

Bernardi, Marta; Lindlacher, Valentin

Working Paper

Connection leapfrog: The impact of 2G roll-out on employment outcomes for first-time connected regions

CEPIE Working Paper, No. 01/25

Provided in Cooperation with:

Technische Universität Dresden, Faculty of Business and Economics

Suggested Citation: Bernardi, Marta; Lindlacher, Valentin (2025) : Connection leapfrog: The impact of 2G roll-out on employment outcomes for first-time connected regions, CEPIE Working Paper, No. 01/25, Technische Universität Dresden, Center of Public and International Economics (CEPIE), Dresden,
<https://nbn-resolving.de/urn:nbn:de:bsz:14-qucosa2-981665>

This Version is available at:

<https://hdl.handle.net/10419/324641>

Standard-Nutzungsbedingungen:

Die Dokumente auf EconStor dürfen zu eigenen wissenschaftlichen Zwecken und zum Privatgebrauch gespeichert und kopiert werden.

Sie dürfen die Dokumente nicht für öffentliche oder kommerzielle Zwecke vervielfältigen, öffentlich ausstellen, öffentlich zugänglich machen, vertreiben oder anderweitig nutzen.

Sofern die Verfasser die Dokumente unter Open-Content-Lizenzen (insbesondere CC-Lizenzen) zur Verfügung gestellt haben sollten, gelten abweichend von diesen Nutzungsbedingungen die in der dort genannten Lizenz gewährten Nutzungsrechte.

Terms of use:

Documents in EconStor may be saved and copied for your personal and scholarly purposes.

You are not to copy documents for public or commercial purposes, to exhibit the documents publicly, to make them publicly available on the internet, or to distribute or otherwise use the documents in public.

If the documents have been made available under an Open Content Licence (especially Creative Commons Licences), you may exercise further usage rights as specified in the indicated licence.

CEPIE Working Paper No. 01/25

Center of Public and International Economics

**CONNECTION LEAPFROG: THE IMPACT OF 2G
ROLL-OUT ON EMPLOYMENT OUTCOMES
FOR FIRST-TIME CONNECTED REGIONS**

July 2025

Marta Bernardi
Valentin Lindlacher

Editors: Faculty of Business and Economics, Technische Universität Dresden.

This paper is published on the [Open Access Repository Qucosa](#).

The complete Working Paper Series can be found at the [CEPIE Homepage](#) | [EconStor](#) | [RePEc](#)

Connection Leapfrog: the impact of 2G roll-out on employment outcomes for first-time connected regions

Marta Bernardi^a, Valentin Lindlacher^{b,*}

^a*marta.bernardi@tu-dresden.de. TUD Dresden University of Technology*

^b*valentin.lindlacher@tu-dresden.de. TUD Dresden University of Technology and CESifo*

July 22, 2025

Abstract

For the developing world, instant connectivity was first established through the expansion of second-generation (2G) mobile networks. Leveraging exogenous variation in network disruptions induced by lightning strikes as an instrumental variable, we analyze panel data from 2,040 regions across 13 developing countries between 1990 and 2015. Our findings reveal economically meaningful increases in employment (approximately 32–43%), driven primarily by a shift from self-employment toward formal wage employment, notably within agriculture, coupled with substantial rises in unpaid labor among women.

Keywords: Mobile Coverage, Structural Transformation, Panel Inference, Technological Development, Micro Interventions, Aggregate Implications

JEL Codes: O33, O12, O14, E24, E27

*Corresponding author. Helmholtzstr. 10, 01069 Dresden, Germany. We thank conference and seminar participants at the Royal Economic Society (RES) Conference, CSAE Conference, RGS PhD Workshop, CGDE PhD Workshop, Berlin Development Economics Workshop, German Development Economics Conference, TUD Brown Bag Seminar, Cognetti de Martis Department of Business and Economics Seminar for valuable feedback.

1. Introduction

The global diffusion of second-generation (2G) mobile networks in the late 1990s and early 2000s marks the first time that large segments of the world’s population gained real-time, low-cost instant connectivity over larger distances ([Aker and Mbiti, 2010](#)). This technological leap, enabling voice calls and SMS messaging over far greater distances and user densities, dramatically lowers communication costs and, for many individuals, constitutes their initial entry point into the digital economy. While subsequent generations of mobile technology have attracted substantial attention ([Adema et al., 2022](#); [Guriev et al., 2021](#)), we know relatively little about how these early, basic communication tools shape labor markets previously completely unconnected and that were at the outset of digital integration. We ask how the rollout of 2G networks affects labor market structures in countries that were historically disconnected and what this implies about how digital infrastructure fosters economic development across sectoral structures. To unpack these aggregate effects, we perform a granular breakdown by employment type and sector-revealing precisely which subsectors, from formal wage roles to key service industries, capture the largest gains from foundational 2G connectivity.

In this paper, we aim to provide causal evidence on the labor market impacts of early mobile network adoption, leveraging variation in 2G mobile coverage over two periods across 2,040 administrative regions in 13 countries from Africa, Asia, and Latin America between 1990 and 2015. Our empirical strategy exploits exogenous variation in network disruptions caused by lightning strikes, which impair wireless signal propagation and tower functionality, to instrument for local mobile coverage. Conditional on regional and continent×wave fixed effects and rainfall trends, lightning-induced disruptions offer plausibly exogenous variation in mobile connectivity, enabling a credible instrumental variable approach.

We find that a typical increase in regional 2G mobile coverage between the two survey waves we exploit (roughly 50 percent) substantially raises labor force participation by about 24–40 percent, evaluated at the mean, depending on demographic controls. Similarly, overall employment rises significantly by approximately 32–43 percent relative to baseline levels. Our results reveal compositional shifts away from self-employment toward formal wage employment, particularly among non-literate workers. Moreover, there are substantial increases in unpaid work, especially among females, suggesting nuanced labor market adjustments. Sector-specific analyses reveal notable gains in agricultural employment and declines in service-sector employment, suggesting improved market information and connectivity enable a reallocation of labor toward sectors with comparative advantages..

Secondly, we find significant sectoral reallocation within the labor market, where improved mobile connectivity particularly benefits the agricultural sector, likely through better market access and real-time information that enhances productivity and income stability. Conversely, we observe a notable contraction in service-sector employment, plausibly reflecting also reduced reliance on informal and intermediary-driven service roles due to improved direct communication and coordination. Our estimates align with previous literature informed

by extensions of job search models incorporating network externalities ([Zenou, 2008](#)), which has hypothesized that improved connectivity would disproportionately benefit sectors already characterized by higher baseline activity levels. In contrast, other sectors might experience relative contractions due to shifts in employment driven by lowered search costs. In our findings, we find this hypothesis partially confirmed by the higher shares of employment in agriculture, which represents the sector more developed at baseline, and a corresponding decline in manufacturing employment.

Thirdly, focusing on employment types, we document a marked shift from informal self-employment toward formal wage employment. This transition indicates that enhanced connectivity lowers transaction costs and uncertainty, potentially increasing the attractiveness of formal employment structures. Simultaneously, we find an increase in unpaid domestic and family labor, predominantly among women, suggesting complex household labor reallocation dynamics in response to improved information flows.

The robustness and credibility of our results depend on the relevance, strength, and exogeneity of our instrumental variable. Therefore, we conducted different tests to validate the continuous measure of lightning strikes as a reliable predictor of regional 2G connectivity, ensuring its relevance and otherwise exogeneity concerning labor market outcomes. We demonstrate that our first-stage results remain robust when controlling for both fixed and variable rainfall, which we consider the most intuitive potential confounder affecting both lightning incidence and agricultural sector trends. Our use of a continuous rather than a binary instrument differs from the existing literature; however, we confirm that our key findings remain consistent when employing a binary measure. Furthermore, we apply machine learning techniques to systematically explore the relationship between lightning strikes and a broad array of environmental and geo-physical time-invariant factors, informing our selection of control variables.

To verify the robustness of our findings, we conduct several tests. We perform a leave-one-out robustness check, confirming that our results remain consistent even when excluding each country individually from our sample. Additionally, we implement a placebo test leveraging data from the previous decade (the 1980s) for seven of the thirteen countries in our sample. By artificially assigning the treatment to the earlier decade, we show that our results in this placebo scenario are significantly weaker and exhibit opposite signs, reinforcing confidence in our primary findings. Lastly, we examine different fixed-effects specifications and error clustering approaches, demonstrating the robustness of our estimates.

Most closely related to our research, [Chiplunkar and Goldberg \(2022\)](#) investigates the labor market effects of mobile internet using the same data source. They find significant employment increases driven primarily by internet accessibility. Our work differs by analyzing the earlier, simpler 2G technology, largely overlooked in the existing literature, with some notable exceptions ([Aker and Mbiti, 2010](#); [Jensen, 2007](#)). Moreover, we employ a balanced sample across two periods, allowing us to specifically investigate the extensive margin impact of this foundational technology. We also utilize a continuous instrument exploiting richer variation in

network disruptions. Furthermore, our study uniquely investigates combined heterogeneities by education and gender.

Beyond mobile internet, fixed-line broadband has also drawn considerable research attention. [Hjort and Poulsen \(2019\)](#) shows employment increases from internet speed upgrades via submarine cables, especially benefiting higher-skilled individuals. Similarly, [Goldbeck and Lindlacher \(2024\)](#) finds large employment increases resulting from initial internet access at basic speeds. More broadly, [Hjort and Tian \(2025\)](#) extensively surveys the internet connectivity literature.

For developing countries, there is substantial literature on non-digital infrastructure, particularly transportation (e.g., [Asher and Novosad, 2020](#); [Banerjee et al., 2020](#); [Donaldson, 2018](#); [Michaels, 2008](#)) and electricity (e.g., [Moneke, 2020](#); [Dinkelman, 2011](#)). This literature reports strong labor market impacts for infrastructural development, with, for example, [Dinkelman \(2011\)](#) highlighting higher female labor market participation as an effect of increased access to electricity. While [Moneke \(2020\)](#) finds sector-specific employment gains for different types of road connections.

In comparison, 2G technology has received limited attention. Notable exceptions include [Jensen \(2007\)](#) who demonstrate reduced market inefficiencies through mobile phones, and [Aker and Mbiti \(2010\)](#), highlighting improved market efficiency for grain prices in Niger. Additionally, [Manacorda and Tesei \(2020\)](#) examines mobile coverage's influence on political protests. Furthermore, mobile money, which does not require mobile internet, has been extensively studied, starting with [Jack and Suri \(2014\)](#), who find positive welfare impacts. [Mensah \(2021\)](#) further illustrates global economic benefits from enhanced mobile connectivity.

For developed economies, broadband internet availability often correlates with positive employment outcomes ([Akerman, Gaarder, and Mogstad, Akerman et al.; Atasoy, 2013](#)), though this relationship remains debated, as highlighted by conflicting results from [Czernich \(2014\)](#).

Besides [Chiplunkar and Goldberg \(2022\)](#), who investigated several countries, many papers investigate mobile internet and employment in single countries ([Bahia et al., 2024, 2021](#); [Caldarola et al., 2022](#)). Also, fixed-line broadband attracts internet attention. [Hjort and Poulsen \(2019\)](#) investigates a speed upgrade through submarine cable connections and finds an increase in employment, in particular for high-skilled jobs and individuals with higher education. [Goldbeck and Lindlacher \(2024\)](#) used a similar strategy using the first submarine cable connections, which allowed for internet at basic speeds. They find larger employment increases both in services and agriculture.¹

By examining the initial rollout of mobile networks, we emphasize the critical role basic connectivity plays in shaping labor market structures, and we document that investments in fun-

¹More broadly, [Hjort and Tian \(2025\)](#) surveys the evolving literature on the economic impact of internet connectivity.

damental digital infrastructure can yield considerable economic returns, particularly in environments characterized by pronounced informational constraints and substantial barriers to labor market participation.

The remainder of the paper proceeds as follows. In [Section 3](#), we detail our empirical framework and identification strategy. [Section 4](#) describes the construction and sources of our dataset and variables. Our core results on labor market outcomes, sectoral shifts, and employment types are presented in [Section 5](#). [Section 6](#) provides robustness checks and placebo tests. Finally, [Section 7](#) summarizes our findings and discusses their implications.

2. Measuring Access to Mobile Network

The global expansion of second-generation (2G) mobile networks in the late 1990s and early 2000s represented a critical shift from analog (1G) to digital mobile technologies. Unlike earlier analog systems, digital 2G networks enabled secure and reliable voice communication, SMS messaging, and very basic data transfer at significantly lower costs and higher capacities, laying the foundation for widespread mobile connectivity. Before this technological transition, many developing regions had minimal or no telecommunications infrastructure. With fixed-line penetration rates below 1% as shown by the gray dashed line in Panel A of [Figure 1](#). We observe that fixed-line connections were absent in the countries within our sample during the first wave and present only in very small shares in the second wave. This finding confirms the key fact that mobile connectivity served as the initial widespread technology enabling instant communication in our sample.

The practical expansion of 2G connectivity requires not only the physical construction of transmission towers and associated backbone infrastructure, often through microwave links or fiber optic cables, but also user adoption via mobile subscriptions and handsets. Following [ITU \(2025\)](#) by the early 2000s, mobile subscription growth in developing regions had accelerated markedly, rising from fewer than 5 subscriptions per 100 inhabitants in 1995 to over 25 by 2005 as depicted by the black line in [Figure 1](#).

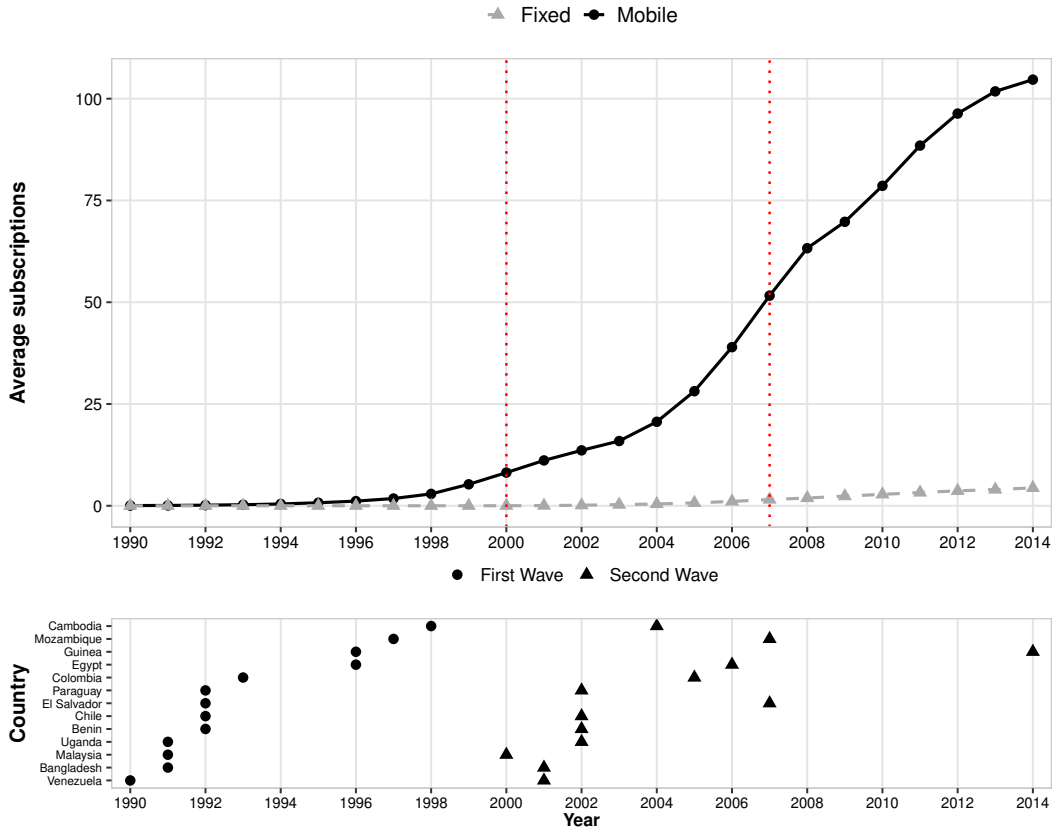
In the 13 countries included in our sample, mobile penetration rates around the year 2000 were initially low, typically below 5 subscriptions per 100 inhabitants, but experienced rapid growth thereafter.

In [Figure 1](#), we plot in Panel A fixed and mobile yearly average subscriptions per 100 inhabitants in our sample countries, and in Panel B we indicate with dots the year of the first survey wave for each country, and with a triangle the year of the second survey wave.

It is visible how the share of the population subscribed to mobile services was basically zero in the first wave, increasing substantially, but not yet reaching full coverage, by the second wave.

