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Energy and Digital Infrastructure Complementarities

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Abstract

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This paper studies the complementarities between energy and digital infrastructure in developing countries. Using geospatial data on power transmission lines, power plants, cell towers, and fiber-optic nodes matched to settlement-level wealth indicators across sub-Saharan Africa, and detailed subnational data from Liberia, we estimate the joint effects of proximity to energy and digital infrastructure on local economic development. We test whether the marginal returns to one infrastructure type are increasing in the availability of the other. Our results confirm significant positive complementarity effects. Across sub-Saharan Africa, both digital and power infrastructure proximity are strongly associated with higher settlement wealth, with stable positive interaction coefficients (semi-elasticities) of approximately 1.5 International Wealth Index points across all control specifications, indicating that marginal returns to each infrastructure type are substantially amplified by the presence of the other. These findings are robust across linear fixed-effects regressions and nonparametric Local-Linear Causal Forest (LLCF) estimates; the LLCF further reveals that proximity to the complementary infrastructure type is the single strongest predictor of treatment effect heterogeneity, a direct nonparametric signature of complementarity. The quality of digital connectivity as measured by internet speed is an important mediator. In Liberia, energy consumption per connection also interacts positively with cell tower proximity, confirming complementarity at the intensive margin of energy usage. Our findings support coordinated, spatially bundled investment in both infrastructure types as a development policy priority.

Keywords: Infrastructure complementarity, electrification, digital connectivity, economic development, Africa
JELs: O18, O13, L96, H54, O55

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1 Introduction

Access to reliable electricity and digital connectivity—principally mobile internet—are widely regarded as foundational inputs for economic development. Yet in much of sub-Saharan Africa (SSA) both remain scarce: as of 2022, roughly 600 million Africans lacked electricity access, and only about 36% of the population in least developed countries used mobile internet despite 83% being covered by 3G or better networks (GSMA Intelligence, 2024). Crucially, the populations lacking electricity and those lacking internet connectivity overlap substantially, particularly in rural areas (Digital Impact Alliance, 2023). This raises a fundamental question for infrastructure policy: are energy and digital infrastructure complements—so that the returns to investing in one are increasing in the availability of the other—and, if so, what are the implications for the sequencing and spatial targeting of investments?

This paper provides evidence on the complementarity between energy and digital infrastructure using two empirical approaches. First, we exploit continental-scale geospatial data matching settlement-level wealth indicators across Africa to proximity measures for power transmission lines, power plants, cell towers, and fiber-optic nodes, estimating interaction effects in a cross-sectional framework with region fixed effects. Second, we use detailed subnational data from Liberia—combining cell tower locations, energy demand surveys, and settlement-level wealth indices—to study complementarities at finer spatial resolution. In both settings, we test whether proximity to energy infrastructure amplifies the development returns to digital infrastructure, and vice versa.

Our contribution is to provide the first systematic, multi-scale empirical test of energy-digital infrastructure complementarity. While a growing literature documents complementarities between transport and energy (Abbasi et al., 2022; Selod et al., 2024; Vanden Eynde & Wren-Lewis, 2023) and between transport and digital infrastructure (Lebrand et al., 2024), the energy-digital nexus has received little direct empirical attention despite strong theoretical priors and mounting policy interest (World Bank, 2023; Energy for Growth Hub, 2021). This paper fills that gap.

The remainder of the paper is organized as follows. Section 2 reviews the related literature. Section 3 describes our data sources and measurement strategy. Section 4 presents the empirical framework. Section 5 reports results. Section 6 concludes.

2 Literature Review

This paper relates to three strands of literature: (i) the development effects of electrification, (ii) the development effects of digital connectivity, and (iii) the emerging literature on infrastructure complementarities. We review each in turn, emphasizing quantitative findings and the limited but growing evidence on energy-digital interactions.

2.1 Development Effects of Electrification

A large empirical literature studies the causal effects of electricity access on economic outcomes in developing countries, with mixed but generally positive findings. Dinkelman (2011) exploits the topographic placement of electricity lines in South Africa's KwaZulu-Natal province and finds that electrification significantly increased female employment, primarily through a release of home production time. Lipscomb et al. (2013) uses the geographic placement of hydropower plants in Brazil as an instrument and finds significant positive effects of electrification on the Human Development Index, driven by increases in labor productivity, income, and housing quality.

In Vietnam, Khandker et al. (2013) use panel data and find that household electrification increased total income by 28% and expenditure by 9% over a six-year period. van de Walle et al. (2017) document long-term gains from electrification in rural India, including higher consumption, asset accumulation, and labor supply. Grogan & Sadanand (2013) find large employment effects of rural electrification in Nicaragua, particularly for women. More recently, Kassem (2024) studies grid expansion in Indonesia and finds that electrification spurred industrial development by increasing firm entry in newly electrified areas, while Burlig & Preonas (2024) study grid extension in Brazil using a regression-discontinuity design and document positive effects on local economic activity, though concentrated in areas with complementary infrastructure.

However, recent experimental evidence has tempered expectations. In a randomized control trial of grid extension in rural Kenya, Lee et al. (2020b) find that newly connected households used electricity primarily for lighting and mobile phone charging—spending only about $2/month on power—with no detectable effects on income, assets, or broader welfare after 18 months. Lee et al. (2020a) synthesize the evidence and argue that the heterogeneity of findings across settings likely reflects differences in complementary factors: electricity alone is insufficient without appliances, productive equipment, market access, and—crucially—digital connectivity to unlock its full economic potential.

At the macro level, Mensah (2024) studies electricity shortages across Africa and finds that power outages significantly increase unemployment—by up to 5–14 percentage points depending on the specification—underscoring that both access and reliability matter for economic outcomes.

2.2 Development Effects of Digital Connectivity

A parallel literature documents large effects of mobile and broadband internet on economic development. Hjort & Poulsen (2019) exploit the staggered arrival of submarine fiber-optic cables at African coastlines and find that access to fast internet significantly increased employment rates, with large positive effects spanning both skilled and unskilled workers. Mensah & Traore (2024) use a similar identification strategy and find that high-speed internet increased the probability of receiving FDI in services by 5.7 percentage points at the district level.

At the household level, Bahia et al. (2023) use an instrumental variable approach in Tanzania and find that 3G mobile broadband coverage raised labor force participation and increased wage employment; Bahia et al. (2024) similarly find that mobile broadband boosted total household consumption in Nigeria. Masaki et al. (2020) study Senegal and estimate that 3G coverage raised total household consumption by 14% and reduced extreme poverty by 10%. On structural transformation, Caldarola et al. (2023) find that mobile internet access in Rwanda facilitated the reallocation of labor from agriculture to services, particularly for skilled workers. At the macro level, Calderon & Cantu (2021) study 48 African countries and find that digital infrastructure—measured by mobile and internet subscriptions—significantly raises GDP growth, primarily through total factor productivity.

A key finding across this literature is that the effects of digital connectivity are highly heterogeneous and depend on complementary factors. Masaki et al. (2020) explicitly note that electricity access is a key constraint on internet adoption in Senegal, while Bahia et al. (2023) and Bahia et al. (2024) both document that electricity availability is linked with increased mobile broadband adoption. The GSMA Intelligence (2024) report quantifies this gap: adults in rural SSA are 48% less likely to use mobile internet than their urban counterparts, in significant part because of unreliable electricity for device charging.

2.3 Infrastructure Complementarities

The theoretical case for infrastructure complementarity is straightforward: if two inputs enter a production function with a positive cross-partial derivative, the marginal product of each is increasing in the level of the other. In the infrastructure context, this implies that the economic returns to energy access are larger in areas with digital connectivity, and vice versa (Blimpo & Cosgrove-Davies, 2019). When both are absent, adding either one alone may yield disappointing returns—a prediction consistent with the muted effects found in some electrification RCTs (Lee et al., 2020b,a).

Transport-Energy Complementarities

The most developed empirical literature on infrastructure complementarity studies the interaction between transport (roads) and energy (electricity). Abbasi et al. (2022) analyze data from 27 SSA countries and find that proximity to both roads and the electricity grid raises employment probability by 8.4 percentage points—compared with 4.0 pp for grid proximity alone—implying a complementarity effect of over 100%. Using data from the Horn of Africa, Lebrand & Herrera Dappe (2021) show that the combined impact of road and electricity access on reducing the agricultural employment share is 2.5 times larger than roads alone: bundled access shifts 26.5 pp out of agriculture versus 10.6 pp for roads only. Lebrand (2022) documents even larger effects for the Lake Chad region, where combined investments in roads, electricity, and telecommunications reduced the agricultural share by 22.3 pp and increased the services share by 17.5 pp. Moneke (2020) studies Ethiopia and finds that combined road-electricity access decreased agricultural employment by 20.2% and increased manufacturing employment by 13.1%.

In Latin America, Selod et al. (2024) study Brazil and find that electrification and highway construction are complementary in generating local economic growth: areas receiving both infrastructure types experienced larger gains in GDP, employment, and firm entry than areas receiving either alone. Vanden Eynde & Wren-Lewis (2023) provide evidence from rural India showing that villages increase dry-season cropping—and shift toward high-value market crops—only when they receive *both* electricity and road access, not when they receive either in isolation.

Transport-Digital Complementarities

Lebrand et al. (2024) extend the complementarity framework to transport and digital infrastructure across 25 African countries. They find that the combined impact of internet access and road proximity on employment and structural transformation is 22% larger than the sum of their isolated effects, confirming complementarity in the digital domain as well. This finding is directly relevant to the present paper: if roads and digital infrastructure are complementary, and roads and electricity are complementary, the transitive logic suggests that energy and digital infrastructure are likely complementary as well—though this requires direct empirical verification.

Energy-Digital Complementarities: Direct Evidence

Despite strong theoretical priors and suggestive indirect evidence, only a handful of studies directly test the complementarity between energy and digital infrastructure.

The most directly relevant economics paper is Mensah & Traore (2024), who find that the FDI-increasing effects of high-speed internet in Africa are concentrated in countries with reliable electricity access and adequate road infrastructure. They interpret this as evidence that the returns to digital infrastructure are conditional on the quality of complementary energy infrastructure, and explicitly call for bundled rather than siloed investment.

Houngbonon et al. (2021) provide micro-level evidence from Senegal using mobile call detail records. Exploiting spatial variation in rural electrification, they find that electricity access significantly increases mobile connectivity—measured by phone subscriptions, smartphone ownership, and communication volumes—with disproportionate effects for women. The mechanism operates through device charging rather than income: electrified rural users do not initiate more calls, but *receive* substantially more calls and texts from urban contacts, suggesting that electricity raises digital inclusion by making rural users reliably reachable.

At the cross-country level, Armey & Hosman (2016) demonstrate that electricity distribution—the share of the population with access—is a statistically and economically significant determinant of internet adoption in low-income countries, framing electricity as a fundamental prerequisite that ICT-for-development initiatives too often neglect. Li et al. (2025) extend this to the East African Community, finding a strong positive link between electricity connection rates and ICT usage in Burundi, Kenya, and Rwanda.

Several broader studies also point to energy-digital complementarity without testing it directly as an interaction effect. Calderon & Cantu (2021) find that the growth effects of digital infrastructure in Africa operate primarily through total factor productivity, and note that these TFP gains are strongest in countries with higher electricity access. The World Bank (2023) report states explicitly that "digital technology and electricity are mutual complements for firms and household production functions" and documents that unreliable electricity is one of Africa's most binding constraints on digital adoption. The Energy for Growth Hub (2021) report reviews 106 World Bank infrastructure projects in Africa and finds strikingly low levels of cross-sector coordination between energy and digital investments, despite the theoretical case for complementarity.

The complementarity also runs in the reverse direction: digital infrastructure enables energy access. The pay-as-you-go (PAYG) solar sector in SSA—where companies like M-KOPA and Fenix International use mobile money to finance off-grid solar home systems—represents a commercially significant example. Research in Tanzania finds that mobile money users are 5.7 percentage points more likely to adopt solar panels than non-users (International Energy Agency, 2023). In Kenya, the government expanded electricity access from 40% to 70% partly through PAYG solar leveraging mobile money platforms (International Monetary Fund, 2020). This bidirectional relationship suggests that coordinated rollout can create virtuous cycles: electricity enables device charging and digital inclusion, while digital payments make energy access financially viable for low-income households.

2.4 Contribution

This paper contributes to the literature by providing the first systematic test of energy-digital infrastructure complementarity in a production-function framework, using both continental-scale and country-specific data. We follow the empirical approach pioneered by Abbasi et al. (2022) and Lebrand et al. (2024)—estimating interaction effects between infrastructure proximity measures on development outcomes—but apply it to the energy-digital pair that has received the least attention despite arguably the strongest theoretical priors.

3 Data

We draw on two complementary empirical settings: a continental-scale analysis covering all of Africa, and a detailed country-level analysis for Liberia.

