipitation, lightning intensity, and interaction between time trends and the following variables: distance to the coast, lightning intensity interacted with time trends, latitude and longitude of district centroid. Country controls also include Polity IV score, and interaction between time trends and the following variables: universal electricity access dummy, natural resource dependence, and the country's income classification, all measured at the baseline. Regional Ctrl

* Significant at 10 percent level ** Significant at 5 percent level *** Significant at 1 percent level

Table A4: Robustness checks: Mobile Phones and Economic Activity using Harmonized and non-harmonized Nightlights Data

Dep. Var : Growth in Nightlight Intensity						
IV						
	(1)	(2)	(3)	(4)	(5)	(6)
Harmonized (DMSP/VIIRS) Nightlights Data						
Mobile Coverage (all)	0.0763*** (0.0086)	0.0801*** (0.0100)				
2G Coverage			0.1267*** (0.0346)	0.0740** (0.0316)		
3G/4G Coverage					0.2993*** (0.0274)	0.2899*** (0.0274)
Mean dep. var	0.0156	0.0156	0.0156	0.0156	0.0273	0.0273
First-stage F test	211.1006	205.4618	32.6652	31.1160	234.0716	212.8843
Non-Harmonized (DMSP) Nightlights Data						
Mobile Coverage (all)	0.0780*** (0.0133)	0.0953*** (0.0152)				
2G Coverage			0.2109*** (0.0720)	0.2021*** (0.0733)		
3G/4G Coverage					0.2312*** (0.0273)	0.2045*** (0.0248)
Mean dep. var	0.0264	0.0264	0.0263	0.0263	0.0404	0.0404
First-stage F test	211.1006	205.4618	32.6652	31.1160	234.0716	212.8843
District Ctrl	Yes	Yes	Yes	Yes	Yes	Yes
Country Ctrl	Yes	Yes	Yes	Yes	Yes	Yes
Regional Ctrl	No	Yes	No	Yes	No	Yes
District FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
# of Countries	106	106	105	105	86	86
# of Districts	33759	33759	33577	33577	17176	17176
Observations	500580	500580	497850	497850	119587	119587

Notes: District Controls include, average annual temperature and total precipitation, and interaction between time trends and the following variables: distance to the coast, latitude and longitude of district centroid. Country controls also include Polity IV score, and interaction between time trends and the following variables: universal electricity access dummy, natural resource dependence, and the country's income classification, all measured at the baseline. Regional Ctrl include spatially weighted GDP and Trade % of GDP at the regional level. Robust standard errors clustered at district level in parenthesis.

* Significant at 10 percent level ** Significant at 5 percent level *** Significant at 1 percent level