Distinguishing explicitly between 2G and subsequent technologies (such as 3G and broadband) is fundamental for our empirical strategy, as later-generation networks differ signifi-

Figure 1: Average in Sample % Change in Mobile and Fixed line subscriptions



Notes: ITU Data on mobile subscriptions and fixed-line subscriptions per 100 individuals averaged by year within the countries in our sample (13). The bottom panel reports the two years where each country is observed in the study in the first and second wave, respectively.

cantly in terms of bandwidth, costs, data capabilities, and associated socioeconomic impacts (ITU, 2025). While advanced networks facilitate extensive mobile internet use, multimedia communication, and rich content access, the 2G technology we examine primarily reduced barriers to entry into basic telecommunications, via voice calls and SMS. This technological limitation is analytically beneficial, allowing us to identify the initial impact of simple mobile connectivity on labor market outcomes before the complexities of subsequent technological generations that granted internet access. We look at this window of time with only access to mobile connection, but no previous fixed line, and yet no internet broadband, as a quasi-natural experiment that allows us to isolate the effect of simple instantaneous connection.

3. Empirical Strategy

In this section, we outline our identification strategy to estimate the causal impact of 2G (GSM) mobile coverage on labor market outcomes.² Following Guriev et al. (2021); Manacorda and

²GSM (Global System for Mobile Communications) is a widely adopted standard that laid the foundations for international roaming and subsequent network generations.

Tesei (2020); Caldarola et al. (2022); Mensah (2021), we adopt a quasi-experimental design by employing an Instrumental Variable approach where we instrument for 2G mobile coverage using lightning strikes exposure. We exploit within-continent variation in 2G mobile coverage in a long difference-like framework, with two periods at the regional level while controlling for rainfall at baseline and showing robustness to a large array of different controls combinations.

3.1. Baseline Specification

Our initial step is to examine the raw Ordinary Least Squares (OLS) correlations between the regional share of the population with access to 2G mobile coverage in the second wave and the regional labor market outcomes.³ Specifically, we estimate the following baseline model:

$$Y_{rc(r)w} = \alpha + \beta_1 2G_{rw} + \text{rain}'_r \beta_w + \beta_2 X_{rw} + \mu_{c(r)w} + \mu_r + \epsilon_{rc(r)w}, \quad (1)$$

where $Y_{rc(r)w}$ denotes the labor market outcomes of interest in region r (in continent $c(r)$) in wave w ($w \in \{1, 2\}$). We focus on four main distinct outcomes: (i) labor force participation share, (ii) employment share, (iii) the sectoral share of employment (i.e., agriculture, manufacturing, and services), and (iv) the employment types shares (i.e., wage employment, self-employment, and unpaid work). The key explanatory variable, $2G_{rc(r)w}$, measures the share of the population living in the region that is covered by the span of 2G mobile coverage infrastructure in region r , as part of continent c , in wave w .

We estimate over two periods for each country (on a balanced panel). The first period is during the 1990s. A period prior to the 2G mobile coverage rollout. The second period is during the 2000s, when countries deployed their first mobile connections. Further, we restrict the population in the sample ranging from 25 to 65 years old to have results interpretable in terms of the workforce population.

The vector rain_r contains population weighted mean rain in 1990 interacted with a binary time-varying coefficient β_w that corresponds to the survey wave, we include it because it represents the most plausibly confounding factor correlating with our instrument (Figure B3) and at the same time correlating with many other natural characteristics of the geography. We also show robustness to controlling for a time varying form of rain (Table B1), but we opt for a time invariant indicator due to the very limited changes in rain time trends and to exclude the presence of a backdoor in our causal chain represented by the endogeneity of the rainfall trends and the sectoral labor markets trends. Our main specification includes only a time-invariant

³Population data are from GHRC (2023) and are gridded 0.9km×0.9km (30 arc seconds) data on population density in the year 2000, the year has been chosen because at this time none of our countries was treated, so an eventual change in the demographic structure caused by the effect of technological infrastructure would not be captured. Details on population weighting are reported in Appendix A.3.

rain control (rain'_t), but in our robustness analysis, we also include the vector X_{rw} that captures time-varying region-level aggregates of individual-level controls.⁴

Unobserved confounders are partially mitigated by continent×wave fixed effects ($\mu_{c(r)w}$) and region fixed effects (μ_r). The region fixed effects account for any region-specific level characteristics that do not vary with time, such as the coastal or mountainous nature of a region, mineral resources, or the agricultural value of land. In addition, if something changes with time in the larger continent macro-region, for example, the general level of economic development and international shock exposure over a decade, this is accounted for by the continent times wave fixed effects for each continent specifically. What is left for us to exploit is the within-continent variation across regions over our two survey waves.

Standard errors are corrected for a two-way clustering at the regional level to account for correlation over time, at this level also the treatment varies (Abadie et al., 2022), and at the country-year level to account for within-country-year correlation following the literature (Gurieiev et al., 2021).⁵

3.2. First Stage

Our baseline ordinary least squares (OLS) specification, shown in Equation 1, offers an initial, descriptive assessment of the relationship between the regional labor market outcomes and the regional level of 2G mobile coverage infrastructure expansion. However, the deployment of 2G infrastructure is likely endogenous. Regions that are more economically and industrially developed and that already possess complementary infrastructures (e.g., electrification networks or paved roads) might be predisposed both to higher 2G mobile coverage and therefore to moving on distinct growth trajectories. As a result, the coefficient estimated in the baseline OLS may capture these differential trends rather than the true causal effect of 2G mobile coverage. In addition, omitted variable bias is a concern if relevant factors that we overlooked, which lie on the causal pathway, are not included in our regression framework.

To address these endogeneity issues and mitigate omitted variable bias, we employ a Two-Stage Least Squares (2SLS) strategy using lightning strike frequency as an instrument for 2G mobile coverage. Lightning strikes provide a plausible exogenous source of variation because they can severely damage telecommunication equipment, including base stations and antennas, through high-voltage discharges and power surges. These surges can degrade or destroy key components needed to maintain mobile coverage, leading to partial or even complete outages.

This instrument is motivated by the empirical approach of Manacorda and Tesei (2020) for 2G mobile coverage and has been similarly utilized in studies focusing on a later time period to predict the presence of 3G coverage (Gurieiev et al., 2021; Caldarola et al., 2022; Mensah, 2021).

⁴These include: share of individuals that completed primary, secondary, and tertiary education, a binary gender indicator, and age reported as a continuous variable together with its square form to capture non-linearities.

⁵We also run alternative fixed effects specifications (Table C2 (wave fixed effects instead of continent×wave fixed effects) and control combinations reported in Table C3.

We acknowledge the potential issues posed by the fact that the same instrument, lightning strikes, is employed across the literature to predict the presence of different infrastructure, as pointed out by [Mellon \(2024\)](#). But we believe that the difference in timing and geography between the 2G and the 3G infrastructural connection deployment makes it plausible that the two different technologies are predicted by the same instrument in different places at different times, for example in the case of the countries in our sample the 3G connection infrastructure was deployed only in the decade following our analysis.

However, we extend the instrument’s design by employing a continuous measure of lightning-strike frequency rather than a binary indicator. This continuous measure captures whether lightning occurs and the extent of repeated or intense events, providing an exogenous source with larger variation for 2G mobile coverage.⁶

We assume that lightning strikes affect labor market outcomes solely through their impact on digital infrastructure, thus fulfilling the exclusion restriction. Since lightning events are unlikely to correlate with individual labor market decisions and regional demand changes for labor, they can be considered exogenous to our regional labor market outcome variables.

We specify the first stage of the IV strategy as follows:

$$2G_{rc(r)w} = \pi_0 + \pi_1 \cdot \text{Lightning_Strikes}_{rc(r)w} + \pi_2 \cdot K_{rw} + \text{rain}_r \pi_w + X_r' \pi_w + \xi_r + \nu_{wc} + \epsilon_{rc(r)w}, \quad (2)$$

where $\text{Lightning_Strikes}_{cr}$ denotes the share of the population living in areas affected by lightning strikes in the region computed from the population-weighted geo-located mean frequency of lightning strikes in region r in wave w .⁷ The share of population exposed to lightning strikes is constructed in a similar way to shares of the population exposed to 2G mobile coverage. We include the same controls and fixed effects as in [Equation 1](#).

Under this specification, we obtain an estimate of the average effect of an increase in lightning strikes across all regions in our sample. The first stage of our 2SLS framework determines the instrument compliers for which a Local Average Treatment Effect (LATE) can be identified. In our setting, the compliers are those regions where a higher frequency of lightning strikes is associated with lower levels of 2G connectivity (and vice versa). We assume that there are no defiers—that is, no region exhibits the counterfactual behavior whereby an above-average frequency of lightning strikes coincides with above-average 2G connectivity.

⁶The binary version of the instrument using a median split is provided for robustness in [Table B1](#) (Column 2).

⁷The lightning strikes are measured as the mean of monthly strikes in 2015 from [GHRC \(2023\)](#)., strikes have been almost completely constant within geographies in the last century so 2015 is chosen for data availability reasons but it remains constant in time

Furthermore, we verify that the first-stage relationship is consistently in the expected direction across the three continents.⁸

A common worry with weather-based instruments is that they might correlate with other climate or topographical features that directly influence labor markets (Mellon, 2024). Although one could argue that such controls can introduce collider bias, the estimates remain stable, suggesting that lightning primarily operates via telecommunications infrastructure disruption. We also explore the correlation patterns between the lightning strikes instrument and the natural controls by running a Random Forest (Figure B2) and LASSO models (Figure B3) and we find that none of natural and geographic controls that we explore completely explains the variation in lightning strikes and that none of them is completely shrunk to zero by the LASSO model.

3.3. Second Stage

In our 2SLS estimation, the second stage regresses labor market outcomes on the predicted share of the population with access to 2G mobile coverage, obtained from the first stage regression:

$$Y_{rc(r)w} = \alpha + \beta_1 \cdot \widehat{2G}_{rc(r)w} + \beta_2 \cdot X_{gw} + \text{rain}_r \beta_w + X_r' \beta_w + \xi_r + \nu_{cw} + \epsilon_{crw}, \quad (3)$$

where $\widehat{2G}_{crw}$ is the fitted 2G mobile coverage from the first stage. Under a valid instrument, β_1 consistently identifies the effect of 2G mobile coverage on the labor market outcomes. We include continent \times wave (ν_{cw}) and region (μ_r) fixed effects and cluster standard errors at the region level. In Equation 2, Equation 1, and Equation 3, we outline a full specification that incorporates demographic time-varying controls. However, our preferred specification throughout the paper includes only rain, interacting with a linear trend, as a control. We show robustness specifications including socio-demographics, and also add further geographical variables.

Employing a TWFE estimation within a 2SLS empirical strategy, we aim to contain endogeneity concerns. To further strengthen our claim, we also run a time placebo study in Table E5. In this robustness exercise, we recover data for seven out of thirteen countries in our sample for the survey-census wave before the first one in our sample period, and we artificially shift the 2G infrastructure deployment to the 1990s. We show that if we had to arbitrarily assume that our treatment happened a decade earlier, we would hardly find any trace of the actual impact effect we are trying to estimate. The partial pre-sample period data availability also allows us to show some evidence of parallel pretrends in the previous decades.

⁸In Figure B1, we document results from randomized inference tests, which address potential low statistical power in continent-specific first-stage regressions, showing that only the Asian continent, for which we have only two countries, appears to exhibit a defier-type correlation in the first stage.

4. Data

This section describes the data sources and sample selection criteria employed in our analysis. We combine three principal datasets and a rich set of socioeconomic, geographic, and climatic controls. Our final sample encompasses 13 countries from the Americas, Africa, and Asia. More in detail, these four primary data sources include: (i) IPUMS-International for individual labor market outcomes aggregated to regional shares and associated sociodemographic characteristics ([Minnesota Population Center, 2020](#)); (ii) Collins Bartholomeus for geographic coverage data ([Bartholomeus, 2025](#)); (iii) NASA’s Hydrometeorological Resource Center for raster data on lightning strikes ([GHRC, 2023](#)); and (iv) PRIO GRID for raster-based environmental and natural resource controls ([Tollefsen et al., 2012](#)).

4.1. Individual Outcomes

IPUMS-International harmonizes census data and nationally representative surveys across countries to facilitate comparability over time.⁹

We aggregate raw individual-level data into regional-level shares of labor market outcomes.¹⁰

The dataset collects information from national-level statistical offices and makes the survey and census information comparable across countries, allowing us to measure the same labor market outcomes across developing countries. The data are a repeated cross-sectional of individuals organized into households and include both demographic and socioeconomic questions.

Starting from the full IPUMS-International dataset, we limit our sample to individuals aged 25–65 to capture the working-age population. IPUMS-International provides detailed information on four labor market outcomes: (i) labor force participation (*LABFORCE*), (ii) employment status (*EMPSTAT*), (iii) employment sector (*INDGEN*), and (iv) employment type (*CLASSWK*), as well as information on the age, gender, and education level of the individuals that we employ as controls in some of our specifications.

Sectoral employment follows the three-sector classification recommended by [Duernecker and Herrendorf \(2022\)](#), categorizing the IPUMS-International harmonized industries into primary (agriculture and mining), secondary (manufacturing and construction), and tertiary (services) sectors. For heterogeneity analyses, we also leverage the detailed industry-level data (for details on sector construction, see [Table A.2](#)).

Employment type relies on responses around the formality of employment and self-employment declarations, allowing us to exploit three different categories of employed in-

⁹For most countries, waves are available every ten years.

¹⁰Regions are the finest geographical unit available. They are usually below the state level. Regional boundaries follow GADM Version 4.1, reconciled with IPUMS-International’s harmonized sub-national unit definitions. IPUMS-International ensures internal consistency across census years by providing time-invariant regions.

dividuals: those employed under a wage contract, those employed informally, and those self-employed.

4.2. Mobile Coverage

We rely on a geo-referenced dataset compiled by the GSM Association (GSMA) in collaboration with Collins Bartholomeus, a digital map supplier that aggregates coverage reports from multiple mobile network operators. The resulting annual data starts from 1999 and details the presence of 2G networks at a finely disaggregated geographic level.¹¹ The same coverage data have been used previously to study mobile infrastructure expansion and its economic implications (Mensah, 2021).

Following previous literature (Guriev et al., 2021; Manacorda and Tesei, 2020), we construct a population-weighted measure of coverage at the regional level. Specifically, we overlay GSM coverage maps onto gridded population data from the NASA Socioeconomic Data and Applications Center (CIESIN-Columbia University, 2025) and calculate the population share residing in covered areas within each administrative region (details in Appendix A.3). Figure 2 illustrates Venezuela, showing sub-national divisions and 2G mobile coverage for the year 2000 in the left panel.¹²

4.3. Lightning Strike Data

We construct our instrumental variable from a 0.5-degree raster dataset provided by NASA's Global Hydrometeorology Resource Center (GHRC), measuring average Lightning Strike intensity in 2015. We calculate the mean lightning intensity per region to obtain a consistent measure across the entire sample. Then, following the same procedure as for mobile coverage, detailed in Appendix A.3, we obtain a population-weighted measure of strike frequencies, indicating the share of people living in the region exposed to strike intensity.

Figure 2 provides a visual representation of lightning strike weighted frequency for Cambodia in the right panel. The two panels of the figure together show the negative correlation pattern that we exploit in the first stage of our empirical strategy, by predicting the presence of 2G with the absence of strikes.

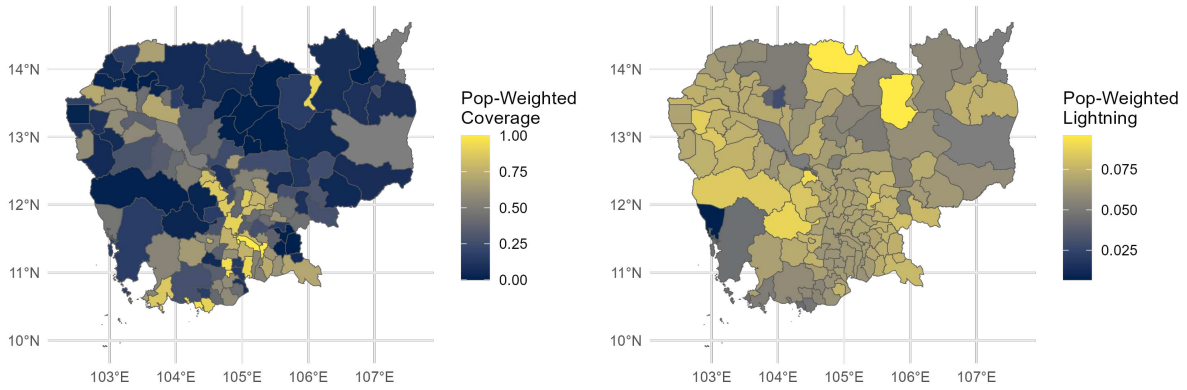
We proceed by visualizing the variation in our continuous instrument, shares of population-weighted lightning strikes regional exposure, that we employ in our main specification in Figure D1.