3.1 Outcome Variables

Our primary outcome is the *International Wealth Index* (IWI), a settlement-level asset-based wealth index for 44 SSA countries constructed by Lee & Braithwaite (2022). The IWI is a cross-country comparable index scaled $[0, 100]$, predicted using a machine learning model trained on Demographic and Health Survey (DHS) data and combining day- and nighttime satellite imagery, high-resolution population estimates (WorldPop), and OpenStreetMap features. The resulting dataset covers approximately 876,000 populated settlements at 1 square-mile resolution in our estimation sample. Lee & Braithwaite (2022) target IWI estimates from DHS surveys since 2017 to construct their high-resolution estimates. We argue that these derived estimates are valid in our case because energy and digital infrastructure are not detectable from medium-resolution satellite imagery, and these assets are also not well represented in OpenStreetMap. We also control for various OSM-derived infrastructures and amenities in our models. Yet, to guard against this criticism, we also run regressions using a PCA-based IWI derived from similar items (questions) available in all DHS surveys across SSA between 2010 and 2022, yielding a dataset of 39,000 village/household clusters across 34 countries for which we can obtain a direct IWI measurement.

For Liberia, we use the Meta/CIESIN *Relative Wealth Index* (RWI) (Chi et al., 2022) matched to 17,000 settlements in a dataset provided by VIDA for analytical work within the World Bank's Distributed Access through Renewable Energy Scale-Up (DARES) platform. The RWI predicts relative standard of living within countries using de-identified connectivity data, satellite imagery and other data sources.

3.2 Digital Infrastructure Assets

We measure digital infrastructure proximity using three complementary sources. The **OpenCellID** database (OpenCellID Project, 2024) provides the locations of approximately 1.9 million cell towers across Africa. For each settlement, we compute the distance (in km) to the nearest cell tower using spherical geometry (`s2` package), yielding the variable d_{OCID}. We complement cell tower proximity with distance to the nearest fiber-optic backbone node from two sources: the **Africa Bandwidth Maps** (ABWM, Q3 2025) dataset (Africa Bandwidth Maps, 2025), which documents fiber nodes and inter-node links from commercial and public sources, yielding d_{ABWM}; and the **ITU broadband infrastructure** node-tie dataset (November 2024) (International Telecommunication Union, 2024), yielding d_{ITU}. These three distance measures are combined into a single digital infrastructure proximity variable $d_{\mathrm{digital}} = \min(d_{\mathrm{OCID}}, d_{\mathrm{ABWM}}, d_{\mathrm{ITU}})$, capturing proximity to the nearest digital network asset of any type.

As an alternative measure of digital connectivity, we use **OOKLA Speedtest** data (Ookla, 2024), which records average download and upload speeds at $\sim$610 m tile resolution. We compute the geometric mean of mobile download and upload speeds (in kbps).

For Liberia, we have obtained a detailed dataset of 1,157 mobile towers from the Liberia Telecommunications Authority (LTA). As in the SSA case, for each of the 17,000 settlements in Liberia (VIDA dataset), we compute the distance to the nearest tower.

3.3 Energy Infrastructure Assets

Energy infrastructure proximity is measured using two sources. **Power transmission lines** are drawn from a dataset combining OpenStreetMap, the European Commission Joint Research Centre (JRC) electricity grid for Africa (Kakoulaki & Moner-Girona, 2026), the World Bank's Africa Electricity Transmission and Distribution Grid Map (World Bank Group, 2017), and predictive mapping of the distribution network following Arderne et al. (2020), yielding the variable d_{lines}. **Power plants** are taken from a merged dataset combining the Global Energy Monitor's Global Integrated Power Tracker, the World Resources Institute (WRI) Global Power Plants Database, and additional sources, covering generating capacity in MW across fuel types. We compute d_{plants} as the distance to the nearest power plant. We also include distance to OSM-based power infrastructure points (transformers, generators) from the Africa Infrastructure Database by Krantz (2024). These distances are combined into $d_{\mathrm{power}} = \min(d_{\mathrm{lines}}, d_{\mathrm{plants}}, d_{\mathrm{points}})$.

For Liberia, we use a settlement-level energy demand survey that records energy demand per connection (kWh/day) and distance to the existing transmission grid as alternative energy access proxies. Distance to the nearest nightlight centroid also serves as a proxy for grid access in this setting. This data was provided by VIDA for the World Bank regional DARES.

3.4 Control Variables

All specifications include a rich set of controls to account for confounding spatial factors. We include the distance to the nearest non-residential road from OpenStreetMap. **Population** is measured using settlement-level population estimates from the IWI dataset by Lee & Braithwaite (2022), which also includes variables on building count, and building area. We also include the share of the population aged 0–14 from the Gridded Population of the World version 4 (GPW4). **Market access** is captured by travel time to the nearest city with at least 50,000 and 1 million inhabitants, and travel time to the nearest port, based on the global accessibility maps of Nelson (2022). We also control for distances to education, health, and water/utility facilities, as well as to essential shops, public transport, and industrial plants, all taken from the Africa Infrastructure Database (Krantz, 2024). For Liberia, we additionally include the count of conflict or security incidents within a 50 km radius provided in the VIDA dataset.

3.5 Summary of Estimation Samples

The continental Africa analysis uses a cross-sectional dataset of approximately 876,000 IWI settlements with complete data on all key variables, spanning 44 SSA countries—by Lee & Braithwaite (2022). A second DHS-based sample of approximately 39,000 DHS cluster-level observations is used for robustness checks. The Liberia analysis uses a smaller but richer and more authoritative dataset of 17,000 settlements from a nationally representative energy demand survey matched to cell tower locations and settlement wealth data.

4 Empirical Framework

We employ two complementary empirical approaches. The first is a standard linear fixed-effects regression that allows direct estimation of interaction terms and has a transparent structural interpretation. The second is a semi-parametric causal machine learning estimator—the Local-Linear Causal Forest (Friedberg et al., 2020) (LLCF)—that relaxes the linearity assumption while still permitting a continuous relationship between predictors and outcome, and that also allows for estimating heterogeneous (local) treatment effects. Since LLCF requires rich data, we only apply it to the full IWI estimation sample (Lee & Braithwaite, 2022).

4.1 Linear Fixed Effects

Our baseline specification is:

$$Y_{ic} = \alpha_c + \beta_1 \tilde{d}_{ic}^{\text{digital}} + \beta_2 \tilde{d}_{ic}^{\text{power}} + \beta_3 \left(\tilde{d}_{ic}^{\text{digital}} \times \tilde{d}_{ic}^{\text{power}} \right) + \mathbf{X}_{ic}' \boldsymbol{\gamma} + \varepsilon_{ic}, \tag{1}$$

where Y_{ic} is the IWI of settlement i in administrative unit (district) c, α_c is a fixed effect absorbing all time-invariant unit-level confounders, $\tilde{d}_{ic}^{\text{digital}} = -\log(d_{ic}^{\text{digital}} + 1)$ and $\tilde{d}_{ic}^{\text{power}} = -\log(d_{ic}^{\text{power}} + 1)$ are negated log-distances to digital and power infrastructure (so that higher values indicate closer proximity), $\mathbf{X}_{ic}$ is a vector of controls, and ε_{ic} is an idiosyncratic error term. The interaction term $\tilde{d}^{\text{digital}} \times \tilde{d}^{\text{power}}$ tests our central hypothesis: a positive $\hat{\beta}_3$ indicates that settlements closer to power infrastructure benefit more from proximity to digital infrastructure, and vice versa—i.e., the two infrastructure types are complements. We also estimate specifications replacing distance proxies with OOKLA mobile internet speed, and three-way interaction models.

All regressions are estimated with subnational (first-level administrative unit) fixed effects using the `fixest` package (Bergé et al., 2026), with standard errors clustered at the same level.

4.2 Local-Linear Causal Forest

The linear interaction specification imposes a parametric functional form and cannot detect nonlinear complementarities or spatially heterogeneous treatment effects. We therefore complement the linear estimates with a causal machine learning approach based on the Generalized Random Forest (GRF) framework of Athey et al. (2019) and Wager & Athey (2018), specifically using Local-Linear Causal Forests (Friedberg et al., 2020) as implemented in the `grf` R package.

Identification. We adopt the *unconfoundedness* (conditional independence) assumption: conditional on the rich set of observable characteristics $\mathbf{X}$ described in Section 3, the potential outcomes $Y(\omega)$ are independent of the treatment realization $W = \omega$ for all $\omega \in \Omega$, i.e. $Y(\omega) \perp W \mid \mathbf{X}$. Here W is a continuous treatment—log proximity to digital or power infrastructure—and Y is the IWI. Under this assumption, the quantity of interest is the Conditional Average Partial Effect (CAPE):

$$\tau(\mathbf{X}_H) = E\left[\frac{\partial Y}{\partial W} \,\middle|\, \mathbf{X}_H \right], \tag{2}$$

where $\mathbf{X}_H \subseteq \mathbf{X}$ captures the subspace of covariates that drive treatment effect heterogeneity.

Double/Debiased ML and the R-Loss. We follow Robinson (1988), Chernozhukov et al. (2018), and Nie & Wager (2021) and adopt a partial linear model with district fixed effects:

$$Y_{ic} = \alpha_c + \tau(\mathbf{X}_{H,ic}) \cdot W_{ic} + g(\mathbf{X}_{ic}) + \epsilon_{ic}, \tag{3}$$

$$W_{ic} = \alpha_c + f(\mathbf{X}_{ic}) + \eta_{ic}, \tag{4}$$

where i indexes settlements and c indexes GADM Level-1 districts, α_c is a district fixed effect, $g(\cdot)$ and $f(\cdot)$ are unrestricted nuisance functions, and $E[\epsilon_{ic} | \mathbf{X}_{ic}] = E[\eta_{ic} | \mathbf{X}_{ic}] = 0$. By the Frisch-Waugh-Lovell (FWL) theorem, the CAPE $\tau(\cdot)$ is identified after projecting out α_c via within-district demeaning. Letting $\ddot{Y}_{ic} = Y_{ic} - \bar{Y}_c$, $\ddot{W}_{ic} = W_{ic} - \bar{W}_c$, and $\ddot{\mathbf{X}}_{ic} = \mathbf{X}_{ic} - \bar{\mathbf{X}}_c$ denote group-demeaned variables, all analysis variables are demeaned prior to estimation; the interaction term $\tilde{d}^{\text{digital}} \times \tilde{d}^{\text{power}}$ is computed before demeaning (FWL consistency, since the FE estimator demeans the product, not the product of demeaned terms). Let $m(\ddot{\mathbf{X}}) = E[\ddot{Y}|\ddot{\mathbf{X}}]$ and $e(\ddot{\mathbf{X}}) = E[\ddot{W}|\ddot{\mathbf{X}}]$ denote the residual nuisance functions on demeaned data. Subtracting conditional expectations and denoting residuals $\tilde{Y} = \ddot{Y} - m(\ddot{\mathbf{X}})$ and $\tilde{W} = \ddot{W} - e(\ddot{\mathbf{X}})$ yields Robinson's (1988) centered specification: $\tilde{Y} = \tau(\ddot{\mathbf{X}}_H) \cdot \tilde{W} + \epsilon$. The CAPE $\tau(\cdot)$ is identified by the *R-Loss* (Nie & Wager, 2021):

$$\hat{\tau}(\cdot) = \arg\min_{\tau} \left\{ E\left[\tilde{W}^2 \left(\frac{\tilde{Y}}{\tilde{W}} - \tau(\ddot{\mathbf{X}}_H) \right)^2 \right] \right\}, \tag{5}$$

which can be interpreted as a weighted regression of the pseudo-outcome $\tilde{Y}/\tilde{W}$ on $\ddot{\mathbf{X}}_H$ with weights $\tilde{W}^2$. The causal forest uses the R-Loss as its node-splitting criterion to adaptively partition the covariate space into regions where the treatment effect is approx. constant (Athey et al., 2019).

Estimation Procedure. We implement the following multi-step estimation procedure. First, we estimate the nuisance functions $\hat{m}(\ddot{\mathbf{X}}) = \hat{E}[\ddot{Y}|\ddot{\mathbf{X}}]$ and $\hat{e}(\ddot{\mathbf{X}}) = \hat{E}[\ddot{W}|\ddot{\mathbf{X}}]$ using *local-linear regression forests* (Friedberg et al., 2020), which augment the standard forest splits with a ridge-regularized local linear correction to improve estimation of smooth targets.[1] The linear correction variables (features to include in the local regression step) are selected via LASSO cross-validation. Crucially, both first-stage forests use *honest estimation* (Wager & Athey, 2018): each tree uses a separate subsample for choosing splits and for populating the leaf estimates, yielding out-of-bag (OOB) predictions that serve as a forest-native form of leave-one-out cross-fitting and guard against overfitting the nuisance functions (Chernozhukov et al., 2018).

Second, the residuals $\tilde{Y}$ and $\tilde{W}$ are computed. An initial causal forest is fitted to identify the covariates with above-average variable importance for treatment effect heterogeneity ($\mathbf{X}_H$). A LASSO regression of the pseudo-outcome $\tilde{Y}/\tilde{W}$ on all demeaned covariates $\ddot{\mathbf{X}}$ (weighted by $\tilde{W}^2$) is used to select the linear correction variables for the final local-linear forest. The final *Local-Linear Causal Forest* (LLCF) is then fitted using the selected heterogeneity covariates ($\mathbf{X}_H$) and linear correction variables. The causal forest minimizes the R-Loss within locally weighted neighborhoods, combining the adaptive covariate splitting of RF with local linear corrections.