¹¹Because of a change in the data collection protocol, information for 2005 and 2010 is not directly observed. To maintain a balanced panel, we linearly interpolate coverage for these missing years from the nearest available years (i.e., 2004 and 2006 for 2005 and 2009 and 2011 for 2010). This interpolation follows prior approaches in the connectivity literature (Guriev et al., 2021) and allows us to exploit continuous coverage data consistently over the sample period.

¹²Maps illustrating coverage share in the second wave of our sample are provided in Figure D4, Figure D5, and Figure D6.

Figure 2: Cambodia 2G % and Lightning Strikes

Cambodia



Notes: Mean Lightning Strikes weighted frequency plotted for Cambodia in the second wave.

4.4. Working Panel

We start with all countries from IPUMS-International countries classified by the World Bank as Low- or Middle-Income economies in 2000. We additionally rely on countries with data prior to the 2G mobile coverage rollout,¹³ This ensures that 2G technology plausibly represents the first significant telecommunication infrastructure and that there is enough covered population to be able to size the impact of connectivity. To avoid potential future technology confounding effects, we check that the countries in our sample had access to 3G technology infrastructure years later our estimates. Guinea is the only country that had the second wave of the survey relatively late, in 2014, and for which we have the presence of small 3G connection networks across the country in our data; we report about it in [Figure A.1](#).

We employ three main analytical samples due to data availability constraints in the outcome variables. The full sample (13 countries, 4,080 observations) is used for employment shares, labor force participation, and educational outcomes; a slightly reduced sample without outcomes for Bangladesh (12 countries, 3,616 observations) is used for sectoral employment; a reduced sample without Mozambique (12 countries, 3,794 observations) is used for employment type outcomes.

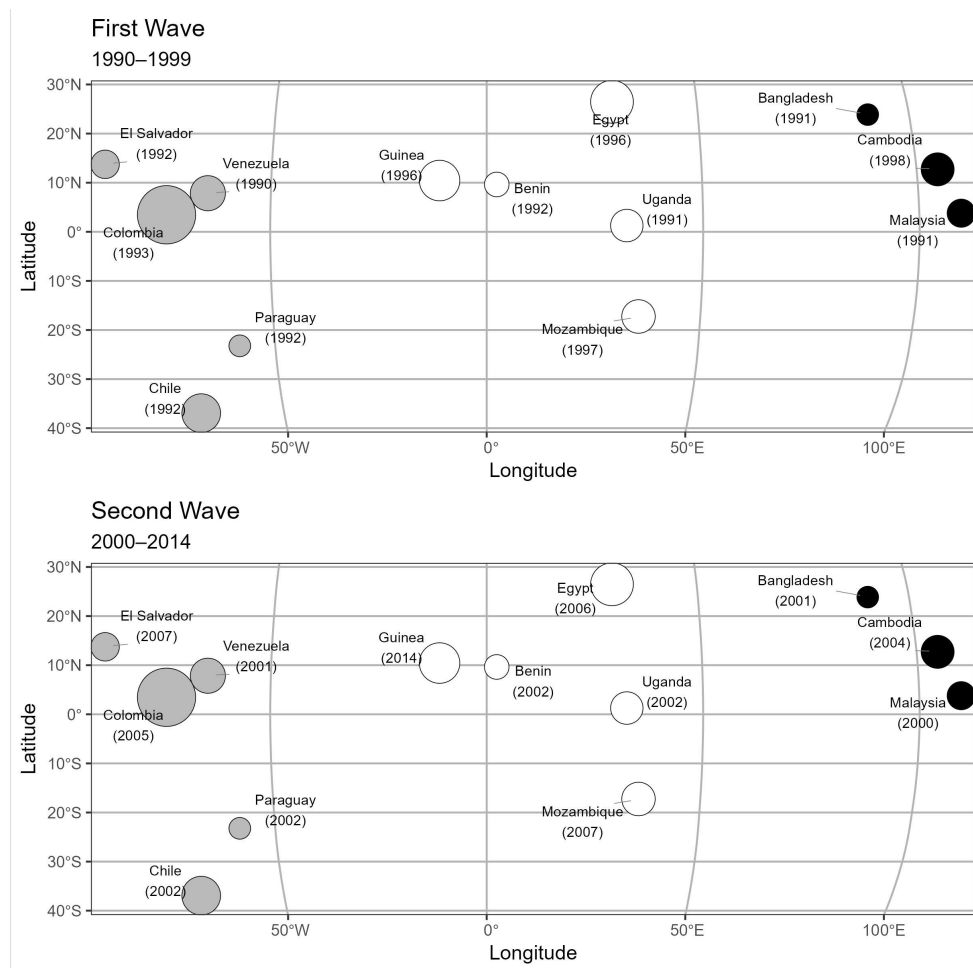
The final balanced regional panel dataset comprises 2,040 sub-national regions observed in two waves over 15 years, formed by integrating IPUMS-International [Minnesota Population](#)

¹³This means before 1999, the latest. We restrict the sample to those countries that do not reach an overall country share of coverage of 5%.

Center (2020) outcomes with geo-coded coverage data, lightning strike intensity, and environmental controls.

A detailed country-by-year and region breakdown is provided in Table A.1. Below Figure 3 visually summarizes the geographic and temporal distribution of our sample, illustrating the number of regions per country across both census waves.

Figure 3: Doerling Cartogram of Countries in the Sample

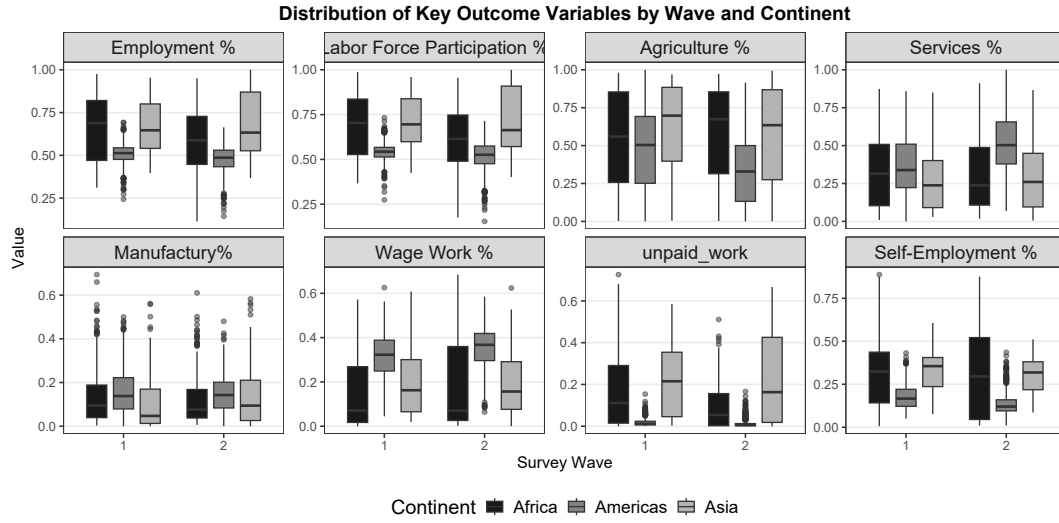


Notes: Showing the Doerling Cartogram of our countries in the two appearances in the sample.

Each point in Figure 3 corresponds to one of the countries in the sample, and the size of the ball reflects the number of regions observed in that country in each appearance. Panel A shows the sample in the first wave of appearance, and in Panel B, in the second, the specific calendar years where we observe the countries are also visible as annotations in the plot.

In Figure 4, the density distribution of the main outcomes is reported in a box plot showing mean and variance across continents and waves in the sample, reflecting the dimensions of variation that we exploit in our empirical strategy.

Figure 4: Density distributions: Outcomes



Notes: Showing the boxplot distribution of the IPUMS-International Labor market Outcomes regional shares in our sample across appearances.

Descriptive Statistics. In [Table 1](#), a summary of the key outcome, endogenous and control variables, is presented together with the instrument by country and appearance for the two groups, below and above median lightning strikes. We show variation in the instrument in a binary fashion for clarity, but we exploit the full variation in the distribution of the instrument by using a continuous measure of lightning strikes as a predictor of 2G mobile coverage.

Table 1: Summary Table by Continent, Appearance, and Level of Lightning Strikes**Table 2:** Lightning Strikes Below Median

High	Wave	Continent	Age	Gender	Strikes	Primary	Secondary	University	2G (cov)
0	1	Africa	33.18 (1.50)	0.55 (0.04)	0.00 (0.00)	0.11 (0.12)	0.01 (0.03)	0.00 (0.01)	0.00 (0.00)
0	2	Africa	32.88 (1.57)	0.55 (0.04)	0.06 (0.02)	0.16 (0.14)	0.02 (0.04)	0.00 (0.01)	0.14 (0.17)
0	1	Americas	33.93 (1.31)	0.48 (0.03)	0.00 (0.00)	0.39 (0.09)	0.10 (0.07)	0.01 (0.01)	0.00 (0.00)
0	2	Americas	35.22 (1.48)	0.49 (0.02)	0.06 (0.04)	0.41 (0.06)	0.20 (0.09)	0.02 (0.02)	0.11 (0.16)
0	1	Asia	33.23 (1.00)	0.51 (0.04)	0.00 (0.00)	0.25 (0.14)	0.03 (0.03)	0.01 (0.01)	0.00 (0.00)
0	2	Asia	33.69 (1.27)	0.52 (0.03)	0.07 (0.02)	0.28 (0.11)	0.04 (0.04)	0.01 (0.01)	0.22 (0.17)

Table 3: Lightning Strikes Above Median

High	Wave	Continent	Age	Gender	Strikes	Primary	Secondary	University	2G (cov)
1	1	Africa	33.55 (1.70)	0.52 (0.05)	0.00 (0.00)	0.14 (0.12)	0.15 (0.13)	0.05 (0.07)	0.00 (0.00)
1	2	Africa	33.31 (1.80)	0.51 (0.04)	0.03 (0.03)	0.20 (0.13)	0.22 (0.17)	0.07 (0.09)	0.92 (0.14)
1	1	Americas	34.26 (1.16)	0.51 (0.03)	0.00 (0.00)	0.42 (0.11)	0.16 (0.10)	0.01 (0.02)	0.00 (0.00)
1	2	Americas	35.84 (1.41)	0.51 (0.02)	0.05 (0.04)	0.42 (0.07)	0.25 (0.11)	0.04 (0.04)	0.90 (0.13)
1	1	Asia	33.89 (1.49)	0.52 (0.03)	0.00 (0.00)	0.47 (0.19)	0.04 (0.03)	0.02 (0.03)	0.00 (0.00)
1	2	Asia	34.65 (1.66)	0.51 (0.03)	0.07 (0.02)	0.44 (0.13)	0.05 (0.04)	0.04 (0.04)	0.84 (0.16)

Notes: Showing mean and standard deviation for key variables in the sample.

5. Results

We present our findings on the impact of 2G mobile network coverage on labor market outcomes in the thirteen countries in our sample.¹⁴ The endogenous *treatment* variable in our 2SLS estimations is the share of the population living in an area of the region where the infrastructure of 2G mobile coverage is active. We measure it with the share of the population living in an area of the region on average affected by lightning strikes with a relatively higher intensity. By leveraging this instrumental variable, we aim to address potential endogeneity concerns and obtain results that should be interpreted as Local Average Treatment Effects

¹⁴Countries in the sample. Americas: El Salvador, Colombia, Chile; Africa: Benin, Mozambique, Guinea, Uganda; Asia: Malaysia, Bangladesh, Cambodia.

(LATE), representing the average local effects for the complier regions across the 2040 regional units in the sample.

5.1. First Stage

We run as a first step the first stage regression on which our 2SLS identification strategy is relying. We show that our instrument is relevant, so that lightning strikes are a strong statistically significant predictor of mobile coverage presence in our sample. As shown by the first stage regressions in [Table 4](#), the coefficients on lightning strikes are negative and statistically significant at conventional levels across all specifications. Without additional controls, the coefficient is -2.65 (Column 1). After adding baseline (1990) percentage of population that is affected by rain in a region and share of demographic variables in Columns (2) and (3), the relationship remains strong, -2.62 and -1.80 , respectively. Collectively, these first-stage results strongly support our identification strategy, indicating that lightning-induced disruptions in mobile network operations serve as a credible and relevant source of exogenous variation for 2G mobile coverage.¹⁵

Table 4: First Stage

Mobile Coverage	(1)	(2)	(3)
Lightning Strikes	-2.650^* (1.079)	-2.617^* (1.050)	-2.450^{**} (0.759)
# Obs.	4080	4080	4080
# Countries	13	13	13
R^2 Adj.	0.74	0.74	0.75
Region FE	Yes	Yes	Yes
Continent x Wave FE	Yes	Yes	Yes
Rain Controls	No	Yes	Yes
Further Controls	No	No	Yes
Mean Dep. Var.	0.26	0.26	0.26

Notes: The table presents the first-stage regression results. Lightning strike intensity from XX is population weighted and normalized between 0 and 1. Model (2) controls for baseline (1990) rain levels, interacted with the wave dummy. Controls in Column (3) are time-varying socio-demographics (age, age squared, and gender). Standard errors are corrected for a two-way clustering at the regional and country-year level and reported in parentheses. *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, + $p < 0.1$.

We present an array of tests and partial assumptions relaxations to ensure the relevance and robustness of the instrument in our empirical specifications ([Appendix B](#)). First, we run our specification using a binary instrument nearer to the literature benchmark and show that using it, our first stage appears still negative and significant ([Table B1](#), Column 2). Secondly, we add baseline socio-demographic controls interacted with wave dummies and show that this leaves our first stage relationship unchanged as reported in [Table B3](#). Thirdly, we document the first

¹⁵The F statistic, indicating that the instrument is strong, is reported in the estimation tables.

stage separately for each study continent using randomized inference to account for varying sample sizes in [Figure B1](#). Then we explore different fixed effects specifications, using wave instead of wave-continent fixed effects in [Table B1](#). And in [Table C4](#) we use wild bootstrapped standard errors while clustering at the country level.

To bring further evidence that we are employing a strong instrument, we report in [Table C7](#), [Table C6](#), and [Table C5](#) the estimates of our specification run using a control function instead of our IV in a 2SLS procedure. In this way, we regress our outcomes on the endogenous mobile coverage, controlling for the first stage residuals in a one-step procedure that does not need to assume a non-weak instrument. Looking at our estimates in this weak instrument robust setting, we observe that our estimates remain in the same bulk of magnitude and significance, signaling the fact that our findings are not flipped when weak-instrument assumptions are relieved.

5.2. Labor Force Participation and Employment

Our naïve OLS regressions in [Table E1](#) show that a one-percentage-point increase in mobile coverage is associated with a 0.017 percentage-point rise in labor force participation and a 0.022 percentage-point rise in the employment share-equivalent to only about 2.8% and 3.6% of their respective sample means. These modest correlations likely reflect attenuation bias arising from classical measurement error in our regional coverage metric and potential downward bias from endogenous network rollout, as operators tend to target better-served, wealthier regions where marginal gains in participation are lower. Indeed, the substantially larger magnitudes observed in our 2SLS estimates indicate that these attenuation biases dominate, leading the naïve OLS estimates to significantly underestimate the true causal effect of improved mobile coverage, particularly in underserved regions.

Our IV estimates reflect two empirical facts. First, lightning exposure substantially lowers labor-market outcomes in reduced form: a one-unit increase in lightning strikes reduces labor force participation by 0.872 percentage points and employment share by 0.847 percentage points, as reported in [Table E2](#). Second, lightning has a strong first-stage impact, reducing mobile coverage by approximately 2.65 percentage points, as shown in [Table 4](#). Dividing the reduced-form effects by this first-stage coefficient yields our 2SLS estimates of roughly 0.33 for labor force participation and 0.32 for employment share.

These reduced-form estimates ([Table E2](#)) provide valuable insights into our IV findings. The large negative impacts of lightning exposure on labor force participation (−0.872 percentage points) and employment share (−0.847 percentage points) directly reflect the substantial disruptions in mobile connectivity triggered by lightning strikes. Such significant reduced-form effects underscore the immediate and economically meaningful consequences of losing connectivity for labor market engagement. Paired with the robust first-stage relationship between lightning strikes and mobile coverage (−2.65 percentage points; [Table 4](#)), these findings affirm that our IV strategy effectively leverages meaningful variation in connectivity to isolate causal

effects. The size and statistical significance of these reduced-form results thus strongly reinforce our confidence in the validity of the 2SLS estimates, highlighting enhanced connectivity as an influential driver of improved labor market outcomes.

For our labor force participation estimates reported in [Table 5](#), the coefficient on instrumented mobile coverage is 0.33, which, given the typical 0.52-point increase in coverage from wave 1 to 2, translates into a 0.17 percentage-point rise $\approx 28\%$ of the mean participation rate. This effect is unchanged when we add baseline rainfall and demographic controls, and it also holds under alternative fixed-effects specifications reported in [Table C1](#).

Table 5: 2SLS: Regional LFP and Employment Share

	LFP (1)	Emp % (2)	Emp % Active Sample (3)
Mobile Coverage	0.389** (0.132)	0.381** (0.131)	0.053 (0.058)
# Obs.	4080	4080	4080
# Countries	13	13	13
Region FE	Yes	Yes	Yes
Continent x Wave FE	Yes	Yes	Yes
Further Controls	Yes	Yes	Yes
Mean Dep. Var.	0.61	0.57	0.94
Wald F-stat	10.43	10.43	10.43

Notes: This table presents the 2SLS results on labor force participation and employment shares. Columns (1) and (2) reports results for lfp and employment shares in the full sample, while Column (3) reports results for employment shares in the active sample. In all specifications, the instrument is a continuous measure of the share of the population affected by lightning strikes. And we are controlling for the baseline levels of rain (1990) age, age squared and genders shares in each region interacted with a wave dummy. Standard errors are corrected for a two-way clustering at the regional and country-year level and reported in parentheses. *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, + $p < 0.1$.

For the full sample, [Table 5](#) Column 1, without additional controls, yields a coefficient of 0.353 on mobile coverage. Given the typical increase in coverage from wave 1 to wave 2, approximately 0.52 on average in our sample, this translates into an interpretable increase in employment of about 0.183 percentage points—equivalent to roughly 31.9% of the mean employment share (0.575). Controlling for rainfall in Column 2 produces a nearly identical estimate (0.356), leading to an interpretable effect of 0.185 percentage points (32.2% of the mean). When demographic controls are added in Column 3, the coefficient rises to 0.48, and the corresponding effect increases to 0.249 percentage points, amounting to 43.4% of the mean employment share.

In contrast, the labor-active sample shows much smaller effects. Column 3 [Table 5](#) yields a coefficient of 0.061, implying an interpretable effect of 0.031 percentage points, or only 3.3% of the mean employment share (0.941). Column 2 and Column 3, which introduce rainfall and demographic controls, respectively, yield very similar estimates (coefficients of 0.062 and 0.06,

with interpretable effects of 0.032 and 0.031 percentage points, corresponding to around 3.4% and 3.3% of the mean). These results indicate that while improvements in mobile coverage have a robust and sizeable impact on the overall employment share in the total sample, the effect on the labor-active segment is relatively modest.

The difference between the full sample and the labor-active sample indicates that improved mobile connectivity is more effective at boosting overall employment, mainly by encouraging individuals to join the labor market. In the full sample, with an average employment share of 0.575, enhanced mobile coverage is linked to notable employment gains, suggesting that it opens up new opportunities for those not yet participating. Meanwhile, in the labor-active sample, where the employment share is already high (0.941), there is little room for further improvement. These results highlight the role of mobile connectivity in promoting broader economic inclusion.

We show different robustness checks later in [Section 6](#). We show that the results are robust against different specifications of the variance-covariance matrix, fixed effects, and covariates included. Further, we show robustness by providing leave-one-out estimations and placebo exercises using earlier survey rounds.

5.3. *Employment Type Results*

[Table 6](#) presents the 2SLS estimates on the shares of self-employment, wage work, and unpaid work across three samples: the full sample (which includes both labor-active and inactive individuals), the labor-active sample, and the employed sample.

The OLS baseline estimates in [Table E1](#) reveal very small and statistically insignificant associations between mobile coverage and employment types: a negligible negative association with self-employment (-0.005 percentage points), a small positive correlation with wage employment (0.012 percentage points), and a positive yet insignificant association with unpaid employment (0.035 percentage points). These modest correlations likely reflect attenuation due to measurement error in coverage and endogenous targeting of network investments toward economically advantaged areas.

In contrast, the reduced-form estimates ([Table E2](#)), which capture the direct impact of lightning-induced disruptions in mobile connectivity, indicate economically substantial shifts in employment composition: lightning strikes significantly reduce wage employment by 0.434 percentage points, while producing large but statistically insignificant reductions in self-employment (-0.162 percentage points) and unpaid employment (-0.481 percentage points). These pronounced reduced-form effects suggest meaningful compositional changes in employment types due to exogenous disruptions in connectivity, thus supporting our IV approach in capturing substantial underlying labor-market dynamics.

Turning to the 2SLS estimates ([Table 6](#)), in the full sample, mobile coverage significantly reduces the self-employment share by 0.069 points (28.8% of the mean of 0.24), while signifi-

cantly increasing wage work by 0.153 points (31.2% of the mean of 0.491) and unpaid work by 0.164 points (186.4% relative to its mean of 0.088).

Overall, the stark contrast between the OLS and the reduced-form/2SLS results underscores the substantial bias corrected by our instrumental variable strategy.

Table 6: 2SLS: Employment Type

	Self Emp (1)	Wage Work (2)	Unpaid Work (3)
Mobile Coverage	0.001 (0.081)	0.136*** (0.031)	0.173* (0.064)
Mean Dep. Var.	0.24	0.25	0.09
Obs.	3794	3794	3794
# Countries	12	12	12
Region FE	Yes	Yes	Yes
Continent \times Wave FE	Yes	Yes	Yes
Rain Control	Yes	Yes	Yes
Wald F-stat	16.00	16.00	16.00

Notes: This table presents the results of the 2SLS regressions with fixed effects at the regional level and continent \times appearance level on the employment types (self-employment, wage work, unpaid work, and other employment) shares as outcomes. All models are run on the full sample controlling for the baseline level of rain in 1990. Mozambique is excluded as it has no employment type variable. Standard errors are corrected for a two-way clustering at the regional and country-year level and reported in parentheses. *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, + $p < 0.1$.

In [Table E3](#) Panel A where we report the estimates for the labor-active sample, it is observable how these effects remain directionally consistent but lose statistical significance, with a smaller reduction in self-employment (-0.284 points), and smaller increases in wage work (0.211 points) and unpaid work (0.138 points). While in [Table E3](#) Panel B reporting results for the employed sample, self-employment declines further by 0.348 points, while wage work and unpaid work rise modestly (by 0.200 and 0.132 points, respectively), though none of these estimates attain statistical significance.

Overall, these results indicate that enhanced mobile connectivity is linked to a compositional shift away from self-employment towards wage work, with the effect on unpaid work varying notably by sample. The differences observed between the full and labor-active samples highlight the role of labor market participation: when non-active individuals are included, even modest absolute changes in unpaid work translate into large relative effects due to their very low baseline levels.

5.4. Employment Sector Results

Turning to the effects on employment sectoral shares, [Table E1](#) reports that a one-percentage-point increase in mobile coverage is associated with a small and statistically insignificant increase of 0.004 percentage points in agricultural employment (approximately 1.5% of its sample mean),

a similarly insignificant decrease of -0.007 percentage points in manufacturing (about 5.0% of the mean), and a negligible increase of 0.005 percentage points in service sector employment (roughly 1.3% of the mean). These weak and imprecise OLS estimates suggest limited evidence of sectoral labor reallocation under naïve estimation and likely reflect attenuation due to measurement error and endogenous rollout of mobile infrastructure.

By contrast, the reduced-form estimates reported in [Table E2](#) provide compelling evidence of meaningful sectoral shifts resulting from exogenous disruptions in connectivity. A one-unit increase in lightning strikes reduces agricultural employment by 0.401 percentage points, has a small and statistically insignificant effect on manufacturing employment (-0.042 percentage points), and is associated with a statistically insignificant increase of 0.033 percentage points in service sector employment. When combined with the first-stage estimate of -2.65 percentage points ([Table 4](#)), these reduced-form effects suggest a sizable and policy-relevant reallocation of labor away from agriculture and toward other sectors, particularly when interpreted through our 2SLS design.

Table 7: 2SLS: Employment Sector

	Agriculture (1)	Manufactury (2)	Services (3)
Mobile Coverage	0.246* (0.106)	0.012 (0.021)	0.164 (0.108)
# Obs.	2988	2988	2988
# Countries	10	10	10
Region FE	Yes	Yes	Yes
Continent \times Wave FE	Yes	Yes	Yes
Rain Control	Yes	Yes	Yes
Mean Dep. Var.	0.23	0.08	0.20
Wald F-stat	8.12	8.12	8.12

Notes: This table presents the results of the 2SLS regressions with fixed effects at the regional and continent times appearance level on the employment sectors (agriculture, manufacturing, and services) shares as outcomes. All models are run on the full sample controlling for the baseline (1990) level of rain, interacting with a linear time trend to control for potential multicollinearity. Bangladesh, Uganda, and Guinea are excluded as it has no sector variable. Standard errors are corrected for a two-way clustering at the regional and country-year level and reported in parentheses. *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, + $p < 0.1$.

[Table 7](#) reports our 2SLS estimates of the impact of mobile coverage on sectoral employment shares in agriculture, manufacturing, and services. All specifications control for regional and continent-by-wave fixed effects, baseline (1990) rainfall interacted with a linear time trend, and cluster standard errors at the regional level. Only ten countries are included (Bangladesh, Guinea, and Uganda are excluded for missing sector-level employment information in the data).

[Table 7](#) displays results for the full sample. A one-point exogenous expansion in coverage raises agricultural employment by 0.155 points (59.6% of mean 0.26), yields a small positive

but insignificant change in manufacturing (0.016 points, 22.9% of mean 0.07), reported in Column 2, and reduces the services share by -0.013 points (-6.8% of mean 0.19, insignificant), reported in Column 3. In Panel A of [Table E4](#) we report labor-active sample estimates, from Column 1 agriculture increases by 0.162 points (36.8% of mean 0.44), from Column 2 manufacturing falls by -0.022 points, and services decline by -0.140 points (-37.8% of mean 0.37). Panel B shows that among employed individuals, agriculture still increases by 0.149 points (35.5% of mean 0.42), manufacturing remains unchanged, and services falls by -0.124 points (-30.0% of mean 0.43).

Discussion and Comparison with Prior Studies

Our results indicate that expanding 2G mobile coverage significantly increases labor force participation and reshapes employment composition toward agricultural and formal wage employment, and away from self-employment and, in certain specifications, services. These compositional effects are robust across different specifications and notably larger in magnitude once endogeneity and measurement errors are addressed via our instrumental variable strategy. The observed shifts into agriculture and wage employment suggest that even foundational connectivity infrastructure substantially reduces information frictions, encouraging entry into the formal labor market and enabling more efficient market participation and resource allocation.

These findings complement existing literature documenting impacts of advanced mobile technologies. For example, [Caldarola et al. \(2022\)](#) finds that 3G connectivity in Rwanda substantially boosted employment in services, whereas our results highlight stronger shifts into agriculture and wage employment. This contrast may reflect technological limitations of 2G, which provides primarily voice and SMS capabilities rather than broadband data services. Such basic connectivity may thus disproportionately benefit sectors and employment types reliant on simple communication rather than more advanced information services.

Our sectoral findings, particularly the positive impact on agriculture, align closely with earlier studies like [Jensen \(2007\)](#), who demonstrated how mobile phones reduced information asymmetries in agricultural markets, enhancing productivity and market participation. Similarly, the significant shift toward wage employment aligns with studies highlighting the formalizing effect of improved connectivity by reducing transaction costs and increasing access to formal job market information.

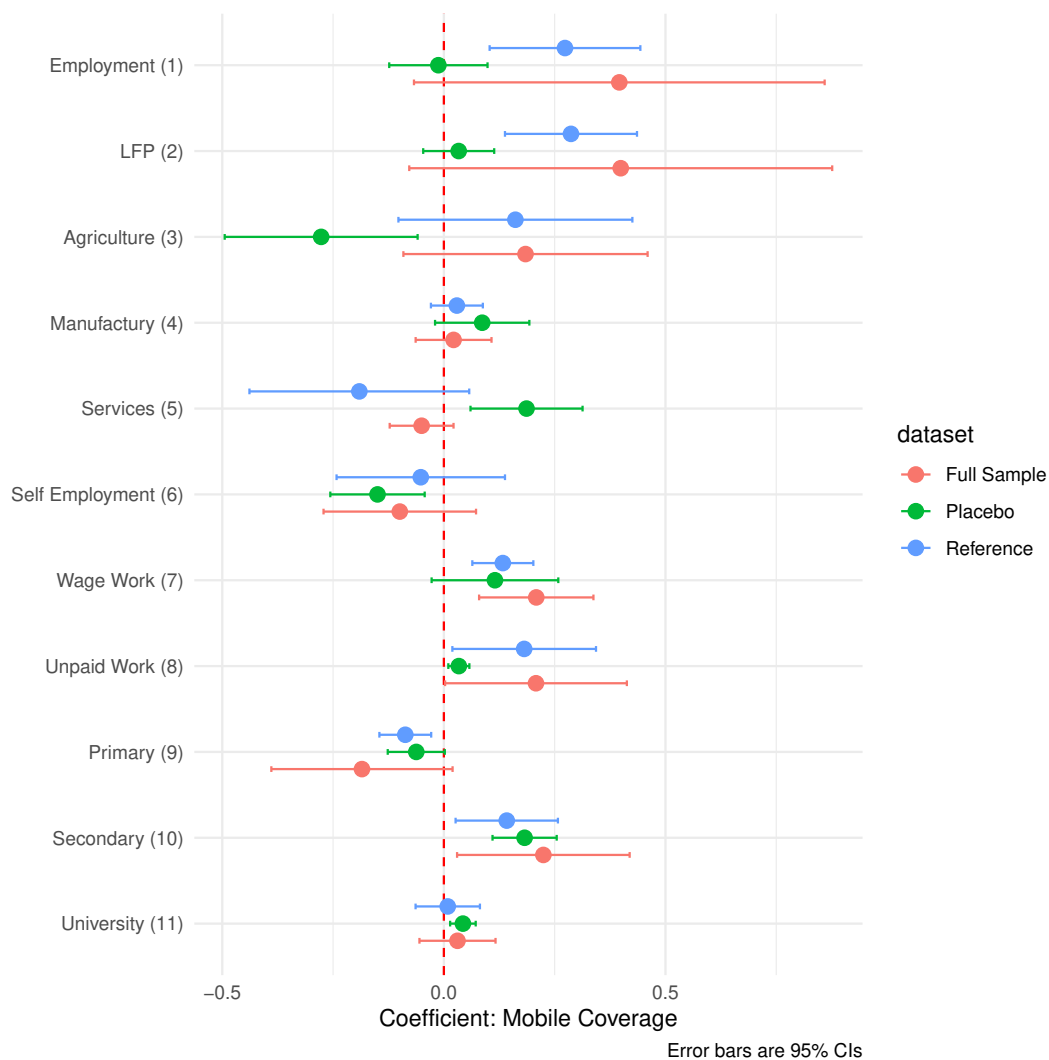
Nevertheless, the observed modest or even negative effects on services diverge notably from the positive outcomes documented for advanced connectivity technologies. This divergence could arise from the relatively limited capabilities of 2G infrastructure, which may be insufficient to substantially support the information-intensive activities common in service sectors, thereby limiting service-sector growth relative to more advanced networks. Or could be hiding underlying heterogeneities in the service employment for different sub-categories of workers leading to a total negative offset.

6. Robustness

6.1. Placebos

One of the main threats to our micro LATE identification is the presence of differences in the pre-trends between treated and control regional units in our sample, which we might be capturing with our estimation. To speak to these concerns, we set up a placebo setting for the countries that have IPUMS-International outcomes for previous periods. In this way, we build a three-appearance sample for six out of 13 countries, and we shift the treatment to the early '90s, the period that is considered the baseline in the reference design. We then estimate the effect by having as a baseline the data from the '80s. In [Table E5](#) and [Table E6](#) we table the results of the placebo regressions that are summarized in [Figure 5](#).

Figure 5: Placebo 2SLS vs estimates for countries for which we have data



7. Conclusion

This paper provides empirical evidence on the causal impact of foundational mobile connectivity, specifically the roll-out of second-generation (2G) networks, on labor market outcomes in historically disconnected regions across 13 developing countries. Leveraging exogenous variation induced by lightning strikes, we establish that a typical increase of roughly 50 percentage points in regional 2G mobile coverage significantly boosts labor force participation (by approximately 24–40% relative to baseline means) and overall employment shares (32–43% of baseline levels).

Our analysis reveals substantial compositional shifts in employment structures, highlighting a robust transition from self-employment toward formal wage work, particularly among non-literate populations. Additionally, agricultural employment experiences notable gains, whereas service-sector employment decreases, suggesting labor reallocations driven by improved access to market information facilitated by basic mobile connectivity. These sectoral and employment-type adjustments underscore the role of reduced informational frictions in reshaping local labor markets.