We treat each of the three "treatments" in turn: log digital proximity $\tilde{d}^{\text{digital}}$, log power proximity $\tilde{d}^{\text{power}}$, and their product $\tilde{d}^{\text{digital}} \times \tilde{d}^{\text{power}}$ (the interaction term in log-space). The CAPE on the interaction term directly captures how the joint proximity effect on wealth varies with observed characteristics—a test of heterogeneous complementarity.

Average Partial Effects and Inference. To estimate the Average Partial Effect (APE) and its standard error, we use the doubly-robust estimator following Athey & Wager (2019) and the `grf` package. In the binary treatment case, the doubly-robust (AIPW) score is $\hat{\Gamma}_i = \hat{\tau}^{(-i)}(X_i) + \frac{W_i - \hat{e}^{(-i)}(X_i)}{\hat{e}^{(-i)}(X_i)[1-\hat{e}^{(-i)}(X_i)]}(Y_i - \hat{\mu}^{(-i)}(X_i, W_i))$ (Athey et al., 2019). For our *continuous* treatment W, the debiasing weight generalizes to account for the conditional variance of the residualized treatment:

$$\hat{\Gamma}_i = \hat{\tau}_i + \frac{\tilde{W}_i}{\hat{v}_i}\left(\tilde{Y}_i - \hat{\tau}_i \cdot \tilde{W}_i\right), \tag{6}$$

where $\hat{v}_i = \hat{E}[\tilde{W}_i^2|\ddot{\mathbf{X}}_i]$ is a cross-fitted estimate of the conditional variance of the residualized treatment, obtained via honest OOB predictions from a RF (Nie & Wager, 2021). The APE is $\bar{\tau} = n^{-1}\sum_i \hat{\Gamma}_i$ with standard errors from the variance of $\hat{\Gamma}_i$. To assess treatment effect heterogeneity, we follow Athey & Wager (2019) in comparing the average doubly-robust scores in the upper and lower halves of the estimated CATE distribution. We also report the *Best Linear Projection* (BLP) as a calibration test: a regression of the doubly-robust scores $\hat{\Gamma}_i$ on the CATE predictions $\hat{\tau}_i$, where a coefficient near 1 on $\hat{\tau}_i$ indicates well-calibrated effect heterogeneity (Chernozhukov et al., 2018).

[1] Specifically, as detailed in Friedberg et al. (2020) and also in the grf documentation, a classical Random Forest is fit first and used to generate a set of instance-level weights $\omega_i(\mathbf{x}_j)$ that can be used to fit a weighted ridge regression specific to instance j. Thus, the local linear correction does not imply estimating a regression on a small sample, but rather using instance-specific weights derived from a Random Forest (RF) to estimate a regression for instance j using all instances (i). The RF in this sense functions as a kernel or weighting method in high dimensions.

Unconfoundedness. The key identifying assumption is that there are no unobserved confounders driving both infrastructure placement and settlement wealth. This is difficult to guarantee in a cross-section. We argue that the district fixed effects (absorbed via within-group demeaning) together with our rich covariate set—encompassing population, market access, and competing infrastructure types—absorb the main drivers of endogenous infrastructure placement, including agglomeration effects and political economy considerations. In particular, if political favoritism toward birth regions (cf. Abbasi et al. 2022) is broad-based and affects multiple infrastructure types simultaneously, it will be captured by the ML nuisance models. We acknowledge remaining limitations: we cannot rule out reverse causality (wealthy settlements may attract more infrastructure investment), and we cannot test the unconfoundedness assumption directly. Results should be interpreted as partial equilibrium associations, consistent with—but not causally identified as—complementarity effects.

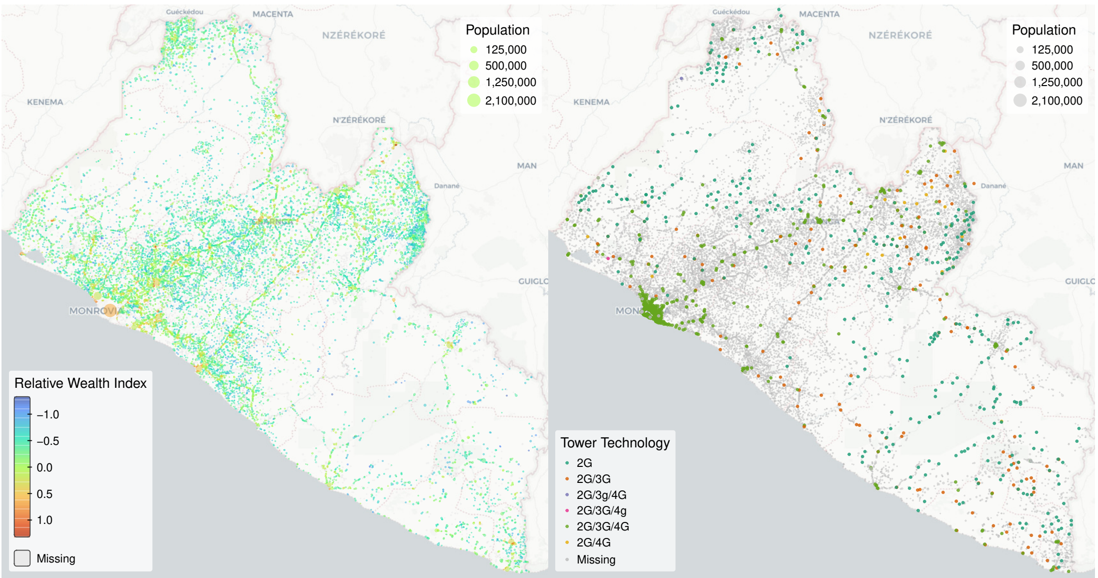
5 Results

We present results, beginning with Liberia, then proceeding to the continental Africa analysis with classical methods followed by the causal ML (LLCF) results for heterogeneity analysis. Robustness results using the DHS-based wealth index are in the Appendix.

5.1 Liberia

The Liberia analysis uses a more granular measure of energy access—energy demand in kWh/day per connection from a nationally representative survey—paired with high-resolution digital access data (distance to the nearest cell tower from the telecom regulator). Figure 1 maps the spatial distribution of the Relative Wealth Index across 17,047 settlements and 1,157 cell tower locations.

Figure 1: Liberia Settlement Data: Relative Wealth Index and Cell Tower Locations.



Notes: The left panel shows the Meta/CIESIN Relative Wealth Index (Chi et al., 2022) for 17,047 settlements mapped by VIDA (size differs according to population). The right panel shows 1,157 cell tower locations obtained from the regulator.

To conduct the analysis, we select a set of 10 variables summarized in Table 1. The VIDA dataset contains a number of variables related to energy access and usage, from which we select the distance to transmission grid in km as the main access indicator and energy demand per connection in kWh/day as the main usage indicator. The dataset also provides measures of distance to the main road and to the nearest hub as accessibility indicators, population of each settlement alongside the number of education and health facilities, and armed conflict incidents within 50km for the years 2023-25 derived from the ACLED database (Raleigh et al., 2010). A median distance of 4.6km to a cell tower implies limited connectivity in many settlements.

Table 1: Descriptive Statistics: Liberia (Settlement Sample)

Variable	N	Ndist	SD	Min	25%	Mean	50%	75%	Max
Relative Wealth Index	13705	1313	0.29	-1.32	-0.54	-0.35	-0.38	-0.19	1.32
Energy demand per connection [kWh/day]	17047	374	0.07	0.34	0.34	0.36	0.34	0.36	1.10
Distance to cell tower [km]	17047	17047	3.73	0.00	2.83	5.32	4.61	6.95	38.35
Distance to transmission grid [km]	17047	16880	25.39	0.00	5.33	25.07	16.73	37.98	130.32
Distance to the main road [km]	17047	2547	1.08	0.00	0.42	0.33	0.00	0.00	18.94
Distance to nearest hub [km]	17047	14068	14.67	0.00	10.57	21.46	17.73	28.99	89.89
Population	16971	576	16415	3.30	19.80	314.00	36.30	92.40	2109382
Healthcare facilities	17047	13	1.89	0.00	0.00	0.06	0.00	0.00	224.00
Education facilities	17047	19	1.72	0.00	0.00	0.05	0.00	0.00	140.00
Armed incidents within 50 km (2023-25)	17047	41	11.08	0.00	1.00	7.26	2.00	8.00	42.00

Notes: The Relative Wealth Index (RWI) is from Meta/CIESIN (Chi et al., 2022). Energy demand (kWh/day per connection) is from a nationally representative survey. Distance to cell tower is computed against the 1,157 cell towers provided by the regulator. Other variables are provided by VIDA.

Table 2 further shows pairwise correlations of these variables. As expected, the RWI is positively correlated with energy demand, population, and amenities, and negatively with remoteness (distance to towers, grid, roads, and hubs). All distance variables are positively correlated, and negatively with population and amenities. Health facilities are quite concentrated in populated areas ($r = 0.94$), while education facilities appear more dispersed ($r = 0.35$).

Table 2: Pairwise Correlations: Liberia (Settlement Sample)

#	Variable	1	2	3	4	5	6	7	8	9
1	Relative Wealth Index	1								
2	Energy demand per connection [kWh/day]	.247	1							
3	Distance to cell tower [km]	-.253	-.158	1						
4	Distance to transmission grid [km]	-.155	-.082	.033	1					
5	Distance to the main road [km]	-.218	-.127	.173	.117	1				
6	Distance to nearest hub [km]	-.215	-.125	.295	.159	.198	1			
7	Population	.041	.024	-.018	-.009	-.006	-.017	1		
8	Healthcare facilities	.051	.040	-.028	-.011	-.012	-.021	.944	1	
9	Education facilities	.054	.044	-.033	-.018	-.012	-.031	.353	.620	1
10	Armed incidents within 50 km (2023-25)	.199	.191	-.188	-.256	-.113	-.196	.024	.019	.002

Notes: Correlations computed on raw (untransformed) variables. N varies by variable (RWI: 13,705; all others: up to 17,047). See Table 1 for full sample sizes. Distance variables measured in kilometres.

For our benchmark regression results, energy demand and armed conflict enter in levels, while all distance variables enter as $-$km (negative kilometres from the settlement to each feature), so that larger values correspond to greater proximity; we take the natural log of population, education and health facilities, as these measures are highly skewed. We estimate a simple baseline without interactions, followed by a specification including the interaction of distance to tower with energy demand capturing the intensive margin, and an interaction with distance to grid capturing the extensive margin of energy access. We also include a full specification with all interactions. We employ district fixed effects in all specifications. Table 3 reports the regression results.

Energy demand per connection is strongly and positively associated with the Relative Wealth Index in all specifications, with coefficients ranging from 0.521 (column 1, no interactions) to 0.677 (column 4, full interactions). Settlements with higher average energy consumption per connection are wealthier—though the direction of causality remains unclear—and the $-$km measure for the nearest cell tower is positively associated with wealth in the baseline specification (col 1: 0.0170).

A central finding is the positive interaction between energy demand and cell tower proximity. The coefficient on ($-$Distance to tower) $\times$ Energy demand ranges from 0.0577 (column 2) to 0.0451 (column 4), indicating that the marginal effect of energy demand on RWI is larger when the settlement is closer to the digital network. At the tower ($-$km = 0), the marginal effect of a 1 kWh/day increase in energy demand is $\hat{\beta}^{\mathrm{ED}} = 0.72$. At the median distance of 4.6 km ($-$km = -4.6), this effect falls to $\hat{\beta}^{\mathrm{ED}} \approx 0.46$—a 36% reduction; at the 75th percentile (7.0 km), it falls further to approximately 0.32, a 55% reduction.

Column (3) adds the (−tower km) × (−grid km) interaction (0.0002), confirming a complementary relationship between access to the transmission grid and cell tower proximity on wealth. At the tower, $\beta^{\mathrm{EA}} = 0.4\%$; at median distance to tower (4.6km), $\beta^{\mathrm{EA}} = 0.31\%$; and at 75% (7km), $\beta^{\mathrm{EA}} = 0.21\%$. Column (4) shows the full three-way specification: the digital access gradient in the energy-wealth relationship persists even when controlling for grid proximity and its interactions.

Table 3: Liberia Results—Relative Wealth Index—District Fixed Effects

Dependent Variable:	Relative Wealth Index (Chi et al., 2022)			
Model:	(1)	(2)	(3)	(4)
Variables				
Energy demand per connection [kWh/day]	0.5212***	0.7249***	0.5113***	0.6767***
	(0.0684)	(0.0909)	(0.0682)	(0.1121)
−Distance to cell tower [km]	0.0170***	-0.0038	0.0229***	0.0064
	(0.0018)	(0.0057)	(0.0028)	(0.0079)
−Distance to transmission grid [km]	0.0030***	0.0030***	0.0040***	0.0043**
	(0.0009)	(0.0009)	(0.0009)	(0.0017)
−Distance to the main road [km]	0.0340***	0.0348***	0.0357***	0.0364***
	(0.0073)	(0.0074)	(0.0073)	(0.0073)
−Distance to nearest hub [km]	0.0019**	0.0018**	0.0019**	0.0019**
	(0.0009)	(0.0008)	(0.0009)	(0.0009)
log(Population)	0.0146***	0.0146***	0.0143***	0.0142***
	(0.0022)	(0.0022)	(0.0022)	(0.0022)
log(Healthcare facilities+1)	0.0443**	0.0428**	0.0465**	0.0450**
	(0.0203)	(0.0203)	(0.0204)	(0.0203)
log(Education facilities+1)	0.0718***	0.0685***	0.0695***	0.0666***
	(0.0248)	(0.0249)	(0.0242)	(0.0243)
Armed incidents within 50 km (2023-25)	0.0017*	0.0015	0.0016*	0.0014
	(0.0009)	(0.0010)	(0.0009)	(0.0010)
Interactions				
Tower × Energy demand		0.0577***		0.0451**
		(0.0149)		(0.0200)
Tower × Grid distance			0.0002***	0.0003
			(<0.0001)	(0.0002)
Grid × Energy demand				-0.0010
				(0.0040)
Fixed-effects				
District (136)	Yes	Yes	Yes	Yes
Fit statistics				
Observations	13,644	13,644	13,644	13,644
R^2	0.249	0.251	0.252	0.253
Within R^2	0.124	0.126	0.128	0.130

*Clustered (district) standard-errors in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: All specifications include district fixed effects (136 districts). Distance variables enter as −km (negative kilometres from the settlement), so positive coefficients imply higher RWI when closer to that feature; interactions use the same −km construction for tower and grid. Controls include log population, log healthcare and education facility counts, and armed incident count within 50 km from ACLED. The Relative Wealth Index is from Meta/CIESIN (Chi et al., 2022). Energy demand and grid distance from the World Bank Africa Infrastructure Database (Krantz, 2024); cell tower locations from the Liberian telecom regulator.

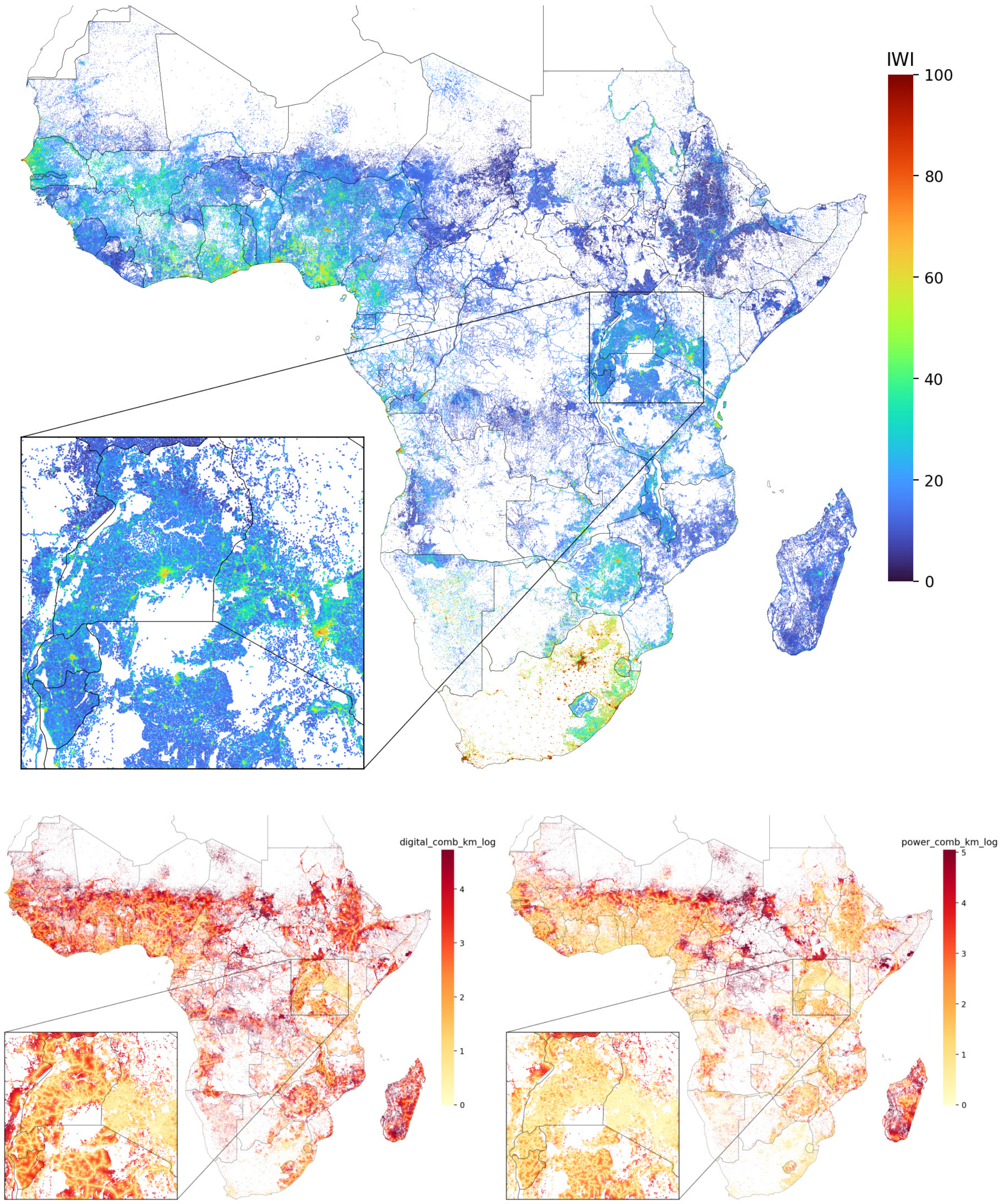
These Liberia results thus suggest significant interactions of digital access with energy access and usage/demand shaping development outcomes. The interaction is stronger on the intensive margin (energy use): at the cell tower an increase in energy use of 1 kWh/day is associated with a 0.72 point increase in the RWI, whereas at 4.6km from the tower (the median settlement) the effect drops to 0.46—a **36%** reduction. In contrast at the tower a 1km increase in distance to the grid decreases the RWI by 0.004, whereas at 4.6km from the tower the coefficient drops to 0.0031—a **23%** reduction. Findings are robust to using distance to nightlights as alternative energy access indicator—reported in Appendix Table 12—yielding a slightly stronger main effect and interaction. We also report semi-elasticities with all predictors in natural logs in Appendix Tables 11 and 13.

5.2 Sub-Saharan Africa

Having found positive evidence of energy and digital interactions in the very localized and specific setting that Liberia offers—with high-quality data on cell towers and settlements at our disposal—we now open up the scene, geographically speaking, and present a similar analysis at a much larger scale—covering almost 1 million settlements across 44 countries in SSA.

Figure 2 illustrates the spatial co-distribution of the three key variables in the continental analysis: the IWI settlement wealth index, combined digital infrastructure proximity, and combined power infrastructure proximity. The maps reveal a clear clustering of wealth and infrastructure access near urban centers and roads.

Figure 2: International Wealth Index, Digital and Power Infrastructure Proximity Across SSA



Notes: Top panel shows the settlement-level International Wealth Index (IWI) from Lee & Braithwaite (2022) for ∼876,000 populated settlements. Bottom-left panel shows combined digital infrastructure proximity—$-\log(d_{\text{digital}} + 1)$ (higher values = closer). Bottom-right panel shows combined power infrastructure proximity—$-\log(d_{\text{power}} + 1)$ (higher values = closer).

To conduct the analysis, we select the variables summarized in Table 4. The key infrastructure proximity variables are d_{digital}—the minimum distance to any digital asset (OpenCellID tower, ABWM fiber node, or ITU broadband point)—and d_{power}—the minimum distance to any power asset (transmission/distribution line, power plant, or OSM point feature like generator/transformer). The IWI outcome ranges from 2 to 98 with a mean of 20.7 and a median of 16.1, indicating substantial right-skew: a minority of wealthy urban settlements pull the mean far above the median. The median settlement lies 17.3 km from the nearest digital asset and 6.0 km from the nearest power asset, though the distributions are highly dispersed (SD of 35.4 and 41.9 km respectively), reflecting the concentrated geography of African infrastructure. OOKLA mobile internet speed averages 11,434 kb/s but is very right-skewed, with a median of 6,077 kb/s. Population controls capture building and population density and demographic structure; accessibility controls include travel time to cities and ports from Nelson (2022); amenity controls cover distances to roads, education, health, utilities, shopping, and industrial facilities from Krantz (2024).

Table 4: Descriptive Statistics: Continental Africa (IWI Sample)

Variable	N	Mean	SD	Min	25%	Median	75%	Max
International Wealth Index [0–100]	876,596	20.7	14.2	1.99	11.8	16.1	24.3	98.2
Distance to cell tower (km)	876,596	128.5	164.9	0.000	11.5	58.0	187.8	1,741
Distance to ABWM fiber node (km)	876,596	34.6	35.8	0.000	13.4	25.2	44.1	1,741
Distance to ITU node (km)	876,596	43.0	44.6	0.004	15.9	30.4	54.0	1,740
Distance to nearest digital infra. (km)	876,596	27.5	35.4	0.000	6.76	17.3	35.7	1,740
Distance to transmission line (km)	876,596	35.0	79.8	0.000	1.51	6.10	22.7	1,740
Distance to power plant (km)	876,596	119.4	100.1	0.000	47.6	91.6	161.7	1,755
Distance to nearest power infra. (km)	876,596	22.4	41.9	0.000	1.48	5.98	20.6	1,740
OOKLA Mobile internet speed (kb/s)	876,596	11,434	13,570	10.2	2,180	6,077	16,412	510,891
Population Controls								
Population (1 sq. mile)	876,596	1,207	4,467	0.000	90.2	265.3	781.1	267,976
Building count	876,596	94.4	536.2	0.000	0.000	0.000	3.00	27,878
Building area (sq. m)	876,596	0.007	0.048	0.000	0.000	0.000	0.000	2.29
Population share aged 0–14	875,919	0.490	0.063	0.150	0.471	0.501	0.525	0.609
Accessibility Controls								
Travel time to city $\geq$ 50k (min)	876,592	169.6	256.7	0.000	47.3	99.1	200.1	9,246
Travel time to city $\geq$ 1M (min)	876,591	455.0	438.4	0.000	176.9	340.2	596.7	9,937
Travel time to any port (min)	876,588	710.4	576.0	1.35	302.6	581.1	967.5	9,835
Travel time to medium/large port (min)	876,588	1,021	842.7	1.35	461.7	795.6	1,268	9,835
Infrastructure/Amenity Controls								
Distance to road (km)	876,596	6.17	12.7	0.000	0.427	2.47	6.86	1,740
Distance to transport infra. (km)	876,596	20.7	20.4	0.000	7.04	15.2	28.5	1,741
Distance to education facility (km)	876,596	15.6	18.1	0.000	3.16	9.16	21.9	1,741
Distance to health facility (km)	876,596	7.80	10.6	0.000	2.33	4.82	9.20	1,742
Distance to other utilities (km)	876,596	29.4	35.0	0.000	7.59	17.9	37.1	1,743
Distance to essential shopping (km)	876,596	25.4	27.9	0.000	7.94	16.9	32.8	1,741
Distance to industrial plant (km)	876,596	33.0	31.4	0.000	10.5	23.8	45.9	1,742

Notes: Sample consists of 876,596 populated settlements across 44 SSA countries from Lee & Braithwaite (2022). Distance variables in raw km; in regressions these enter as $-\log(d+1)$. OOKLA mobile speeds are geometric mean of download and upload speeds from tile-level data. Population and accessibility from the IWI dataset and Nelson (2022). Infrastructure distances are created using selected assets from the Africa Infrastructure Database (Krantz, 2024).

Table 5 reports pairwise correlations among the key regression variables, computed on log-transformed values. Both digital and power proximity are negatively correlated with the IWI (-0.302 and -0.285, respectively), confirming that remoteness from infrastructure is associated with lower settlement wealth. OOKLA mobile internet speed is positively correlated with the IWI (+0.137), reflecting higher data quality in wealthier, better-connected areas. The two proximity measures are strongly positively correlated with each other (0.578), consistent with the spatial co-clustering of energy and digital networks. Both are also positively correlated with road distance (0.549 and 0.396) and travel time to cities (0.678 and 0.494), confirming that infrastructure access is concentrated in more accessible locations—a pattern that makes controlling for accessibility particularly important in the regressions.