Investments in basic digital infrastructure can generate meaningful economic returns, promoting economic inclusion, labor market integration, and improved educational outcomes. Importantly, even low-cost foundational technologies, such as 2G networks, can effectively alleviate informational barriers and stimulate labor market entry, particularly in developing contexts with substantial connectivity deficits. Thus, our results advocate for continued attention to foundational digital infrastructure as a cost-effective pathway toward broader economic development and inclusive growth.

References

- Abadie, A., S. Athey, G. W. Imbens, and J. M. Wooldridge (2022, December). When Should You Adjust Standard Errors for Clustering? *The Quarterly Journal of Economics* 138(1), 1–35.
- Adema, J. A., C. G. Aksoy, and P. Poutvaara (2022). Mobile Internet Access and the Desire to Emigrate. *SSRN Electronic Journal*.
- Aker, J. C. and I. M. Mbiti (2010, August). Mobile Phones and Economic Development in Africa. *Journal of Economic Perspectives* 24(3), 207–232.
- Akerman, A., I. Gaarder, and M. Mogstad. The Skill Complementarity of Broadband Internet *. *The Quarterly Journal of Economics* 130(4), 1781–1824.
- Asher, S. and P. Novosad (2020, March). Rural Roads and Local Economic Development. *American Economic Review* 110(3), 797–823.
- Atasoy, H. (2013, April). The Effects of Broadband Internet Expansion on Labor Market Outcomes. *ILR Review* 66(2), 315–345.
- Bahia, K., P. Castells, G. Cruz, T. Masaki, X. Pedrós, T. Pfutze, C. Rodríguez-Castelán, and H. Winkler (2024, September). The welfare effects of mobile broadband internet: Evidence from Nigeria. *Journal of Development Economics* 170, 103314.
- Bahia, K., P. Castells, G. Cruz, T. Masaki, C. Rodríguez-Castelán, and V. Sanfelice (2021, September). Mobile Broadband Internet, Poverty and Labor Outcomes in Tanzania.
- Banerjee, A., E. Duflo, and N. Qian (2020, June). On the road: Access to transportation infrastructure and economic growth in China. *Journal of Development Economics* 145, 102442.
- Bartholomeus, C. (2025). Collins World Atlases | Collins Maps & Atlases.
- Caldarola, B., M. Grazzi, M. Occelli, and M. Sanfilippo (2022). *Mobile internet, skills and structural transformation in Rwanda*. Number 60 (April 2022) in ILO working paper / International Labour Organization. Geneva, Switzerland: International Labour Organization.
- Chiplunkar, G. and P. P. Goldberg (2022). The Employment Effects of Mobile Internet in Developing Countries. *SSRN Electronic Journal*.
- CIESIN-Columbia University (2025). Gridded Population of the World, Version 4 (GPWv4): Land and Water Area, Revision 11.
- Czernich, N. (2014, December). Does broadband internet reduce the unemployment rate? Evidence for Germany. *Information Economics and Policy* 29, 32–45.
- Dinkelman, T. (2011, December). The Effects of Rural Electrification on Employment: New Evidence from South Africa. *American Economic Review* 101(7), 3078–3108.
- Donaldson, D. (2018, April). Railroads of the Raj: Estimating the Impact of Transportation Infrastructure. *American Economic Review* 108(4-5), 899–934.

- Duernecker, G. and B. Herrendorf (2022, October). Structural Transformation of Occupation Employment. *Economica* 89(356), 789–814.
- GHRC, N. (2023). Earthdata Search.
- Goldbeck, M. and V. Lindlacher (2024). Digital Infrastructure and Local Economic Development: Early Internet in Sub-Saharan Africa. *SSRN Electronic Journal*.
- Guriev, S., N. Melnikov, and E. Zhuravskaya (2021, October). 3G Internet and Confidence in Government. *The Quarterly Journal of Economics* 136(4), 2533–2613.
- Hjort, J. and J. Poulsen (2019, March). The Arrival of Fast Internet and Employment in Africa. *American Economic Review* 109(3), 1032–1079.
- Hjort, J. and L. Tian (2025, March). The economic impact of internet connectivity in developing countries. *Annual Review of Economics*. Accessed: 2025-04-09.
- ITU (2025). The world’s richest source of ICT statistics and regulatory information - ITU DataHub.
- Jack, W. and T. Suri (2014, January). Risk Sharing and Transactions Costs: Evidence from Kenya’s Mobile Money Revolution. *American Economic Review* 104(1), 183–223.
- Jensen, R. (2007, August). The Digital Provide: Information (Technology), Market Performance, and Welfare in the South Indian Fisheries Sector. *The Quarterly Journal of Economics* 122(3), 879–924.
- Manacorda, M. and A. Tesei (2020). Liberation Technology: Mobile Phones and Political Mobilization in Africa. *Econometrica* 88(2), 533–567.
- Mellon, J. (2024, August). Rain, rain, go away: 194 potential exclusion-restriction violations for studies using weather as an instrumental variable. *American Journal of Political Science*, ajpgs.12894.
- Mensah, J. T. (2021). Mobile Phones and Local Economic Development: A Global Evidence. *SSRN Electronic Journal*.
- Michaels, G. (2008, November). The Effect of Trade on the Demand for Skill: Evidence from the Interstate Highway System. *Review of Economics and Statistics* 90(4), 683–701.
- Minnesota Population Center (2020). Integrated Public Use Microdata Series, International: Version 7.3.
- Moneke, N. (2020). Infrastructure and structural transformation: evidence from Ethiopia.
- Olea, J. L. M. and C. Pflueger (2013, July). A Robust Test for Weak Instruments. *Journal of Business & Economic Statistics* 31(3), 358–369.
- Tollefsen, A. F., H. Strand, and H. Buhaug (2012, March). PRIO-GRID: A unified spatial data structure. *Journal of Peace Research* 49(2), 363–374.

Zenou, Y. (2008, June). Job search and mobility in developing countries. theory and policy implications. *Journal of Development Economics* 86(2), 336–355. Accessed: 2025-05-05.

Online Appendix

Connection Leapfrog: the impact of 2G roll-out on employment outcomes for first-time connected regions

by *Marta Bernardi* and *Valentin Lindlacher*

Appendix A. Data

Appendix A.1. Summary table by country

Table A.1: Summary by country and appearance

Country	Wave	Age	Gender	Primary	Secondary	University	W_cov	Instrument	Labor Part	Emp Total	Self Emp	Unpaid Work	Wage Work
Bangladesh	1	33.27 (0.63)	0.5 (0.02)	0.2 (0.05)	0.07 (0.02)	0.01 (0.01)	0 (0)	0 (0)	0.48 (0.03)	0.47 (0.03)	0.53 (0.06)	0.22 (0.05)	0.17 (0.04)
Bangladesh	2	33.42 (0.63)	0.5 (0.02)	0.28 (0.06)	0.1 (0.03)	0.02 (0.01)	0.32 (0.25)	0.07 (0.01)	0.45 (0.02)	0.43 (0.02)	0.33 (0.07)	0.16 (0.04)	0.16 (0.04)
Benin	1	33.08 (1)	0.56 (0.03)	0.12 (0.09)	0.01 (0.01)	0 (0)	0 (0)	0 (0)	0.76 (0.12)	0.75 (0.12)	0.53 (0.15)	0.15 (0.12)	0.06 (0.06)
Benin	2	32.59 (0.98)	0.55 (0.03)	0.15 (0.1)	0.02 (0.02)	0 (0.01)	0.27 (0.37)	0.05 (0.01)	0.79 (0.09)	0.78 (0.09)	0.62 (0.11)	0.11 (0.09)	0.05 (0.04)
Cambodia	1	33.18 (0.75)	0.54 (0.03)	0.24 (0.1)	0.02 (0.03)	0 (0.01)	0 (0)	0 (0)	0.83 (0.08)	0.79 (0.1)	0.36 (0.04)	0.34 (0.13)	0.1 (0.08)
Cambodia	2	33.57 (1.02)	0.54 (0.03)	0.28 (0.12)	0.03 (0.04)	0 (0.01)	0.42 (0.33)	0.07 (0.01)	0.9 (0.08)	0.86 (0.09)	0.37 (0.05)	0.41 (0.14)	0.1 (0.09)
Chile	1	35.25 (0.85)	0.5 (0.03)	0.49 (0.06)	0.21 (0.1)	0.02 (0.03)	0 (0)	0 (0)	0.52 (0.05)	0.48 (0.05)	0.12 (0.03)	0.02 (0.02)	0.38 (0.06)
Chile	2	37.04 (0.75)	0.5 (0.03)	0.47 (0.07)	0.31 (0.1)	0.03 (0.04)	0.75 (0.29)	0 (0)	0.56 (0.06)	0.48 (0.06)	0.11 (0.03)	0.01 (0.01)	0.43 (0.06)
Colombia	1	34.11 (1.21)	0.5 (0.03)	0.4 (0.09)	0.12 (0.07)	0 (0)	0 (0)	0 (0)	0.55 (0.04)	0.53 (0.05)	0.19 (0.06)	0.02 (0.02)	0.3 (0.08)
Colombia	2	35.82 (1.33)	0.5 (0.02)	0.38 (0.05)	0.2 (0.08)	0.04 (0.03)	0.42 (0.42)	0.07 (0.04)	0.48 (0.08)	0.46 (0.08)	0.11 (0.04)	0.01 (0.01)	0.33 (0.09)
Egypt	1	33.96 (1.19)	0.49 (0.02)	0.1 (0.03)	0.25 (0.08)	0.08 (0.08)	0 (0)	0 (0)	0.5 (0.04)	0.44 (0.04)	0.12 (0.05)	0.01 (0.01)	0.31 (0.07)
Egypt	2	33.93 (1.46)	0.49 (0.02)	0.13 (0.03)	0.36 (0.08)	0.12 (0.1)	0.97 (0.13)	0 (0)	0.47 (0.05)	0.43 (0.05)	0.04 (0.02)	0 (0.01)	0.39 (0.05)
El Salvador	1	33.32 (0.6)	0.52 (0.02)	0.28 (0.09)	0.08 (0.07)	0.01 (0.02)	0 (0)	0 (0)	0.54 (0.05)	0.52 (0.05)	0.19 (0.06)	0.02 (0.02)	0.29 (0.1)
El Salvador	2	34.4 (0.74)	0.54 (0.02)	0.37 (0.06)	0.14 (0.08)	0.02 (0.04)	0.98 (0.06)	0.08 (0.02)	0.52 (0.09)	0.48 (0.09)	0.16 (0.03)	0.04 (0.03)	0.31 (0.11)
Guinea	1	34.28 (1.74)	0.56 (0.05)	0.07 (0.07)	0.01 (0.02)	0 (0.01)	0 (0)	0 (0)	0.82 (0.13)	0.79 (0.13)	0.49 (0.18)	0.28 (0.18)	0.02 (0.03)
Guinea	2	33.66 (1.93)	0.57 (0.04)	0.14 (0.1)	0.03 (0.04)	0 (0.01)	0.45 (0.36)	0.08 (0.01)	0.66 (0.12)	0.64 (0.13)	0.52 (0.13)	0.1 (0.07)	0.03 (0.03)
Malaysia	1	34.19 (1.81)	0.49 (0.05)	0.59 (0.1)	0.03 (0.02)	0.03 (0.03)	0 (0)	0 (0)	0.66 (0.07)	0.6 (0.07)	0.2 (0.07)	0.05 (0.06)	0.35 (0.11)
Malaysia	2	35.31 (1.8)	0.49 (0.02)	0.49 (0.09)	0.04 (0.01)	0.05 (0.03)	0.72 (0.31)	0.07 (0.03)	0.62 (0.05)	0.58 (0.06)	0.19 (0.06)	0.02 (0.04)	0.33 (0.1)
Mozambique	1	32.69 (1.26)	0.55 (0.04)	0.06 (0.06)	0.01 (0.01)	0 (0.01)	0 (0)	0 (0)	0.75 (0.11)	0.73 (0.12)	NaN (NA)	NaN (NA)	NaN (NA)
Mozambique	2	32.8 (1.14)	0.54 (0.04)	0.12 (0.1)	0.02 (0.03)	0 (0.01)	0.3 (0.38)	0.03 (0.01)	0.75 (0.1)	0.73 (0.1)	NaN (NA)	NaN (NA)	NaN (NA)
Paraguay	1	34.32 (1.19)	0.49 (0.02)	0.41 (0.09)	0.09 (0.06)	0.01 (0.02)	0 (0)	0 (0)	0.57 (0.04)	0.56 (0.04)	0.26 (0.07)	0.03 (0.02)	0.28 (0.12)
Paraguay	2	34.15 (0.89)	0.49 (0.02)	0.47 (0.06)	0.15 (0.07)	0.02 (0.03)	0.29 (0.4)	0.1 (0.01)	0.61 (0.06)	0.58 (0.04)	0.29 (0.05)	0.04 (0.03)	0.27 (0.11)
Uganda	1	31.85 (1.19)	0.53 (0.04)	0.34 (0.12)	0.01 (0.01)	0 (0)	0 (0)	0 (0)	0.73 (0.1)	0.72 (0.11)	0.34 (0.06)	0.28 (0.13)	0.09 (0.08)
Uganda	2	31.44 (1.11)	0.5 (0.03)	0.4 (0.11)	0.05 (0.05)	0.01 (0.01)	0.38 (0.34)	0.06 (0.01)	0.6 (0.12)	0.58 (0.12)	0.27 (0.06)	0.22 (0.1)	0.09 (0.08)
Venezuela	1	33.06 (0.76)	0.46 (0.03)	0.39 (0.1)	0.11 (0.07)	0.01 (0.01)	0 (0)	0 (0)	0.53 (0.06)	0.46 (0.06)	0.17 (0.07)	0.01 (0.01)	0.32 (0.11)
Venezuela	2	34.14 (0.66)	0.5 (0.02)	0.45 (0.05)	0.27 (0.1)	0 (0)	0.21 (0.28)	0.04 (0.03)	0.55 (0.04)	0.5 (0.05)	0.17 (0.04)	0 (0)	0.38 (0.05)

Notes: We report the mean and standard deviation of the key variables in the analysis by country and appearance.

Appendix A.2. Sectoral Variables Construction

Table A.2: IPUMS-International Sector Codes - INDGEN

Code	Sector	Grouped Sector
010	Agriculture, fishing, and forestry	Primary
020	Mining and extraction	Primary
030	Manufacturing	Secondary
040	Electricity, gas, water, and waste management	Tertiary
050	Construction	Primary
060	Wholesale and retail trade	Tertiary
070	Hotels and restaurants	Tertiary
080	Transportation, storage, and communications	Tertiary
090	Financial services and insurance	Tertiary
100	Public administration and defense	Tertiary
110	Services, not specified	Tertiary
111	Business services and real estate	Tertiary
112	Education	Tertiary
113	Health and social work	Tertiary
114	Other services	Tertiary
120	Private household services	Tertiary
130	Other industry, n.e.c.	Tertiary

Notes: We report the categorization of Industry variables as given by IPUMS-International https://international.ipums.org/international-action/variables/INDGEN#codes_section and used by us in the analysis.

Appendix A.3. Population- Weightning

This section outlines the methodology applied to incorporate population weighting into the empirical analysis, detailing the procedures employed to generate the endogenous and instrument variables in the main specifications.

The 2G mobile coverage share, defined as the proportion of *GEOLEVEL2* (subnational unit) covered by 2G connection, is subjected to population weighting using a 0.1-degree population density raster dataset for the year 2000 (https://neo.gsfc.nasa.gov/view.php?datasetId=SEDAC_POP), sourced from the NASA-SEDAC website. Let P_{ij} denote the population density in grid cell j and C_{ij} represent the coverage of 2G technology in year i in the same cell. The population-weighted coverage \hat{C}_{ij} is computed as follows:

$$\hat{C}_{ij} = \frac{\sum_{i,j} P_{ij} \cdot C_{ij}}{\sum_{i,j} P_{ij}}$$

To perform the spatial extraction of the population density within the year-specific coverage shapes is applied an adjustment algorithm that iterates over each grid cell intersecting with the coverage shapefile to determine the share of the cell that is comprehended within the boundaries of the shapefile. Then, the covered population is divided by the total population density within the subnational unit to obtain a normalized share of population-weighted coverage for each year in each subnational unit.