Table 5: Pairwise Correlations: Continental Africa (IWI Sample)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) IWI	1						
(2) d_{digital}	-0.302	1					
(3) d_{power}	-0.285	0.578	1				
(4) OOKLA speed	0.137	-0.116	-0.152	1			
(5) Pop. (1mi^2)	0.468	-0.130	-0.100	0.062	1		
(6) d_{road}	-0.237	0.549	0.396	-0.078	-0.096	1	
(7) TT city 50k	-0.253	0.678	0.494	-0.111	-0.119	0.666	1

Notes: Distance variables are in $-\log(d{+}1)$ form (proximity); population and speed are in log form, as used in regressions. $d_{\text{digital}} = \min(d_{\text{OCID}}, d_{\text{ABWM}}, d_{\text{ITU}})$; $d_{\text{power}} = \min(d_{\text{lines}}, d_{\text{plants}}, d_{\text{points}})$. $N = 875{,}919$.

For the regression analysis, all distance variables enter as $-\log(d+1)$, so that higher values indicate greater proximity and all coefficients are expected to be positive. Population, building count, and internet speed enter in $\log(\cdot)$ form. We estimate six specifications. Columns (1)–(3) include the two-way interaction between digital and power proximity ($d_{\text{digital}} \times d_{\text{power}}$), progressively adding population and building controls (column 1), travel-time accessibility controls (column 2), and amenity and infrastructure controls (column 3). Columns (4)–(6) augment each specification with OOKLA mobile internet speed and its pairwise interactions with digital and power proximity, as well as their triple interaction, following the same control progression. All specifications include GADM 4.1 Level-1 regional fixed effects (641 units). Table 6 reports the results.

Across the African continent, we find strong evidence of complementarity between digital and power infrastructure. In column (1)—the baseline with population controls only—the digital proximity coefficient is 5.019 and the power proximity coefficient is 6.085, confirming that both infrastructure types are strongly and independently associated with higher settlement wealth. The central finding is the interaction term: the product of digital and power proximity enters with a positive and highly significant coefficient of 1.337 in column (1), and remains stable across the control progression, rising slightly to 1.459 in column (3) with the full control set. The positive and stable interaction coefficient indicates that the marginal return to digital proximity is higher in settlements that are also closer to power infrastructure, and vice versa—the defining feature of productive complementarity.

The magnitude is economically meaningful. In column (3)—the fully controlled specification—an approximate doubling in digital proximity raises the IWI by 3.618 points and a doubling of energy proximity raises it by 5.392 points. The interaction coefficient of 1.459 implies that this return is substantially amplified for settlements that also enjoy good power access: at median power proximity, doubling digital proximity yields 1.46 additional IWI points through interaction effects. This complementarity premium makes it comparable in size to the main effect of power proximity alone, implying that coordinated access to both infrastructure types generates returns well in excess of either type taken alone.

When we introduce OOKLA mobile internet speed in columns (4)–(6), the two-way Digital $\times$ Power interaction falls to 0.477–0.524, as part of the interaction effect is now captured by the OOKLA speed channel. Nonetheless, the interaction remains positive and highly significant, confirming that the complementarity between physical infrastructure proximity and power access is not fully explained by observed internet quality. The three-way interaction (OOKLA Speed $\times$ Digital $\times$ Power) is also significant at the 0.01 level with coefficients around 0.10, indicating that settlements near both infrastructure types benefit more when mobile data quality is high—a further layer of complementarity between the intensive and extensive margins of digital access.

Results are robust to progressively richer control sets. The within-R^2 rises from 0.443 in column (1) to 0.508 in column (3), indicating that infrastructure proximity and its interactions account for a substantial share of within-region settlement wealth variation. The interaction coefficient is stable across all three control specifications (1.337–1.459), suggesting it is not driven by omitted amenity or accessibility correlates of infrastructure placement. The sample covers 875,919 settlements across 641 GADM Level-1 administrative units.

Table 6: SSA Results—IWI—Fixed Effects

Dependent Variable:	International Wealth Index (Lee & Braithwaite, 2022)					
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Digital (−km to tower/node)	5.019***	4.197***	3.618***	2.888***	2.158***	1.452***
	(0.1460)	(0.1265)	(0.1277)	(0.4233)	(0.4013)	(0.3838)
Power (−km to line/plant/transformer)	6.085***	5.800***	5.392***	2.877***	2.492***	2.045***
	(0.2159)	(0.2129)	(0.1963)	(0.6271)	(0.6504)	(0.5910)
Digital × Power	1.337***	1.369***	1.459***	0.4772***	0.5219***	0.5241***
	(0.0560)	(0.0567)	(0.0574)	(0.1650)	(0.1733)	(0.1673)
OOKLA Speed (mobile speed in kb/s)				0.8149***	0.8042***	0.7941***
				(0.1297)	(0.1202)	(0.1162)
OOKLA Speed × Power				0.3729***	0.3841***	0.3909***
				(0.0783)	(0.0797)	(0.0736)
OOKLA Speed × Digital				0.2438***	0.2324***	0.2489***
				(0.0458)	(0.0437)	(0.0416)
OOKLA Speed × Digital × Power				0.1003***	0.0985***	0.1098***
				(0.0208)	(0.0212)	(0.0204)
Population Controls	Yes	Yes	Yes	Yes	Yes	Yes
Accessibility Controls	No	Yes	Yes	No	Yes	Yes
Infrastructure/Amenity Controls	No	No	Yes	No	No	Yes
Fixed-effects						
GADM 4.1 Level 1 (641)	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	875,919	875,919	875,919	875,919	875,919	875,919
R^2	0.75693	0.76589	0.78510	0.75733	0.76630	0.78550
Within R^2	0.44336	0.46386	0.50788	0.44427	0.46481	0.50877

*Clustered (GADM1) standard-errors in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: Population Controls include 1 square mile population estimates, building count and building area from Lee & Braithwaite (2022), and the 0-14 population share derived from GPW4. Accessibility Controls include travel time to cities $\geq$ 1 million, cities $\geq$ 50,000, any WPI port, or medium-large WPI ports from Nelson (2022). Infrastructure/Amenity Controls include distance to non-residential roads, other/public transport infrastructure, education and health facilities, other utilities (water/sewerage), essential shopping, and industrial plants—from the Africa Infrastructure Database of Krantz (2024).

The main results use the predicted IWI of Lee & Braithwaite (2022). Appendix Table 10 replicates the analysis on an independent, survey-based DHS wealth index for 38,904 DHS clusters across 34 SSA countries. The results are qualitatively and quantitatively consistent: the digital proximity coefficient ranges from 3.342 to 5.180 (columns 1–3), the power proximity coefficient from 3.555 to 4.604, and the interaction term from 1.088 to 1.208—closely mirroring the IWI magnitudes in Table 6. This argues against the concern that the main results are artifacts of the ML imputation process or driven by satellite-observable confounders that the IWI prediction and the infrastructure variables share. This finding is consistent with Krantz (2024), who show that causal ML estimates using the predicted IWI of Lee & Braithwaite (2022) align with results obtained using direct DHS measurement. We thus proceed to report causal ML results without conducting further robustness exercises against the DHS-based IWI.

5.3 Spatial Heterogeneity with Causal ML

The Local-Linear Causal Forest (LLCF, Section 4.2) applied to the full IWI sample of 875,674 settlements confirms positive and highly significant average partial effects (APEs) for all three treatments. The LLCF APE for digital proximity is 1.602 (SE = 0.013) IWI points per log-km unit and 1.778 (SE = 0.013) for power proximity—both highly statistically significant. The interaction APE is 0.406 (SE = 0.003), confirming that settlements jointly close to both infrastructure types earn a complementarity premium on top of the additive effects. Table 7 summarises the results.

The degree of treatment effect heterogeneity is substantial. Comparing doubly-robust APEs across the upper and lower halves of the estimated CATE distribution yields a high-minus-low gap of 2.326 IWI points for digital proximity (high: 2.765; low: 0.439) and 2.646 for power proximity (high: 3.101; low: 0.455). The interaction effect is similarly polarised: settlements in the upper CATE half average 0.773 interaction IWI points, compared to only 0.039 in the lower half—an eighteen-fold difference that underscores the spatial unevenness of energy-digital complementarity.

Table 7: Local-Linear Causal Forest—Average Partial Effects—IWI (Continental Africa)

Treatment	APE	SE	Local-Linear Causal Forest (LLCF) 95% CI	High CATE	Low CATE	High − Low
Digital (−km to tower/node)	1.602***	(0.013)	[1.576, 1.627]	2.765	0.439	2.326***
Power (−km to line/plant/transformer)	1.778***	(0.013)	[1.753, 1.803]	3.101	0.455	2.646***
Digital × Power	0.406***	(0.003)	[0.399, 0.412]	0.773	0.039	0.734***

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1. All p-values* < 0.001.

Notes: APE = Average Partial Effect estimated via doubly-robust DR scores (Athey & Wager, 2019). SE from variance of DR scores. High/Low CATE = mean DR score in upper/lower half of the CATE distribution; High − Low is their difference (SE = $\sqrt{\sigma^2_{\text{high}} + \sigma^2_{\text{low}}}$). Analysis uses 875,674 complete-case observations with within-district (GADM Level-1) demeaning prior to estimation. All treatments are $-\log(d+1)$ proximity measures. BLP calibration results in Appendix Table 14. Estimation uses `grf` (Athey et al., 2019) with honest subsampling, pilot LASSO for nuisance variable selection, and ridge-tuned local-linear corrections. See Section 4.2 for full methodology.

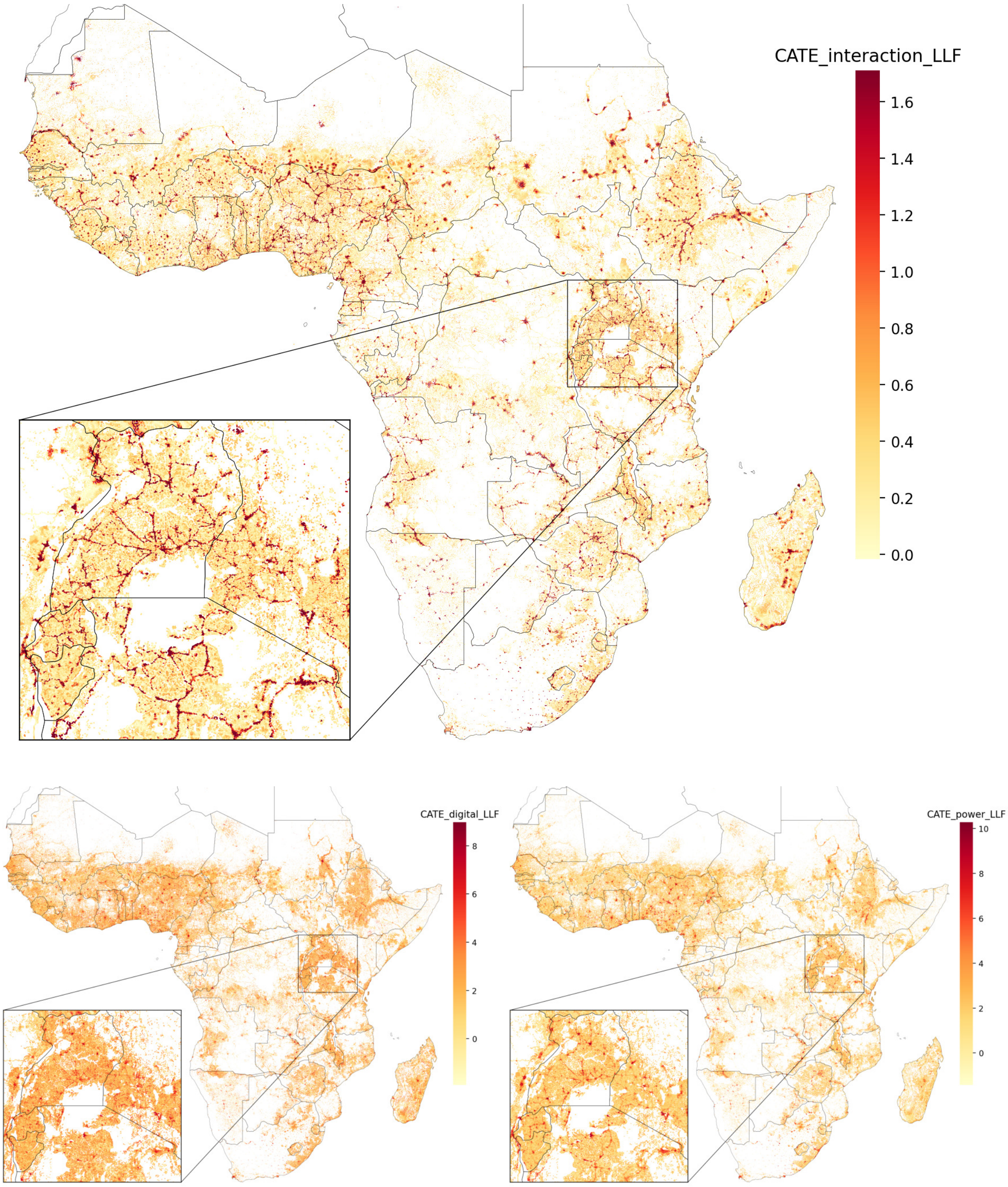
The LLCF APEs are lower than the linear fixed-effects coefficients (digital: 3.618; power: 5.392; interaction: 1.459; Table 6, column 3). This discrepancy is expected. The R-learner objective (equation 5) up-weights observations with high residualized treatment variance, concentrating estimation on settlements at the margin of infrastructure access and downweighting the long tails of the distance distribution that contribute disproportionately to the OLS coefficient. In addition, the causal forest averages locally within each covariate neighbourhood, whereas the FE regression imposes a global slope that partly absorbs nonlinear curvature in the distance-wealth relationship. Importantly, both estimators agree on sign, significance, and relative magnitude ordering ($\hat{\tau}_{\text{power}} > \hat{\tau}_{\text{digital}} > \hat{\tau}_{\text{interaction}}$ per-unit), and both yield highly significant interaction effects. The LLCF estimates are best interpreted as local partial effects for settlements with meaningful variation in infrastructure proximity, not population-weighted averages.

The Best Linear Predictor (BLP) calibration test provides further reassurance on the quality of the CAPE estimates (Appendix Table 14). The *differential.prediction* coefficients—measuring how well the LLCF ranks heterogeneity relative to a linear projection—are 0.975, 0.885, and 0.898 for the three treatments—all close to 1 and highly significant, indicating that the forest reliably identifies *which* settlements have above- vs. below-average treatment effects. The *mean.prediction* coefficients (0.710, 0.621, 0.684) below 1 are consistent with regularization-induced level shrinkage, a standard property of cross-fitted ridge estimators that corroborates the gap with the FE APEs. Compared to the standard Causal Forest (*differential.prediction*: 1.311, 1.195, 1.090), the LLCF coefficients are closer to 1, confirming that the local-linear corrections improve heterogeneity calibration. Further diagnostic plots are in Appendix 6.

A central finding emerges from the variable importance decomposition (Appendix Figure 6): *power infrastructure proximity is the single strongest predictor of the digital proximity CATE* (variable importance: 0.447 out of 1.0), and conversely, *digital infrastructure proximity is the single strongest predictor of the power proximity CATE* (importance: 0.591). This mutual cross-prediction is a nonparametric confirmation of complementarity, entirely free of parametric assumptions: the marginal return to digital proximity is largest precisely where power infrastructure is also nearby, and vice versa. Population density (`pop_wpop`) is the next most important driver in both cases but with substantially lower importance (0.21 and 0.07, respectively), followed by distance to road. For the interaction CATE, digital and power proximity terms together account for approximately 79% of total variable importance ($0.674 + 0.114$).

Figure 3 maps the local-linear CATEs spatially. The interaction CATE (top panel) reveals tight geographic concentration along urbanisation corridors: the highest complementarity returns cluster in the densely networked zones of West Africa (Nigeria, Ghana, Côte d'Ivoire, Senegal), East Africa (Kenya, Ethiopia, Tanzania, the Great Lakes region), and Southern Africa (Zambia, Mozambique). The digital and power CATEs (lower panels) are more spatially diffuse but similarly concentrated in areas of existing infrastructure density. Sparsely populated and remote areas show uniformly low CATEs, consistent with convexity of infrastructure returns: the complementarity premium materialises only where a baseline level of access to *both* networks already exists. From a policy perspective, this suggests that coordinated "bundled" rollout would yield the highest marginal returns in the partially connected belt of settlements, while the lowest-access areas may require larger structural investments before infrastructure complementarity can be fully exploited. Appendix Figure 4 shows similar results using the standard Causal Forest.

Figure 3: Conditional Average Partial Effects (CAPE) of Digital and Power Infrastructure Proximity Across SSA—Local-Linear Causal Forest



Notes: Settlement-level Conditional Average Partial Effects (CAPEs) estimated by the Local-Linear Causal Forest. *Top*: Interaction CATE ($\tilde{d}^{\text{digital}} \times \tilde{d}^{\text{power}}$), capturing the heterogeneous complementarity premium. *Bottom left*: Digital proximity CATE ($\tilde{d}^{\text{digital}}$). *Bottom right*: Power proximity CATE ($\tilde{d}^{\text{power}}$). Insets show the Great Lakes region (Uganda, Rwanda, western Kenya/Tanzania). CATEs reflect within-district variation (GADM Level-1 demeaning applied prior to estimation). Settlements with estimated CATE below the 1st percentile are shown in white.

5.4 Consistency Across Analytical Approaches

The continental and Liberia results, despite using different measurement approaches and spatial scales, point to a consistent finding: digital and energy infrastructure are complements in shaping local development outcomes. In the continental analysis, proximity to both types of infrastructure interacts positively to increase wealth. The quality of connectivity as measured by mobile internet speed, if included, proxies for a significant share of the effect of digital connectivity alone. In Liberia, the intensive margin of energy access (consumption per connection) also interacts with proximity to digital infrastructure (cell towers) to shape wealth. Although the two analyses employ slightly different specifications and cannot make strong causal claims, their alignment across geographic scales and empirical approaches provides encouraging evidence that energy-digital complementarity is a robust empirical phenomenon. The Local-Linear Causal Forest results provide a third pillar of evidence: even after nonparametrically controlling for the full covariate distribution, both infrastructure types retain positive and highly significant APEs, with treatment effect heterogeneity driven primarily by proximity to the complementary infrastructure type—a direct nonparametric signature of complementarity (Section 5.3).

6 Conclusion

This paper provides the first systematic, multi-scale empirical evidence of complementarity between energy and digital infrastructure in developing countries. Using continental-scale geospatial data from Africa and detailed subnational evidence from Liberia, we find strong positive interaction effects between proximity to energy and digital infrastructure on local economic development, as measured by settlement-level wealth indices.

Our results indicate that the complementarity is economically meaningful. At the continental level, the interaction coefficient between digital and power proximity is approximately 1.5 IWI points (Table 6, column 3), implying that the combined marginal return to having both infrastructure types nearby substantially exceeds the sum of their independent effects. In Liberia, the marginal effect of energy demand on wealth is about 36% lower at the median tower distance than at the cell site (Table 3), and the tower–grid interaction indicates complementary proximity patterns. These results are consistent across the IWI sample and the DHS robustness sample (Appendix Table 10), where the digital–power interaction remains positive and sizable across specifications (from about 0.33 to 1.21, depending on column). The alignment across two independent wealth measures and two spatial scales provides confidence that the finding is not an artifact of any single data source.

Our findings support a fundamental policy insight: infrastructure investments in energy and digital connectivity should not be pursued in isolation. The World Bank and other development organizations have long noted low cross-sector coordination in African infrastructure planning (Energy for Growth Hub, 2021). This paper provides empirical justification for "bundled" or spatially coordinated rollout: areas receiving new power infrastructure should be prioritized for simultaneous digital investment, and vice versa, since the marginal return to each is significantly higher in the presence of the other.

We acknowledge important limitations. The analysis is cross-sectional, and reverse causality—wealthy settlements may attract more infrastructure investment—cannot be ruled out. The rich covariate set and subnational fixed effects absorb substantial spatial confounding, but causal identification remains partial. Results should be read as reduced-form associations that are consistent with, but do not definitively prove, productive complementarity in a structural sense.

Causal inference will require dynamic data or quasi-experimental variation in the timing of infrastructure rollout. The LLCF results corroborate the linear interaction findings nonparametrically: APEs of 1.602 (digital) and 1.778 (power) IWI points per log-km unit are estimated with well-calibrated treatment effect heterogeneity, and the high-minus-low CATE gaps—exceeding 2 IWI points for both main treatments—indicate that marginal returns are roughly six times higher in the upper half of the CATE distribution than in the lower half. Crucially, power proximity is the single strongest nonparametric predictor of the digital CATE, and vice versa, directly confirming complementarity beyond the linear specification. Future research should study the mechanisms—income, TFP, firm entry, or digital inclusion—through which energy and digital infrastructure reinforce each other, and leverage quasi-experimental variation in infrastructure rollout timing to establish causal identification.

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Appendix

The appendix contains three sets of supplementary material. **(i)** Tables 8–10 replicate the continental Africa descriptive statistics, correlations, and fixed-effects regressions using a survey-based DHS wealth index in place of the machine-learning IWI, as a robustness check on the main outcome measure. **(ii)** Tables 11–13 provide Liberia robustness results using log-transformed predictors (semi-elasticities) and an alternative nightlight-based energy access proxy. **(iii)** Table 14 and Figures 4–6 provide causal ML diagnostics: BLP calibration tests for both the standard Causal Forest and LLCF estimators, standard Causal Forest CAPE spatial maps, CATE distribution plots, and variable importance rankings.

Sub-Saharan Africa: Robustness Using DHS-Based Wealth Index

This appendix presents robustness results using a DHS-based alternative to the machine-learning IWI from Lee & Braithwaite (2022). The DHS wealth index is constructed from DHS household survey PCA scores aggregated to cluster level, then rescaled to match the mean and standard deviation of the Lee & Braithwaite (2022) IWI. This provides a ground-truth comparison that does not rely on ML predictions from satellite imagery. The sample covers 39,002 DHS clusters across 34 SSA countries (surveys from 2010 onward). Tables 8–10 replicate the descriptive statistics, correlations, and main fixed-effects regressions for this alternative sample.

Table 8: Descriptive Statistics: Continental Africa (DHS Sample)

Variable	N	Mean	SD	Min	25%	Median	75%	Max
IWI (DHS-based, scaled)	39,002	20.7	14.2	-0.756	9.22	16.2	32.2	71.4
Distance to cell tower (km)	39,002	74.9	126.1	0.001	1.50	13.6	95.7	975.4
Distance to ABWM fiber node (km)	39,002	18.1	23.3	0.018	3.77	10.8	24.0	446.6
Distance to ITU node (km)	39,002	24.9	29.5	0.011	5.52	15.3	33.4	580.4
Distance to nearest digital infra. (km)	39,002	12.1	21.6	0.001	1.06	4.18	14.9	446.6
OOKLA Mobile internet speed (kb/s)	39,002	13,422	15,479	13.0	2,864	8,000	19,304	403,044
Distance to transmission line (km)	39,002	14.5	55.4	0.000	0.422	1.39	5.58	725.0
Distance to power plant (km)	39,002	78.1	75.6	0.048	22.0	55.4	112.0	666.3
Distance to nearest power infra. (km)	39,002	7.73	22.0	0.000	0.398	1.33	5.27	573.8
Population Controls								
Population (GPW4)	38,986	12,082	33,344	0.264	586.0	1,911	6,354	565,074
Population share aged 0–14	38,941	0.471	0.074	0.150	0.445	0.489	0.520	0.609
Accessibility Controls								
Travel time to city $\geq$ 50k (min)	39,002	93.4	147.4	0.000	11.9	46.0	112.0	4,582
Travel time to city $\geq$ 1M (min)	39,001	317.1	318.9	0.000	95.1	232.0	451.2	4,582
Travel time to any port (min)	39,001	499.6	386.2	1.31	190.7	428.5	729.0	4,598
Travel time to medium/large port (min)	39,001	766.8	703.0	1.31	343.5	609.3	968.6	4,912
Infrastructure/Amenity Controls								
Distance to road (km)	39,002	2.61	6.49	0.000	0.278	0.844	2.42	573.7
Distance to transport infra. (km)	39,002	11.0	14.5	0.004	1.42	5.86	15.3	575.0
Distance to education facility (km)	39,002	7.15	12.2	0.004	0.790	2.53	8.10	576.7
Distance to health facility (km)	39,002	3.52	6.03	0.002	0.851	2.05	4.22	575.5
Distance to other utilities (km)	39,002	19.6	27.4	0.004	2.88	10.8	25.0	577.3
Distance to essential shopping (km)	39,002	12.9	18.5	0.003	1.42	6.47	16.8	577.0
Distance to industrial plant (km)	39,002	18.5	24.5	0.003	2.16	9.76	25.0	577.3

Notes: Sample consists of 39,002 DHS cluster-level observations (surveys from 2010 onward) across 34 SSA countries. The IWI is constructed from DHS PCA wealth scores, rescaled to match the mean and standard deviation of the Lee & Braithwaite (2022) IWI. All other variables are matched to DHS cluster coordinates using the same sources as the IWI sample. Distance variables in raw km; in regressions these enter as $-\log(d+1)$. OOKLA mobile speeds spatially interpolated as in the main sample.

Table 9: Pairwise Correlations: Continental Africa (DHS Sample)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) IWI (DHS)	1						
(2) d_{digital}	-0.358	1					
(3) d_{power}	-0.252	0.548	1				
(4) OOKLA speed	0.098	-0.063	-0.070	1			
(5) Pop. (GPW4)	0.420	-0.173	-0.111	0.037	1		
(6) d_{road}	-0.254	0.433	0.355	-0.046	-0.117	1	
(7) TT city 50k	-0.290	0.589	0.425	-0.092	-0.205	0.504	1

Notes: All variables in $-\log(d+1)$ form (distances) or log form (population, speed), as used in regressions. $d_{\text{digital}} = \min(d_{\text{OCID}}, d_{\text{ABWM}}, d_{\text{ITU}})$; $d_{\text{power}} = \min(d_{\text{lines}}, d_{\text{plants}}, d_{\text{points}})$. $N =$ 38,904 (estimation sample).