The instrumental variable, lightning strikes, is also subjected to population weighting using data from the same source as the 2G mobile coverage weighting but at a larger resolution (0.5 degrees) to align with the resolution of the instrument's raw data. Let S_{ij} denote the average strikes and P_{ij} represent the population density in grid cell (i, j) . The population-weighted strikes \hat{S}_{ij} are computed as:

$$\hat{S}_{ij} = \frac{\sum_{i,j} P_{ij} \cdot S_{ij}}{\sum_{i,j} P_{ij}}$$

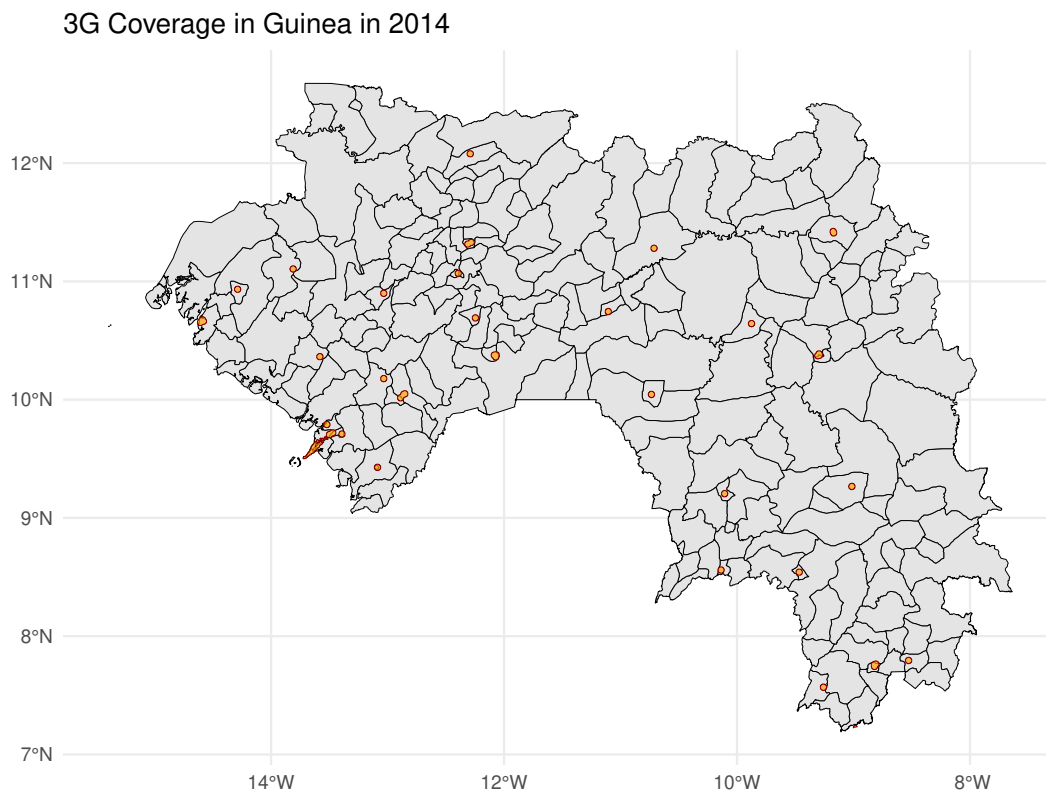
The computation involves overlaying the population and lightning data rasters and performing a cell-wise product, followed by the intersection of the resulting raster with the shapefile of the sub-national administrative units. Subsequently, the sum of the product among the cells within the *GEOLEVEL2* shapes is extracted and then divided by the sum of the population living in the same sub-national unit. In this way the normalized population-weighted average time invariant lightning strikes measure is obtained.

These procedures ensure that both the 2G mobile coverage share and the instrumental variable, lightning strikes, are appropriately population-weighted, providing robustness to the empirical analysis by reducing the scope of the measurement error.

Appendix A.4. Absence of 3G Coverage

Our sample period (2006–2014) captures the early phases of 3G infrastructure rollout across several countries. In our sample, Egypt conducted its second survey in 2006, at the very beginning of 3G deployment when the network was available only in a few regions. Around the same time, El Salvador and Colombia carried out their second survey waves in 2007, when they did not yet have any 3G coverage. Guinea, which appears in the second survey wave in 2014, exhibits very limited 3G coverage. [Figure A.1](#) shows a map that visually illustrates the very sparse spatial distribution of the 3G network in Guinea.

Figure A.1: 3G coverage in Guinea 2014



Notes: We plot the raw 3G coverage spread in Guinea in 2014 during the second wave.

Appendix B. Instrument Robustness

We present an array of tests and partial assumptions relaxations to ensure the relevance and robustness of the instrument in our empirical specifications. As a starter, we run our specification using a binary instrument nearer to the literature benchmark and show that using it, our first stage appears still negative and significant (Table B1, Column 2).

Weak-Instrument Tests. We employ a single endogenous regressor and a single instrument, so we report the Kleibergen–Paap statistic, which is the heteroskedasticity-robust analog to the first-stage F-statistic, as well as the Anderson–Rubin test and the effective F-statistic recommended by [Olea and Pflueger \(2013\)](#). In our main tables, the [Olea and Pflueger \(2013\)](#) statistic takes a value of 47.56, which exceeds the rule-of-thumb threshold of 10, ruling out weak-instrument concerns.

Exogeneity and Sensitivity Analyses. Although lightning frequency is arguably exogenous, we examine potential violations of the exclusion restriction by testing whether lightning might affect economic outcomes beyond its effect on GSM coverage. We also include a specification where we use the baseline socio-demographic controls (age, gender, literacy) interacted with a dummy variable for the wave and show that the first stage direction and bulk magnitude are robust to this addition Table B3. In this way, we aim to ensure that the potentially endogenous evolution of the socio-demographics does not affect the strength of our first-stage estimate.

Continent-Specific First Stages and Compliers. Our empirical strategy plays out in a global setting where we measure an average LATE across 13 countries, therefore, we show how the first stage plays out in each country employing Randomized Inference to overcome cross-continent heterogeneity in sample sizes Figure B1.

In Table B1, we re-estimate variations of Equation 2 for robustness to our main specification (shown in Table 4), but instead of using a continuous instrumental variable, we regress the population-weighted 2G mobile coverage share on a binary indicator. This indicator equals one if the region’s population-weighted share of lightning strikes is above the sample median in the second wave.

Then we show in Table B2 that the first-stage relationship is robust across the three different sample configurations we effectively use by running the 2SLS specification in different outcome categories exhibiting different data availability characteristics.

Table B1: First Stage: Alternative specifications

	(1)	(2)	(3)	(4)	(5)
Lightning Strikes > median		−0.064*** (0.018)			
Lightning Strikes	−2.546*** (0.231)		−2.610*** (0.240)	−2.641*** (0.238)	−2.620 [0.313]
Obs.	4080	4080	4080	4080	4080
# Countries	13	13	13	13	13
R^2	0.74	0.73	0.75	0.74	0.74
Region FE	Yes	Yes	Yes	Yes	Yes
Continent × Wave FE	No	Yes	Yes	Yes	Yes
Wave FE	Yes	No	No	No	Yes
Rain Control	Yes	Yes	Yes	No	Yes
Time Variant Rain	No	No	No	Yes	No
Resource Controls	No	No	Yes	No	No
Dep. Var.	0.26	0.26	0.26	0.26	0.26
Wald F-stat	69.23	9.66	20.24	63.24	3.18

Notes: This table presents the first-stage regression results using alternative specifications. In in Column (1), a version of the main specification is employed where we employ only wave FE instead of continent x wave FE. While in Column (2) a dummy instrumental variable (IV) that represents whether the share of the population affected by lightning strikes is above or below the sample median (normalized between 0 and 1). While In Column (3), the presence of natural resources interacts with a Wave dummy is included as a control. In all three models, control for baseline (1990) rain levels that interacted with the wave dummy to address potential multicollinearity between lightning strikes and socio-economic factors determining both the presence of coverage and second-stage outcomes. In Model (4), the scaled time-varying population-weighted rain mm is added as a control to the model: resource Controls that include: presence of natural resources as gold deposits (vein, placer, surface), diamonds (primary and secondary), petroleum reserves, and gemstones. Standard errors, reported in parentheses, are clustered at the GEOLEV2 level, the treatment variation level. ***, **, and * denote statistical significance at the 0.1%, 1%, and 5% levels, respectively. Both models are run on the full sample.

Table B2: First Stage across Samples

	(1)	(2)
Lightning Strikes	−2.595*** (0.285)	−2.864*** (0.232)
Obs.	3617	3794
# Countries	12	12
R^2	0.77	0.76
Region FE	Yes	Yes
Continent × Wave FE	Yes	Yes
Rain Control	Yes	Yes
Further Controls	No	No
Dep. Var.	0.29	0.27
Wald F-stat	46.54	84.24

Notes: This table presents the first-stage regression results using a continuous instrumental variable (*cont_iv*) that measures the share of the population affected by lightning strikes, normalized between 0 and 1. Both models include controls for baseline (1990) rain levels interacted with a linear time trend to address potential multi-collinearity between lightning strikes and socio-economic factors influencing both 2G mobile coverage and second-stage outcomes. Standard errors, reported in parentheses, are clustered at the GEOLEV2 level, the unit of treatment variation. The two samples represent different subsets of the dataset: in Column (1) we report the first stage for the subsample of countries that report sectoral information, while in Column (2) has the first stage for the subsample that reports employment type information. Statistical significance levels are denoted as follows: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, + $p < 0.1$.

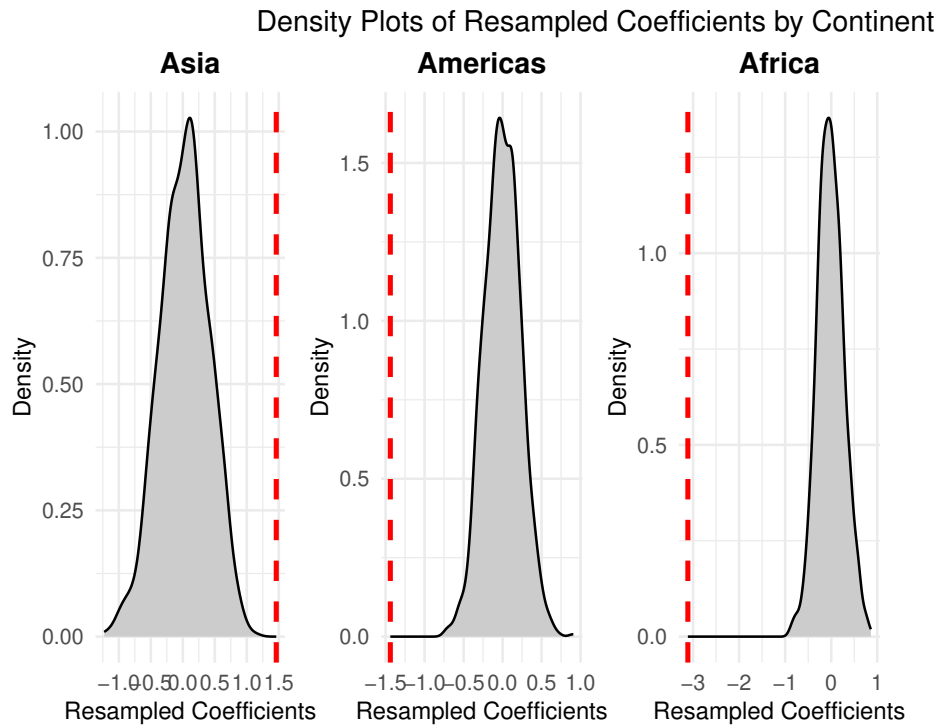
We also consider the possibility that the evolution of the socio-demographic regional averages is endogenous and therefore we run below a specification where we control for their baseline levels interacted with a dummy for the wave and confirm that our first stage estimates are robust to this specification too. We do not include education or literacy controls because we choose to use these information as outcomes and considering them as such makes them by definition a bad control, in [Table B3](#).

Table B3: First Stage with Baseline Socio-demographics controls

	(1)	(2)	(3)
Strikes	-2.391*** (0.247)	-0.032 (0.251)	-0.876** (0.272)
Baseline Gender	-0.008 (0.010)	0.031*** (0.009)	0.027** (0.010)
Baseline Age	-0.237 (0.262)	0.110 (0.219)	0.630* (0.269)
Baseline Age squared	0.288 (0.259)	-0.088 (0.218)	-0.575* (0.268)
Baseline Primary Edu		0.116*** (0.011)	
Baseline Secondary Edu		0.178*** (0.012)	
Baseline Tertiary Edu		0.015 (0.010)	
Baseline Literacy			0.244*** (0.015)
Obs.	4080	4080	3758
# Countries	13	13	13
R ²	0.75	0.80	0.78
Region FE	Yes	Yes	Yes
Continent × Wave FE	Yes	Yes	Yes
Rain Control	Yes	Yes	Yes
Dep. Var.	0.26	0.26	0.26
Wald F-stat	37.29	135.55	88.70

Notes: This table presents the first-stage regression results using a continuous instrumental variable measuring the share of the population affected by lightning strikes (normalized between 0 and 1). The scaled baseline levels of socio-demographics (Age, Age squared, Gender) interacted with the appearance dummy are added as controls one by one to the model. The model is controlling for the share of population affected by rain in 1990 interacted with a wave dummy. Standard errors, reported in parentheses, are clustered at the regional level. Statistical significance levels: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, + $p < 0.1$.

Figure B1: Randomized Inference



Notes: Plotting the distribution of randomized first stage coefficients by country with the dotted red line representing the actual coefficient. All controlling for rain at baseline and using regional and continent times wave fixed effects.

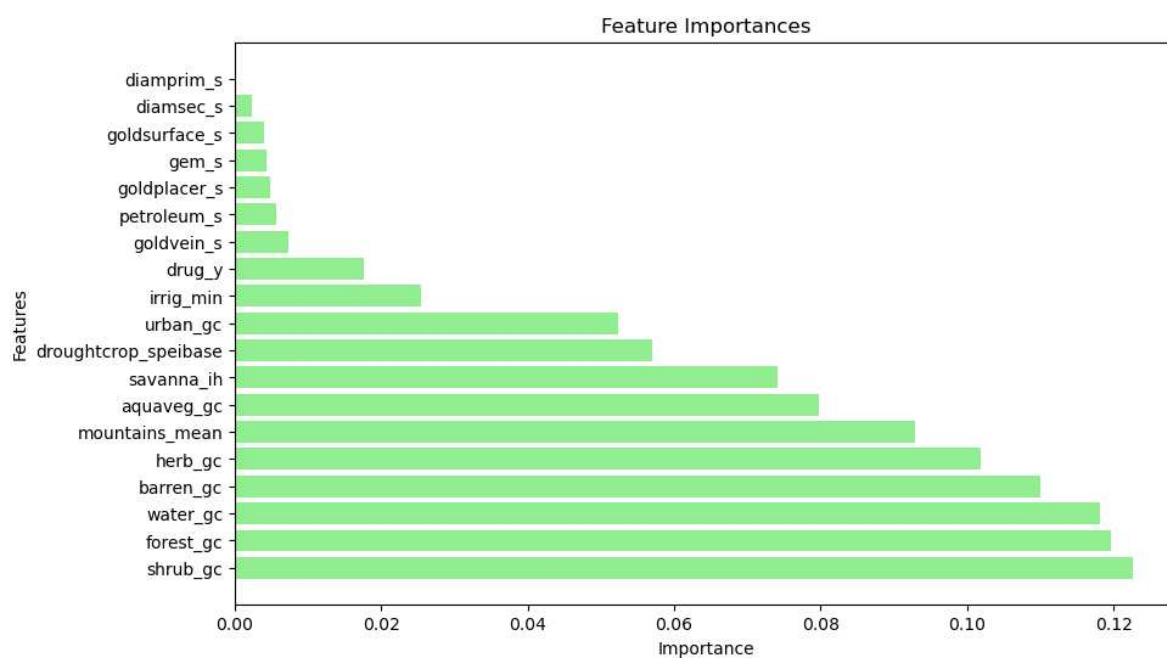
PRIO GRID natural resource data are employed to compute the population-weighted environmental and climate characteristics of the subnational units and use this information as a control to reduce the degree of measurement error in the relationship between the instrument and the endogenous variable following the literature of reference for the instrument [Guriev et al. \(2021\)](#) and [Mensah \(2021\)](#).

Here is the result of a Random Forest model that aims to leverage the potential of capturing non-linear dynamics between environmental and climatic features of the areas under analysis and the frequency of lightning strike incidence. This can enable us to disentangle the effect of multiple control combinations from one of the instruments in our IV design.

We also run a LASSO model to try to determine if only a limited set of controls can be employed and their covariance with other environmental and natural characteristics makes the selection more straightforward.