Table 10: SSA Results—IWI DHS Sample—Fixed Effects

Dependent Variable:	International Wealth Index (DHS Surveys from 2010)					
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Digital (−km to tower/node)	5.180***	4.778***	3.342***	1.570**	1.573**	0.6575
	(0.1621)	(0.1644)	(0.1546)	(0.6257)	(0.6167)	(0.5750)
Power (−km to line/plant/transformer)	4.604***	4.377***	3.555***	2.277*	2.693**	2.451**
	(0.2996)	(0.2804)	(0.2407)	(1.229)	(1.164)	(0.9962)
Digital × Power	1.208***	1.151***	1.088***	0.3284	0.5106	0.6608**
	(0.1057)	(0.0931)	(0.0753)	(0.4037)	(0.3827)	(0.3355)
OOKLA Speed (mobile speed in kb/s)				0.9276***	0.8361***	0.6546***
				(0.1411)	(0.1344)	(0.1224)
OOKLA Speed × Power				0.2595*	0.1853	0.1197
				(0.1462)	(0.1365)	(0.1163)
OOKLA Speed × Digital				0.4060***	0.3600***	0.3025***
				(0.0703)	(0.0680)	(0.0639)
OOKLA Speed × Digital × Power				0.0981**	0.0704	0.0461
				(0.0482)	(0.0450)	(0.0395)
Population Controls	Yes	Yes	Yes	Yes	Yes	Yes
Accessibility Controls	No	Yes	Yes	No	Yes	Yes
Infrastructure/Amenity Controls	No	No	Yes	No	No	Yes
Fixed-effects						
Country × ADM1 Region (709)	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	38,904	38,904	38,904	38,904	38,904	38,904
R^2	0.75177	0.75710	0.77378	0.75252	0.75775	0.77423
Within R^2	0.50531	0.51593	0.54917	0.50681	0.51724	0.55007

*Clustered (GADM1) standard-errors in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: Population Controls include GPW4 and WorldPop population estimates from the Africa Infrastructure Database (AID) of Krantz (2024), and the 0-14 population share derived from GPW4. Accessibility Controls include travel time to cities $\geq$ 1 million, cities $\geq$ 50,000, any WPI port, or medium-large WPI ports from Nelson (2022). Infrastructure/Amenity Controls include distance to non-residential roads, other/public transport infrastructure, education and health facilities, other utilities (water/sewerage), essential shopping, and industrial plants—from the AID.

Liberia: Robustness Using Distance to Nightlights and Log Predictors (Semi-Elasticities)

This appendix reports two robustness checks for the Liberia regressions in Table 3. Table 11 re-estimates the four main specifications with all distance measures entered as $-\log(\text{km}+1)$ rather than $-$km, so coefficients are semi-elasticities with respect to log proximity. The core results carry through: energy demand and cell tower proximity are both positively associated with RWI, and the interaction between tower proximity and energy demand is positive and significant in column (2) (0.259). Table 12 replaces distance to the transmission grid with distance to the nearest nightlight centroid as an alternative, satellite-based proxy for energy access, using the same $-$km scaling as the main specification. Nightlight proximity enters with a positive and significant coefficient across all columns (0.004–0.009), the Tower $\times$ Energy demand interaction remains positive and significant (0.056 in column 2), and the Tower $\times$ Nightlight distance interaction (column 3) is also significant (0.001), confirming that settlements closer to both digital and energy infrastructure are wealthier. Within-R^2 rises to 0.140 once both interaction channels are included. Table 13 combines both robustness dimensions—nightlight proximity and log predictors—with qualitatively unchanged findings.

Table 11: Liberia Robustness—Relative Wealth Index—Log Predictors (Semi-elasticities)

Dependent Variable:	Relative Wealth Index (Chi et al., 2022)			
Model:	(1)	(2)	(3)	(4)
Variables				
Energy demand per connection [kWh/day]	0.6348***	0.9847***	0.6307***	0.5279
	(0.0884)	(0.1917)	(0.0897)	(0.3519)
$-$Distance to cell tower [km]	0.1005***	0.0185	0.1232***	0.1051
	(0.0090)	(0.0420)	(0.0240)	(0.0944)
$-$Distance to transmission grid [km]	0.0621***	0.0623***	0.0738***	0.1365***
	(0.0121)	(0.0122)	(0.0155)	(0.0500)
$-$Distance to the main road [km]	0.1067***	0.1082***	0.1082***	0.1088***
	(0.0101)	(0.0101)	(0.0101)	(0.0101)
$-$Distance to nearest hub [km]	0.0578***	0.0569***	0.0572***	0.0558***
	(0.0137)	(0.0137)	(0.0138)	(0.0136)
Population	0.0066***	0.0066***	0.0066***	0.0068***
	(0.0022)	(0.0022)	(0.0022)	(0.0022)
Healthcare facilities	0.0160	0.0141	0.0163	0.0136
	(0.0191)	(0.0190)	(0.0192)	(0.0189)
Education facilities	0.0504**	0.0481**	0.0479*	0.0469*
	(0.0242)	(0.0243)	(0.0245)	(0.0245)
Armed incidents within 50 km (2023-25)	0.0189*	0.0186*	0.0191*	0.0187*
	(0.0110)	(0.0112)	(0.0110)	(0.0111)
Interactions				
Tower × Energy demand		0.2594**		0.0609
		(0.1263)		(0.2790)
Tower × Grid distance			0.0083	0.0338
			(0.0075)	(0.0330)
Grid × Energy demand				-0.1933
				(0.1499)
Tower × Grid × Energy demand				-0.0800
				(0.1040)
Fixed-effects				
District (136)	Yes	Yes	Yes	Yes
Fit statistics				
Observations	13,644	13,644	13,644	13,644
R^2	0.286	0.287	0.287	0.288
Within R^2	0.168	0.169	0.169	0.170

*Clustered (district) standard-errors in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: Robustness to Table 3 with energy demand and all distance measures in natural logarithms of $-$km (negative kilometres), so semi-elasticities are with respect to proximity in log space; population, facility counts, and armed incidents remain in levels. Interactions use the same $-$km construction for tower and grid. District fixed effects (136 districts). Data sources as in Table 3.

Table 12: Liberia Robustness—Relative Wealth Index—Distance to Nightlights (Energy Access Proxy)

Dependent Variable:	Relative Wealth Index (Chi et al., 2022)			
Model:	(1)	(2)	(3)	(4)
Variables				
Energy demand per connection [kWh/day]	0.5063***	0.7032***	0.4562***	0.6400***
	(0.0680)	(0.0922)	(0.0649)	(0.1279)
−Distance to cell tower [km]	0.0158***	-0.0042	0.0305***	0.0129
	(0.0019)	(0.0058)	(0.0031)	(0.0108)
−Distance to nightlights [km]	0.0040***	0.0040***	0.0086***	0.0053*
	(0.0012)	(0.0012)	(0.0015)	(0.0029)
−Distance to the main road [km]	0.0335***	0.0343***	0.0371***	0.0375***
	(0.0074)	(0.0075)	(0.0082)	(0.0082)
−Distance to nearest hub [km]	0.0016*	0.0016*	0.0017**	0.0017**
	(0.0009)	(0.0009)	(0.0008)	(0.0008)
log(Population)	0.0151***	0.0150***	0.0135***	0.0135***
	(0.0022)	(0.0022)	(0.0021)	(0.0021)
log(Healthcare facilities+1)	0.0458**	0.0442**	0.0434**	0.0432**
	(0.0206)	(0.0206)	(0.0202)	(0.0198)
log(Education facilities+1)	0.0694***	0.0663***	0.0595**	0.0578**
	(0.0247)	(0.0247)	(0.0232)	(0.0231)
Armed incidents within 50 km (2023-25)	0.0022**	0.0020*	0.0021*	0.0020*
	(0.0010)	(0.0012)	(0.0011)	(0.0012)
Interactions				
Tower × Energy demand		0.0557***		0.0471*
		(0.0150)		(0.0276)
Tower × Nightlight distance			0.0009***	0.0003
			(0.0002)	(0.0004)
Nightlight distance × Energy demand				0.0087
				(0.0068)
Tower × Nightlight × Energy demand				0.0014
				(0.0012)
Fixed-effects				
District (136)	Yes	Yes	Yes	Yes
Fit statistics				
Observations	13,644	13,644	13,644	13,644
R^2	0.248	0.250	0.262	0.263
Within R^2	0.123	0.125	0.140	0.141

*Clustered (district) standard-errors in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: Robustness to Table 3 replacing distance to the transmission grid with distance to the nearest nightlight centroid, entered as −km like other distances (see Section 3). Energy demand in raw kWh/day; controls as in Table 3. District fixed effects (136 districts). Data sources as in Table 3.

Table 13: Liberia Robustness—Relative Wealth Index—Nightlights with Log Predictors

Dependent Variable:	Relative Wealth Index (Chi et al., 2022)			
Model:	(1)	(2)	(3)	(4)
Variables				
Energy demand per connection [kWh/day]	0.5538***	0.7800***	0.5058***	0.2684
	(0.0834)	(0.1958)	(0.0821)	(0.4221)
−Distance to cell tower [km]	0.0944***	0.0417	0.2157***	0.2793**
	(0.0090)	(0.0422)	(0.0282)	(0.1208)
−Distance to nightlights [km]	0.0686***	0.0680***	0.1344***	0.1625***
	(0.0120)	(0.0120)	(0.0174)	(0.0587)
−Distance to the main road [km]	0.1110***	0.1120***	0.1190***	0.1189***
	(0.0105)	(0.0104)	(0.0102)	(0.0103)
−Distance to nearest hub [km]	0.0328**	0.0326**	0.0297*	0.0298*
	(0.0153)	(0.0154)	(0.0153)	(0.0152)
Population	0.0065***	0.0065***	0.0054**	0.0054**
	(0.0021)	(0.0021)	(0.0021)	(0.0021)
Healthcare facilities	0.0233	0.0220	0.0164	0.0170
	(0.0196)	(0.0195)	(0.0192)	(0.0189)
Education facilities	0.0456**	0.0443*	0.0309	0.0313
	(0.0226)	(0.0227)	(0.0222)	(0.0221)
Armed incidents within 50 km (2023-25)	0.0188	0.0187	0.0224	0.0224
	(0.0173)	(0.0175)	(0.0162)	(0.0161)
Interactions				
Tower × Energy demand		0.1671		-0.1868
		(0.1266)		(0.3620)
Tower × Nightlight distance			0.0510***	0.0722
			(0.0103)	(0.0447)
Nightlight distance × Energy demand				-0.0800
				(0.1628)
Tower × Nightlight × Energy demand				-0.0616
				(0.1380)
Fixed-effects				
District (136)	Yes	Yes	Yes	Yes
Fit statistics				
Observations	13,644	13,644	13,644	13,644
R^2	0.286	0.286	0.293	0.293
Within R^2	0.167	0.168	0.176	0.176

*Clustered (district) standard-errors in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: Combines the nightlight proxy (Table 12) with energy demand and all distances in natural logarithms of −km; population, facility counts, and armed incidents remain in levels. Interactions use the same −km construction for tower and nightlights. District fixed effects (136 districts). Data sources as in Tables 3 and 12.

Continental Africa: Causal ML Diagnostics and Standard Causal Forest Results

This section provides supplementary diagnostic material for the Local-Linear Causal Forest analysis in Section 5.3, together with results from the standard Causal Forest (CF) estimator for comparison. Table 14 reports BLP calibration tests for both estimators; Table 15 reports Standard CF APEs; Figures 4–6 show spatial CATEs, CATE distributions, and variable importance rankings.

Table 14: Best Linear Predictor (BLP) Calibration Tests—Causal Forest and Local-Linear Causal Forest

		mean.prediction			*differential.prediction*		
Treatment	Estimator	Estimate	Std. Error	t value	Estimate	Std. Error	t value
Digital (−km to tower/node)	Causal Forest	0.862	(0.009)	92.2	1.311	(0.015)	87.1
	Local-Linear CF	0.710	(0.007)	98.9	0.975	(0.011)	90.3
Power (−km to line/plant/transformer)	Causal Forest	0.958	(0.010)	100.0	1.195	(0.014)	88.4
	Local-Linear CF	0.621	(0.006)	105.6	0.885	(0.009)	94.5
Digital × Power	Causal Forest	0.874	(0.010)	89.8	1.090	(0.010)	104.6
	Local-Linear CF	0.684	(0.007)	100.5	0.898	(0.008)	111.9

All p-values $< 10^{-200}$ *(one-sided t-tests; HC3 standard errors).*

Notes: Best Linear Projection of the doubly-robust scores $\hat{\Gamma}_i$ on the mean and differential CATE predictions (Chernozhukov et al., 2018; Athey & Wager, 2019). *mean.prediction* ≈ 1 indicates unbiased mean-level estimation; *differential.prediction* ≈ 1 indicates well-calibrated treatment effect heterogeneity. Values below 1 for *mean.prediction* reflect regularization-induced level shrinkage from the ridge-tuned local-linear corrections. The LLCF *differential.prediction* coefficients (0.975, 0.885, 0.898) are closer to 1 than the corresponding standard CF coefficients (1.311, 1.195, 1.090), indicating that the local-linear corrections improve heterogeneity calibration.