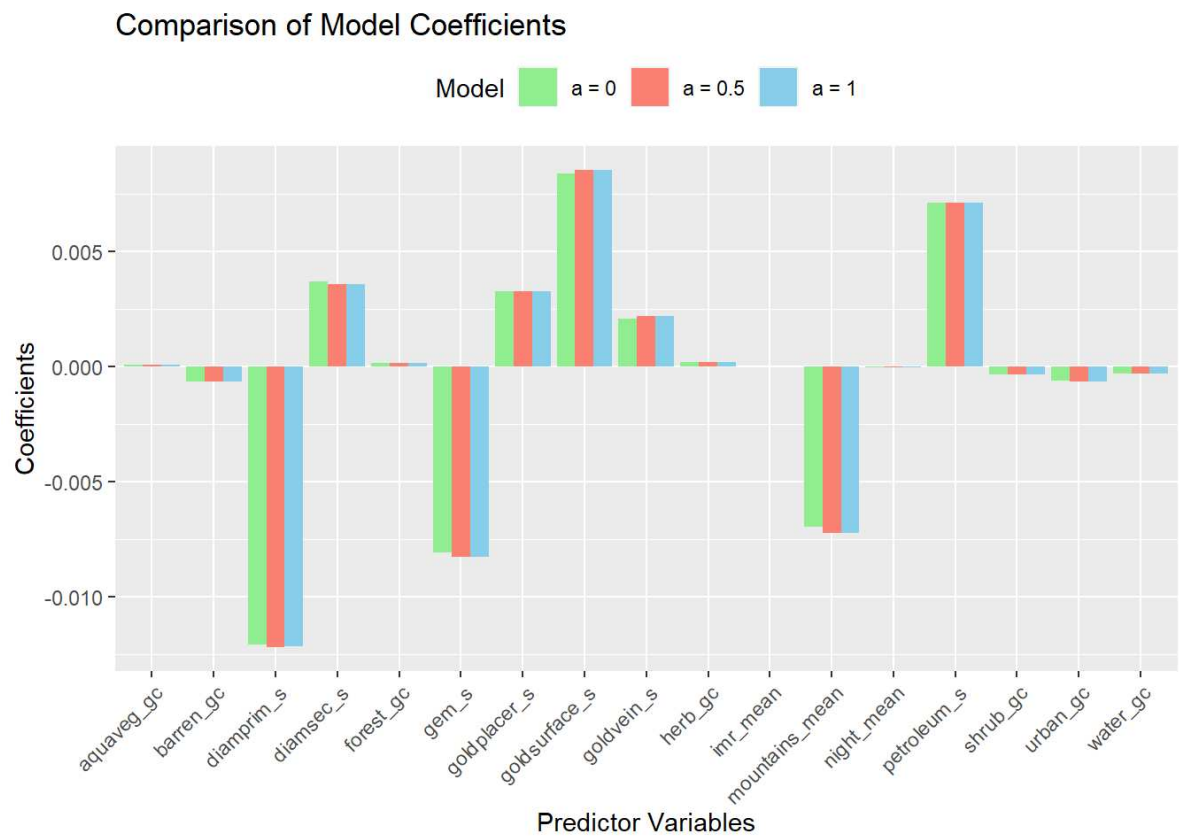
We see that rain is a strong predictor but that otherwise there does not seem to be a one leading group of PRIO controls that can explain the correlation.

Figure B2: Feature Importance



Notes: The model is run using 200 iterations 2 minimum sample splits, 4 minimum sample leaves, 20 maximum depth, and bootstrapping. The hyperparameters are tuned using a Randomized search algorithm in order to minimize the Mean Squared Error (MSE) that is for the model: 0.001368.

Figure B3: LASSO control selection



Notes: Model run using LASSO algorithm in python.

Appendix C. Robustness (2SLS)

Appendix C.1. FE Combinations

Here we present in [Table C1](#), [Table C2](#) the same outcomes of the main analysis for different FE combinations and with the addition of a larger set of demographic controls as well as run on slightly different sample composition.

Table C1: 2SLS Regional FE: Labor force participation share

Labor Force Participation	(1)	(2)	(3)
Mobile Coverage	0.238*** (0.027)	0.243*** (0.028)	0.287*** (0.039)
Rain Control		1.508* (0.665)	1.446* (0.604)
Obs.	4080	4080	4080
# Countries	13	13	13
Region FE	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes
Further Controls	No	No	Yes
Dep. Var.	0.61	0.61	0.61
Wald F-stat	125.73	69.23	69.80

Notes: This table presents the results of 2SLS regressions on the labor force participation share using fixed effects at the regional level. The instrument (a continuous measure of the share of the population affected by lightning strikes) is employed in all specifications. Model (1) is run without additional controls, Model (2) adds a rain control, to control for baseline rainfall trends, and Model (3) further incorporates demographic controls (age, age squared, and education levels). Standard errors are clustered at the regional level. ***, **, * and + denote statistical significance at the 0.1%, 1%, 5% and 10 % levels, respectively.

Table C2: 2SLS Regional FE: Employment share**Panel A: Total Sample**

Employment Shares	(1)	(2)	(3)
Mobile Coverage	0.246*** (0.027)	0.252*** (0.028)	0.301*** (0.040)
Dep. Var.	0.57	0.57	0.57
Wald F-stat	125.73	69.23	69.80

Panel B: Active Sample

	(1)	(2)	(3)
Mobile Coverage	0.061*** (0.012)	0.063*** (0.012)	0.072*** (0.012)
Obs.	4080	4080	4080
# Countries	13	13	13
Region FE	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes
Rain Control	No	Yes	Yes
Further Controls	No	No	Yes
Dep. Var.	0.94	0.94	0.94
Wald F-stat	125.73	69.23	49.68

Notes: This table presents the 2SLS results on employment shares. Columns (1)–(3) report estimates for the total sample using only regional fixed effects, and columns (4)–(6) report estimates for the labor-active sample using the same fixed effects. In all specifications, the instrument is a continuous measure of the share of the population affected by lightning strikes. Standard errors are clustered at the GEOLEV2 level. ***, **, * and + denote statistical significance at the 0.1%, 1%, 5% and 10 % levels, respectively.

We also run the labor force participation outcome in the 2SLS framework controlling for three different sets of natural, resource related and geographic controls.

*Appendix C.2. Additional Controls**Appendix C.3. Alternative Clustering*

We run our main specification testing for alternative error specifications and clustering, presenting the results with country clustering bootstrapping.

Appendix C.4. Control Functions

In addition to our baseline 2SLS estimates, [Table C6](#) (sectoral employment shares), [Table C7](#) (employment-type shares) and [Table C5](#) (aggregate employment and labor-force participation) report results from a control-function (CF) specification. In each CF regression, we first estimate the reduced-form of our endogenous regressor (Mobile Coverage) on the instrument (Lightning Strikes) and the baseline rain using our regional and continent times year FEs and

Table C3: 2SLS: Labor force participation with Natural Controls

Labor Participation Shares	(1)	(2)	(3)
Mobile Coverage	0.435*** (0.104)	0.235*** (0.029)	2.913 (4.804)
Rain Control	2.481* (1.136)	1.424* (0.644)	5.174 (9.236)
Obs.	4080	4080	4080
# Countries	13	13	13
Region FE	Yes	Yes	Yes
Continent × Year FE	No	No	No
Rain Controls	No	No	No
Natural Controls	Yes	No	No
Resource Controls	No	Yes	No
Geographic Controls	No	No	Yes
Dep. Var.	0.61	0.61	0.61
Wald F-stat	127.25	20.77	174.47

Notes: The outcome is Labor force participation regional shares. - **Model (1) - Climate Controls:** Includes environmental factors such as **temperature, precipitation (GPCC), drug cultivation, irrigation coverage, drought impact on crops, and savanna biome coverage.** - **Model (2) - Resource Controls:** Controls for the **presence of natural resources** by including **gold deposits (vein, placer, surface), diamonds (primary and secondary), petroleum reserves, and gemstones.** - **Model (3) - Geographic Controls:** Incorporates **land characteristics and terrain factors**, such as **barren land, forest coverage, shrubland, aquatic vegetation, agricultural land, urban area coverage, water bodies, mountainous terrain, and distance to the capital city.** All regressions include baseline (1990) rain levels interacted with a linear time trend. Standard errors, reported in parentheses, are clustered at the regional level. ***, **, * and + denote statistical significance at the 0.1%, 1%, 5% and 10 % levels, respectively.

Table C4: 2SLS: Labor force participation Alternative errors specifications

LFP %	(1)	(2)
Mobile Coverage	0.333 (0.034)	0.333 [0.455]
# Obs.	4,080	3,920
# Countries	13	13
Rain Control	Yes	Yes
Country level clustering	Yes	Yes
Bootstrapping	No	Yes

Notes: The outcome is Labor force participation regional shares. Column 2 with Country level errors clustering with bootstrapping. All regressions include baseline (1990) rain levels interacted with a linear time trend. Standard errors, reported in parentheses, are clustered at the regional level. ***, **, * and + denote statistical significance at the 0.1%, 1%, 5% and 10 % levels, respectively.

save the residuals. We then re-estimate the outcome equation including both the Mobile Coverage and its residual; the residual term “soaks up” any remaining covariance between Mobile Coverage and unobserved determinants of the labor market outcomes. Standard errors are

two-way clustered (region and country-year). Compared to 2SLS, the CF approach imposes a linear residual-inclusion assumption rather than relying solely on orthogonality, which (i) permits a direct exogeneity test via the residual's significance and (ii) can improve efficiency under correct specification. The fact that the CF estimates for our key coefficients remain quantitatively and statistically similar to the 2SLS results provides further reassurance that our findings are robust to functional-form assumptions and weak-instrument concerns.

Table C5: Control Functions: Employment Outcomes

	Emp	Labor part
Mobile Coverage	0.324*** (0.020)	0.333*** (0.020)
Residuals FS	-0.318*** (0.021)	-0.328*** (0.021)
Rain	1.523*** (0.404)	1.794*** (0.318)
# Obs.	4080	4080
# Countries	13	13
R ²	0.901	0.902

Notes: This table presents the results of the Control Functions regressions on the employment shares and labor force participation shares outcomes using fixed effects at the regional level and continent-by-year fixed effects. In all the three models we control for rain at baseline (in 1990). Standard errors are corrected for a two-way clustering at the regional level to account for correlation over time and at the country-year level to account for within-country-year correlation. ***, **, * and + denote statistical significance at the 0.1%, 1%, 5% and 10 % levels, respectively.

Table C6: Control Functions: Sectoral Employment Shares

	Agri	Manuf	Serv
Mobile Coverage	0.155*** (0.020)	0.016+ (0.010)	-0.013 (0.021)
Residual FS	-0.158*** (0.021)	-0.024* (0.011)	0.018 (0.022)
Rain	1.282*** (0.310)	0.016 (0.103)	-0.988* (0.448)
# Obs.	3274	3274	3274
# Countries	10	10	10
Region FE	Yes	Yes	Yes
Continent × Wave FE	Yes	Yes	Yes
R ²	0.968	0.896	0.916

Notes: This table presents the results of the Control Functions regressions on the three sectoral employment shares outcomes using fixed effects at the regional level and continent-by-year fixed effects. In all the three models we control for rain at baseline (in 1990). Standard errors are corrected for a two-way clustering at the regional level to account for correlation over time and at the country-year level to account for within-country-year correlation. ***, **, * and + denote statistical significance at the 0.1%, 1%, 5% and 10 % levels, respectively.

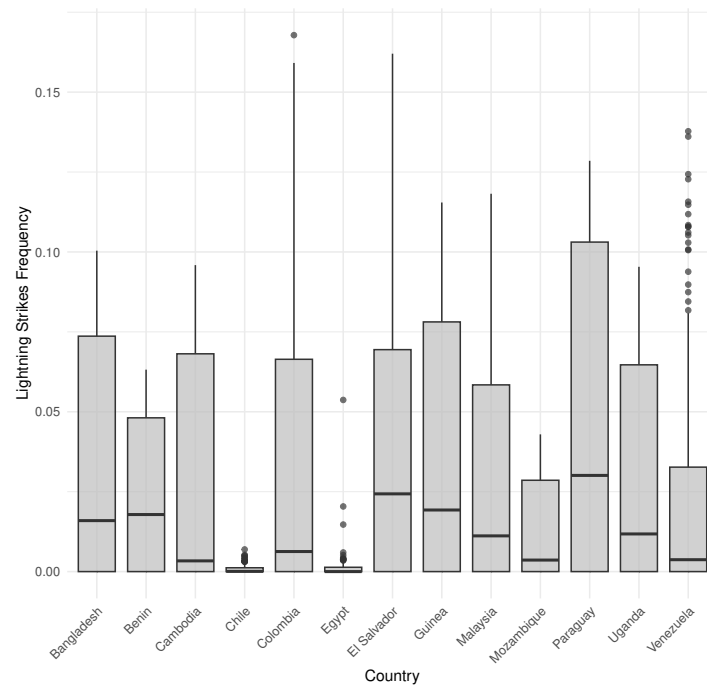
Table C7: Control Functions: Employment Types Shares

	Self-emp	Wage work	Unpaid work	Other emp
Mobile Coverage	−0.069*** (0.020)	0.153*** (0.013)	0.164*** (0.016)	−0.003* (0.001)
Residuals FS	0.060** (0.020)	−0.152*** (0.013)	−0.140*** (0.015)	0.003** (0.001)
Rain	−0.653* (0.261)	0.618* (0.299)	0.661*** (0.199)	−0.022+ (0.012)
# Obs.	3674	3674	3674	3674
# Countries	12	12	12	12
Region FE	Yes	Yes	Yes	Yes
Continent × Wave FE	Yes	Yes	Yes	Yes
R^2	0.922	0.963	0.917	0.878

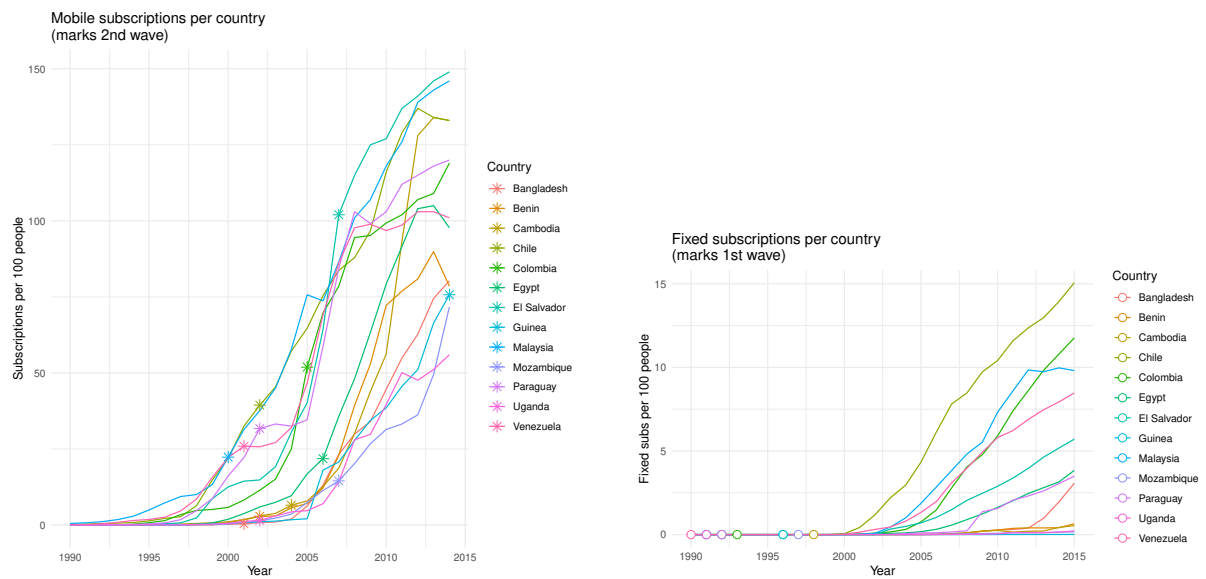
Notes: This table presents the results of the Control Functions regressions on the three employment types shares outcomes using fixed effects at the regional level and continent-by-year fixed effects. In all the three models we control for rain at baseline (in 1990). Standard errors are corrected for a two-way clustering at the regional level to account for correlation over time and at the country-year level to account for within-country-year correlation. ***, **, * and + denote statistical significance at the 0.1%, 1%, 5% and 10 % levels, respectively.

Appendix D. Figures

Figure D1: Instrument Variation



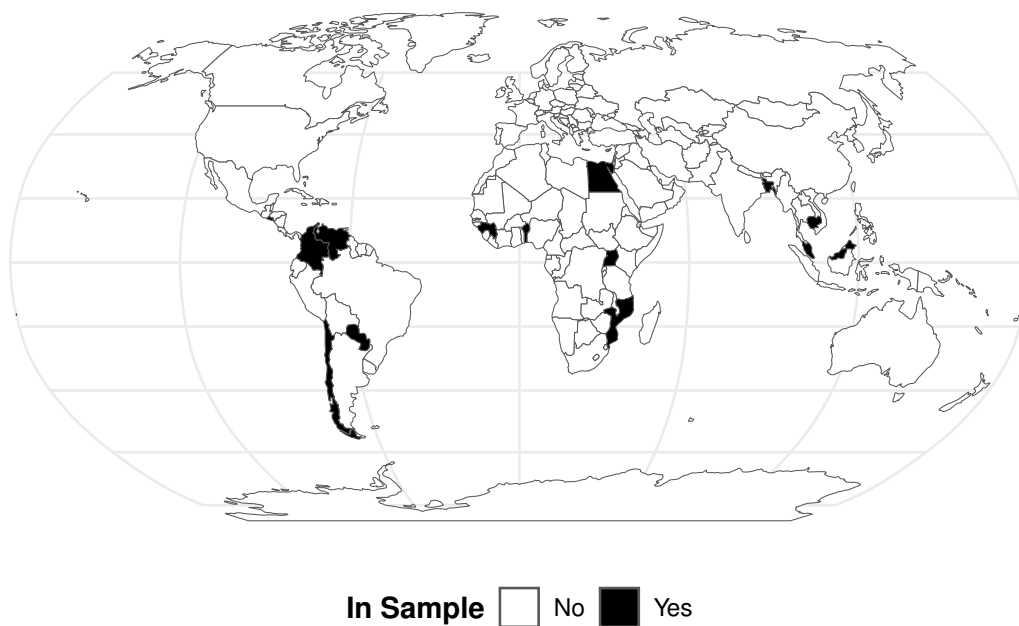
Notes: Plotting the distribution of regional shares of population-weighted lightning strikes, measured as mean lightning strike exposure from grid-level data from the NASA Hydrometeorological Centre



Notes: On the left panel ITU indicator on Mobile subscriptions per 100 inhabitants in countries in the sample. Black triangles indicating when the countries made the second appearance in the sample. While on the right panel ITU indicator on Fixed Broadband subscriptions per 100 inhabitants in countries in the sample. White-filled circles indicating when the countries made the first appearance in the sample.

Figure D3: Countries in the sample

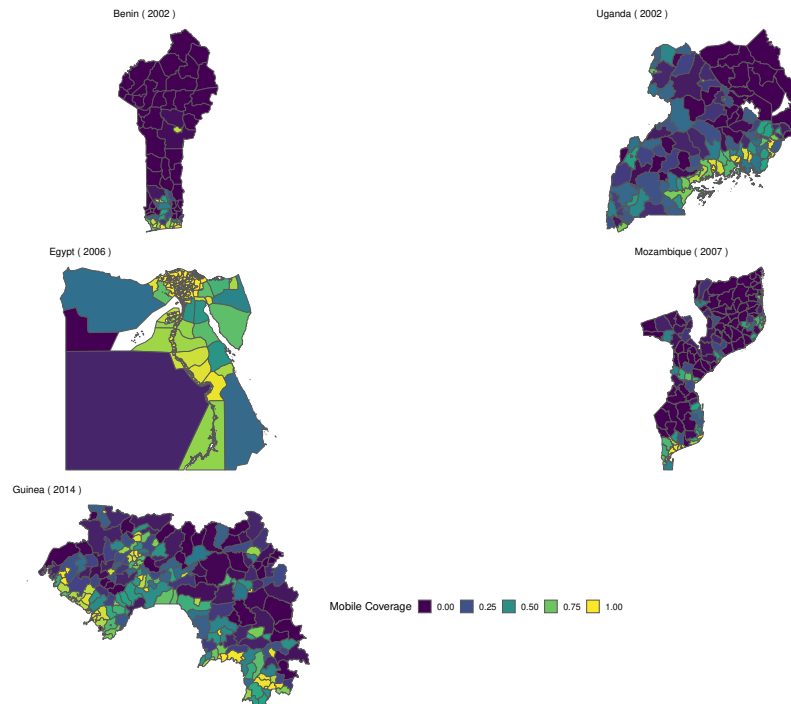
Countries in the Sample



Notes: Plotting the areas of the countries in the sample colored in black. Using R-NaturalEarth 2024 shapes for the borders.

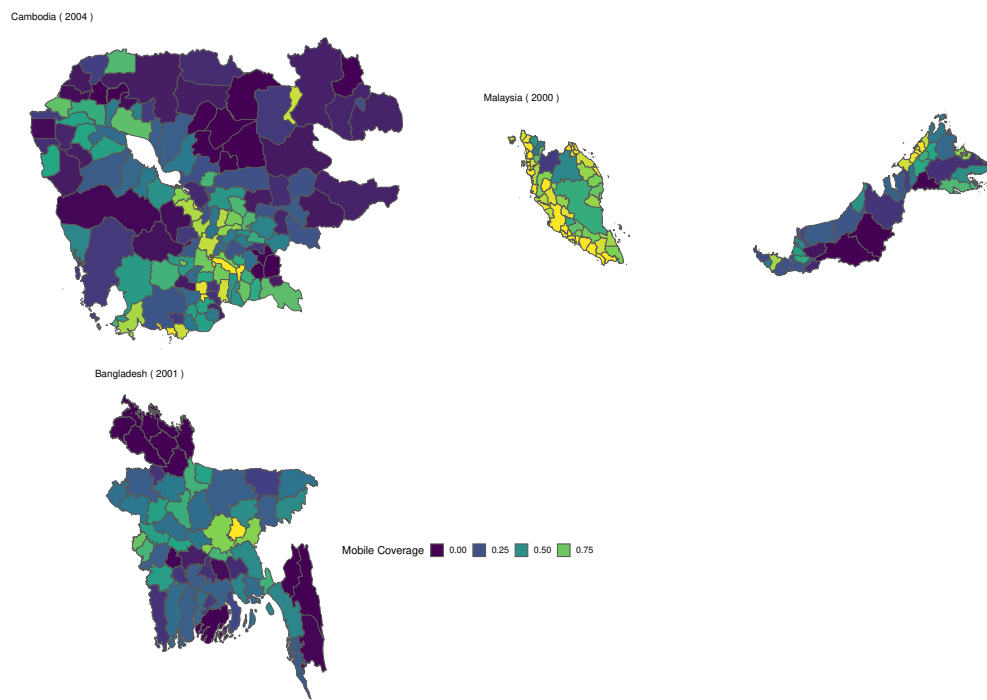
Here, we show the countries in the sample by continent, plotting the administrative units colored by the share of the population with 2G access in the second appearance.

Figure D4: Coverage in the second appearance for African countries in the sample



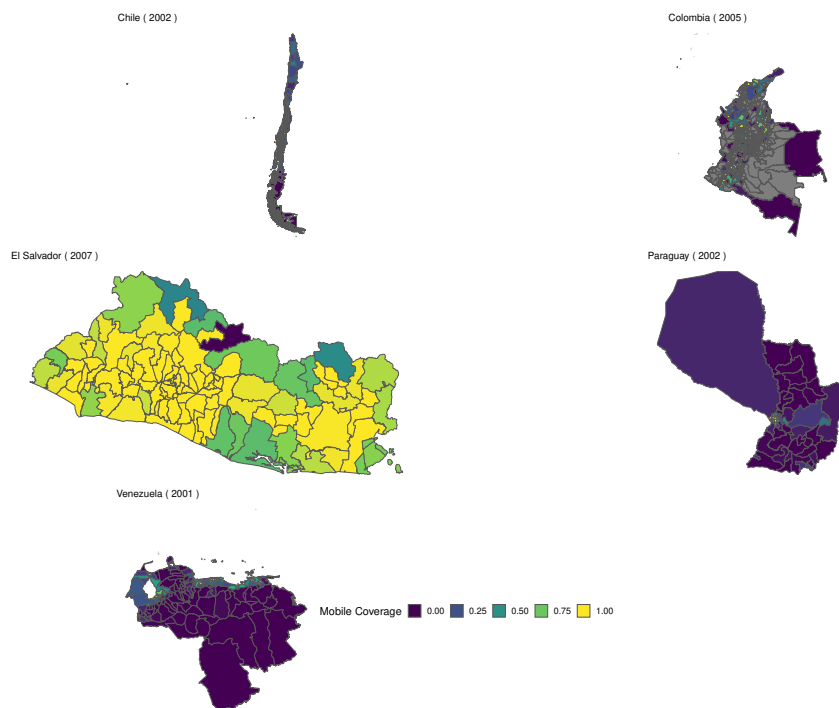
Notes: Plotting the share of the population covered by 2G infrastructure in each of the regions in our sample during the second wave in African countries.

Figure D5: Coverage in the second appearance for Asian countries in the sample



Notes: Plotting the share of the population covered by 2G infrastructure in each of the regions in our sample during the second wave in Asian countries.

Figure D6: Coverage in the second appearance for American countries in the sample



Notes: Plotting the share of the population covered by 2G infrastructure in each of the regions in our sample during the second wave in American countries.

Appendix E. Tables

Table E1: OLS: Labor Market Outcomes

	Manufacture (1)	Agriculture (2)	Service (3)	Self Emp (4)	Wage Emp (5)	Unpaid Emp (6)	Labor Part. (7)	Employment (8)
Mobile Coverage	-0.007 (0.007)	0.004 (0.014)	0.005 (0.014)	-0.005 (0.023)	0.012 (0.013)	0.035+ (0.019)	0.023 (0.017)	0.022 (0.020)
R^2	0.902	0.971	0.926	0.915	0.961	0.911	0.892	0.893
Obs.	3617	3617	3617	3794	3794	3794	4080	4080
N. Countries	12	12	12	12	12	12	13	13
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Continent \times Wave FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Dep. Var.	0.14	0.48	0.38	0.24	0.25	0.09	0.61	0.57

Notes: This table presents the results of the OLS regressions with fixed effects at the GEOLEV2 level and continent \times appearance level on all 8 regional labor market outcomes shares in the analysis ((1) Manufacturing, (2) Agriculture, (3) Service, (4) Self Employment, (5) Wage Employment, (6) Unpaid Employment, (7) Labor Participation, and (8) Overall Employment). All models are run controlling for baseline (1990) level of rain interacted with a linear time trend to control for potential multicollinearity, and all models are run on the total sample. Standard errors are corrected for a two-way clustering at the regional level to account for correlation over time and at the country-year level to account for within-country-year correlation. ***, **, * and + denote statistical significance at the 0.1%, 1%, 5% and 10 % levels, respectively.

Table E2: Reduced Form: Labor market outcomes on Full Sample

	Manuf	Agri	Serv	Self	Wage	Unpaid	LFP	Emp
Strikes	-0.042 (0.058)	-0.401** (0.120)	0.033 (0.089)	0.162 (0.264)	-0.434** (0.135)	-0.481+ (0.245)	-0.872*** (0.157)	-0.847*** (0.162)
R^2	0.895	0.968	0.915	0.915	0.964	0.913	0.902	0.901
# Obs.	3617	3617	3617	3794	3794	3794	4080	4080
# Countries	10	10	10	12	12	12	13	13
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cont. \times Wave FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table presents the results of the Reduced form regressions with fixed effects at the regional level and continent \times appearance level on a categorical education outcome. All models are run controlling for baseline (1990) level of rain interacted with a linear time trend to control for potential multi-collinearity. The first three models are run on the labor active sample, and the last three on the total sample. Standard errors are corrected for a two-way clustering at the regional level to account for correlation over time and at the country-year level to account for within-country-year correlation. ***, **, and * denote statistical significance at the 0.1%, 1%, and 5% levels, respectively.

Table E3: 2SLS: Employment Type Active and Employed Samples

	Self Emp (1)	Wage Work (2)	Unpaid Work (3)
Panel A: Active Sample			
Mobile Coverage	-0.210 (0.155)	0.114 (0.123)	0.166* (0.072)
Mean Dep. Var.	0.37	0.47	0.11
Panel B: Employed Sample			
Mobile Coverage	-0.265 (0.167)	0.096 (0.131)	0.160* (0.072)
Obs.	3794	3794	3794
# Countries	12	12	12
Region FE	Yes	Yes	Yes
Continent \times Wave FE	Yes	Yes	Yes
Rain Control	Yes	Yes	Yes
Mean Dep. Var.	0.39	0.49	0.12
Wald F-stat	16.00	16.00	16.00

Notes: This table presents the results of the 2SLS regressions with fixed effects at the regional level and continent \times appearance level on the employment types (self-employment, wage work, unpaid work, and other employment) shares as outcomes. Models are grouped into two panels corresponding to labor-active and only employed individuals' sample results. All models are run controlling for the baseline level of rain in 1990. Mozambique is excluded as it has no employment type variable. Standard errors are corrected for a two-way clustering at the regional level to account for correlation over time and at the country-year level to account for within-country-year correlation. ***, **, * and + denote statistical significance at the 0.1%, 1%, 5% and 10 % levels, respectively.

Table E4: 2SLS: Employment Sector Active and Employed Samples

	Agriculture (1)	Manufactury (2)	Services (3)
Panel A: Active Sample			
Mobile Coverage	0.281* (0.119)	−0.043 (0.037)	−0.042 (0.041)
Dep. Var.	0.41	0.14	0.39
Wald F-stat	5.73	5.73	5.73
Panel B: Employed Sample			
Mobile Coverage	0.213* (0.099)	−0.058 (0.040)	−0.165* (0.068)
# Obs.	2988	2988	2988
# Countries	10	10	10
Region FE	Yes	Yes	Yes
Continent × Wave FE	Yes	Yes	Yes
Rain Control	Yes	Yes	Yes
Mean Dep. Var.	0.42	0.15	0.42
Wald F-stat	8.12	8.12	8.12

Notes: This table presents the results of the 2SLS regressions with fixed effects at the regional and continent times appearance level on the employment sectors (agriculture, manufacturing, and services) shares as outcomes. Models are grouped into two panels corresponding to labor active and employed sample results. All models are run controlling for the baseline (1990) level of rain, interacting with a linear time trend to control for potential multicollinearity. Standard errors are corrected for a two-way clustering at the regional level to account for correlation over time and at the country-year level to account for within-country-year correlation. Bangladesh, Uganda, and Guinea are excluded as it has no sector variable. ***, **, * and + denote statistical significance at the 0.1%, 1%, 5% and 10 % levels, respectively.

Table E5: 2SLS: Placebo from the 80s

	Agriculture (1)	Manufactury (2)	Services (3)	Primary (4)	Secondary (5)	University (6)	LFP (7)	Employment (8) (8)	Self Employment (9)	Unpaid Work (10)	Wage Work (11)
Mobile Coverage	−0.277* (0.098)	0.087 (0.048)	0.187** (0.057)	−0.062+ (0.030)	0.182*** (0.033)	0.043** (0.013)	0.033 (0.037)	−0.012 (0.051)	−0.150** (0.049)	0.034** (0.011)	0.115 (0.066)
# Obs.	1816	1816	1816	2458	2458	2458	2458	2458	2458	2458	2458
# Countries	7	7	7	7	7	7	7	7	7	7	7
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Continent × Wave FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Rain Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean Dep. Var.	0.32	0.13	0.30	0.29	0.10	0.02	0.56	0.44	0.16	0.04	0.24
Wald F-stat	8.15	8.15	8.15	6.23	6.23	6.23	6.23	6.23	6.23	6.23	6.23

Notes: This table presents the results of the 2SLS regressions with fixed effects at the regional level and continent times appearance level on labor force participation, employment, sectoral employment, and education outcomes. The table is a placebo where we use the 7 countries ¹⁶ that have available older data (from the 80s) and we assign the treatment to the 90s in a placebo fashion, using the 80s as a control group. All models are run on the full sample of 7 countries with available data, controlling for rain at baseline and using continent × appearance and GEOLEV2 fixed effects. Errors are clustered at GEOLEV2, at which the treatment is also varying. ***, **, * and + denote statistical significance at the 0.1%, 1%, 5% and 10 % levels, respectively.

Table E6: 2SLS: Placebo Reference results

	Agriculture (1)	Manufacture (2)	Services (3)	Primary (4)	Secondary (5)	University (6)	LFP (7)	Emp (8)	Self Emp (9)	Unpaid Work (10)	Wage Work (11)
Mobile Coverage	0.161 (0.121)	0.029 (0.027)	-0.191 (0.114)	-0.087** (0.027)	0.142* (0.053)	0.009 (0.034)	0.287** (0.069)	0.273** (0.079)	-0.052 (0.088)	0.181* (0.075)	0.133** (0.032)
Obs.	2559	2559	2559	2768	2768	2768	2768	2768	2458	2458	2458
# Countries	7	7	7	7	7	7	7	7	7	7	7
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Continent \times Wave FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Rain Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean Dep. Var.	0.40	0.16	0.44	0.33	0.17	0.03	0.56	0.52	0.20	0.04	0.29
Wald F-stat	5.15	5.15	5.15	8.47	8.47	8.47	8.47	8.47	6.23	6.23	6.23

Notes: This table presents the results of the 2SLS regressions with fixed effects at the regional level and continent times appearance level on labor force participation, employment, sectoral employment and education outcomes. The table is the reference for the placebo analysis where we use the 7 countries that have available older data (from the 80s) but without reassigning the treatment as placebo and without using the data from the 80s. All models are run on the full sample of 7 countries having available data, controlling for rain at baseline and using continent * appearance and GEOLEV2 fixed effects. Errors are clustered at GEOLEV2 at which also the treatment is varying. ***, **, * and + denote statistical significance at the 0.1%, 1%, 5% and 10 % levels, respectively.