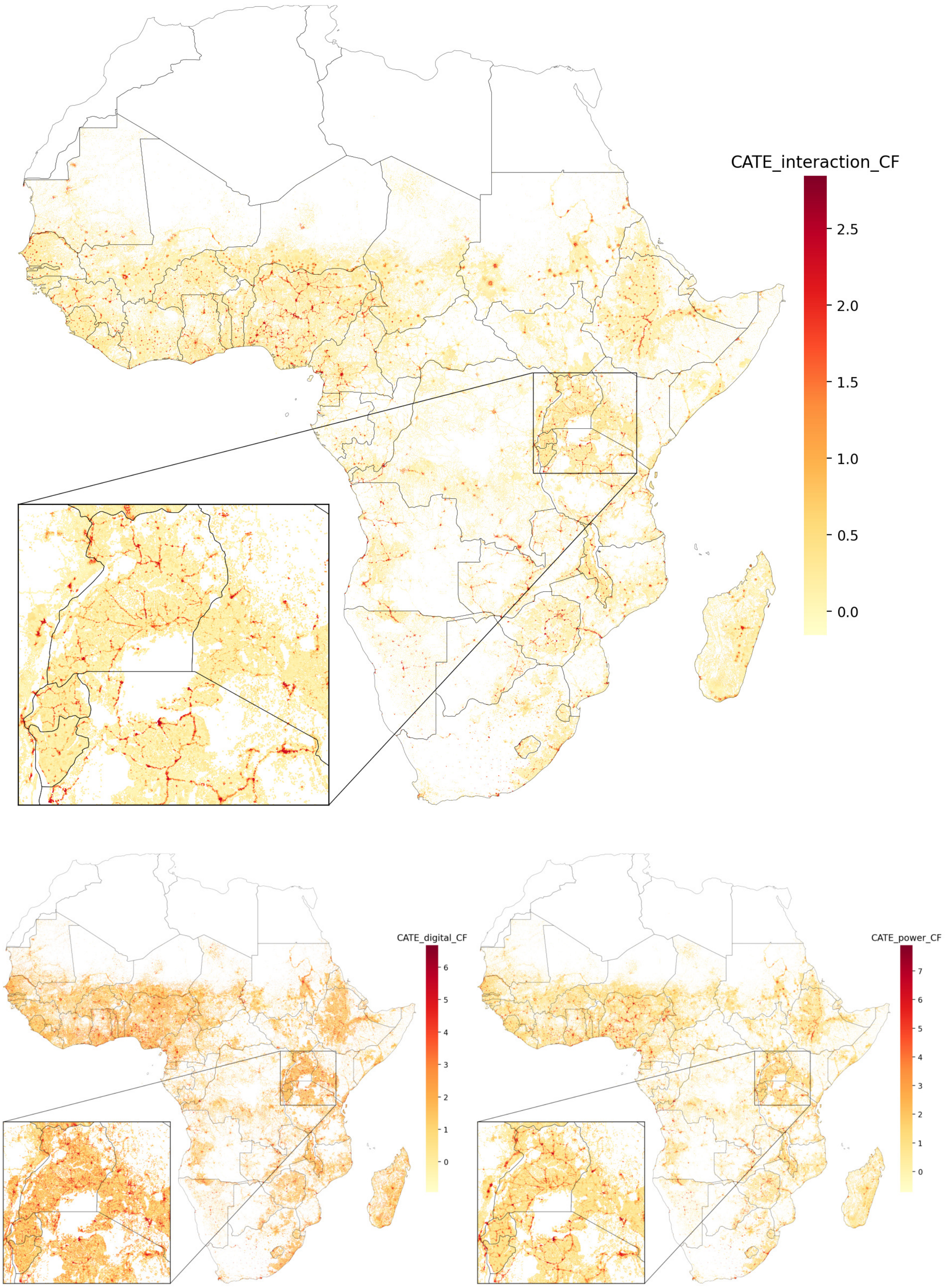
Table 15: Standard Causal Forest—Average Partial Effects—IWI (Continental Africa)

	Standard Causal Forest (CF)					
Treatment	APE	SE	95% CI	High CATE	Low CATE	High − Low
Digital (−km to tower/node)	1.504***	(0.013)	[1.478, 1.529]	2.563	0.444	2.119***
Power (−km to line/plant/transformer)	1.641***	(0.013)	[1.615, 1.667]	2.777	0.505	2.271***
Digital × Power	0.372***	(0.003)	[0.365, 0.378]	0.707	0.037	0.670***

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1. All p-values* < 0.001.

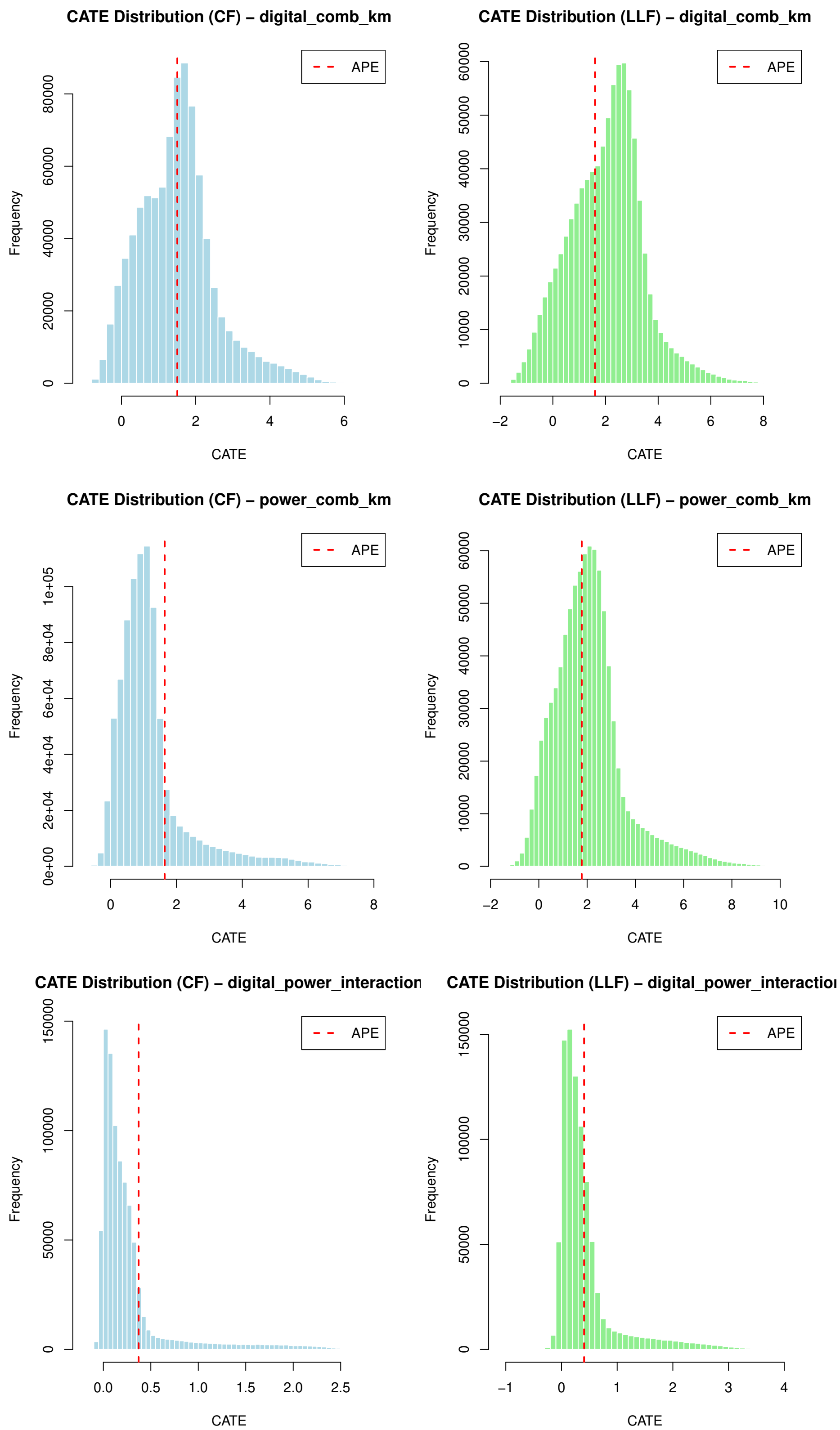
Notes: Standard (non-local-linear) Causal Forest APEs; otherwise the same estimation procedure as Table 7. BLP calibration results in Appendix Table 14. The standard CF slightly underestimates APEs relative to LLCF because local-linear corrections reduce shrinkage in the leaf predictions, yielding better-calibrated level estimates.

Figure 4: Conditional Average Partial Effects (CAPE) Across SSA—Standard Causal Forest



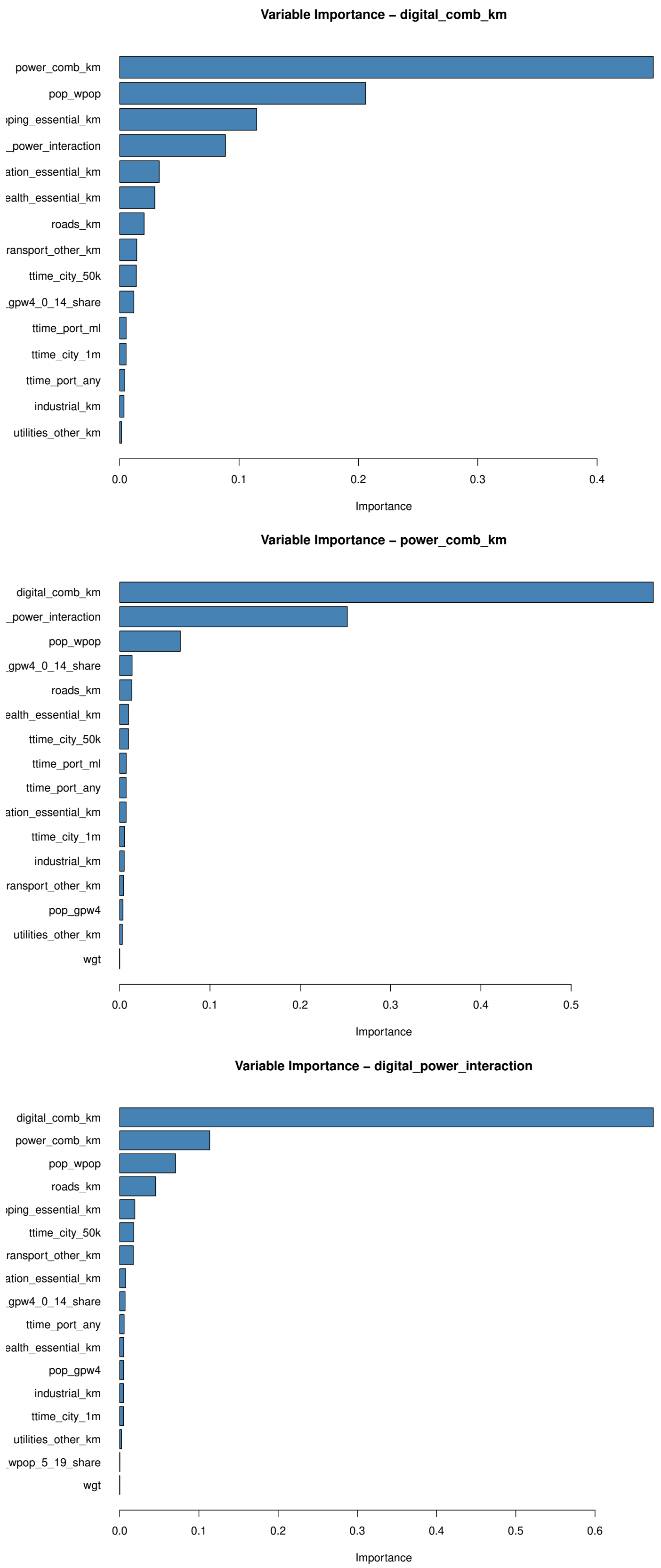
Notes: Spatial CATEs from the standard Causal Forest (without local-linear corrections), for comparison with the LLCF maps in Figure 3. Layout and sample identical to Figure 3.

Figure 5: CATE Distributions—Local-Linear Causal Forest (Continental Africa)



Notes: Distribution of settlement-level CAPE estimates from the Local-Linear Causal Forest for digital proximity (top), power proximity (middle), and the Digital × Power interaction (bottom). Distributions are right-skewed and predominantly positive, consistent with concavity of the distance-wealth relationship. Vertical dashed lines indicate the APEs reported in Table 7.

Figure 6: Variable Importance Rankings—Final LLCF (Continental Africa)



Notes: Variable importance from the final LLCF for digital proximity (left), power proximity (centre), and the Digital × Power interaction (right). Importance is normalised to sum to 1.0 across all selected heterogeneity covariates. Power proximity is the leading predictor of the digital CATE and vice versa, providing direct nonparametric confirmation of energy-digital complementarity. Population density (`pop_wpop`) is the second most important driver for both main treatment CATEs.