Benchmarking Utility Performance in Low- and Middle-Income Countries: How Market Structures Influence Efficiency and Electricity Access

Edgar Aguilar

Substantial Research Paper

Master of Arts in International Economic Relations: Quantitative Methods

School of International Service (SIS)

American University

May 7, 2025

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Abstract

This paper examines how power market structures and governance arrangements shape the operational efficiency of electric utilities in low- and middle-income countries, and whether this efficiency is linked to national electricity access outcomes. Using Data Envelopment Analysis (DEA), the study benchmarks 49 utilities across 37 countries based on core input and output indicators. It then compares efficiency across different market models—including vertically integrated systems, single buyer frameworks, and competitive markets—and governance features such as regulation, unbundling, and the presence of independent power producers. Finally, the analysis estimates regression models linking utility-level efficiency to national electricity access rates in 2022. Results show that utilities in more liberalized and better-regulated environments tend to be more efficient, and that higher efficiency is significantly associated with greater electricity access, even after controlling for income and demographic factors. The findings underscore the importance of performance benchmarking and institutional quality in advancing universal, reliable, and affordable energy access.

Introduction

Expanding reliable and affordable electricity access remains a critical challenge in many low- and middle-income countries. While infrastructure investment is essential, the performance of electric utilities—particularly in distribution—plays a central role in shaping access outcomes. This paper benchmarks the operational efficiency of 49 utilities across 37 countries using Data Envelopment Analysis (DEA) and examines how different power market structures and governance arrangements influence utility performance. It further explores whether higher efficiency is associated with improved national electricity access, offering new evidence to inform utility reform and energy access strategies.

Motivation

Reliable and affordable electricity access is fundamental to economic development, underpinning industrial production, job creation, and the delivery of basic services such as health and education. Yet, as of 2023, an estimated 750 million people around the world still lack access to electricity, with the majority residing in low- and middle-income countries (LMICs), and specifically in Africa (International Energy Agency (IEA), 2024).This persistent energy access gap continues to hinder poverty reduction and broader development goals.

At the center of this challenge lies the performance of power utilities—entities responsible for the generation, transmission, and distribution of electricity. These utilities serve as the backbone of electrification efforts and are critical to both universal energy access and the broader global energy transition. Utilities have been described as the “stewards of the world’s power grids”, and they are uniquely positioned to lead efforts to decarbonize electricity supply while simultaneously expanding access (Loew & Kramskaya, 2024). However, achieving these twin goals hinges on utilities being operationally efficient, financially sustainable, and well-governed.

Many utilities in LMICs fall short of these requirements. Fewer than 40 percent of utilities globally collect enough revenue to cover their operating and debt service costs—the bare minimum for financial viability. The situation is even more dire in lower-income settings: only 28 percent of utilities in LICs and LMICs meet this threshold (Loew & Kramskaya, 2024). Chronic underperformance stems from a range of systemic issues, including high technical and commercial losses, inefficient billing and metering systems, poor customer payment collection, and mismatches between high costs of supply and politically constrained tariffs.

These inefficiencies do not just limit service delivery—they also impose a heavy burden on public finances. Many underperforming utilities rely on recurrent government bailouts or budgetary transfers to remain solvent. In doing so, they divert scarce fiscal resources away from other development priorities. In some countries, such as Honduras, these subsidies have become macroeconomically significant (Aguilar & Rivera, 2023). The state-owned utility Empresa Nacional de Energia Electrica (ENEE) has accumulated debt equivalent to roughly 9 percent of the country's GDP and consistently depends on government support to fund its operations and liabilities (Standard and Poors, 2024). This dynamic creates a fiscal trap in which losses and inefficiencies in the power sector become a persistent drag on national budgets, while simultaneously constraining the utility's ability to expand service or invest in system upgrades.

This pattern is not unique to Honduras. Across many LMICs, utilities operate under high costs—often more than 20 cents per kilowatt-hour—yet are unable to recover these costs due to inefficiencies, weak regulation, or affordability constraints among customers. These structural imbalances often result in utilities slashing investments and maintenance, further degrading service reliability and limiting future access expansion (Loew & Kramskaya, 2024).

Compounding these financial and operational challenges is the relatively outdated understanding of how different power market structures impact utility performance. The late 1990s saw a wave of reforms aimed at liberalizing electricity sectors through vertical unbundling, the introduction of competition, and private sector participation. However, in many regions, the outcomes of these reforms remain poorly monitored or poorly understood today, especially as some countries have reversed earlier reforms or adopted hybrid governance models (Maurya, 2020). The lack of up-to-date, systematic benchmarking across utilities and market structures limits policymakers' ability to identify what works and to target reforms accordingly.

There is thus a pressing need to systematically benchmark utility performance across LMICs. Doing so can illuminate which utilities are performing well and why, and which are lagging behind. This knowledge is essential to share best practices, tailor policy recommendations, and inform investment decisions. Moreover, improving utility performance is not merely a technical goal—it is a foundational step toward achieving universal electricity access (Sustainable Development Goal 7) and meeting climate commitments through a just and sustainable energy transition.

Analytical Approach and Data Sources

This study investigates how power market structures influence the efficiency of electric utilities and, in turn, how utility performance relates to national electricity access outcomes. The central research question guiding this work is: How do market structures shape utility efficiency and electricity access across low- and middle-income countries?

To address this question, the analysis follows a three-stage empirical strategy: (1) benchmarking utility performance using frontier efficiency techniques; (2) analyzing the relationship between market structures and efficiency scores; and (3) examining the link between utility efficiency and electricity access using regression models.

Approach

1. *Benchmarking Utility Efficiency with DEA:*

The first step involves applying Data Envelopment Analysis (DEA), a non-parametric linear programming method that assesses how efficiently utilities transform inputs into outputs relative to their peers. DEA identifies a performance frontier formed by the most efficient utilities in the dataset and calculates an efficiency score for each utility ranging between 0 and 1. Utilities on the frontier score 1.00, while less efficient firms receive lower values, indicating potential for improvement (Pahwa, Feng, & Lubkeman, 2002)

2. *Comparing Efficiency Across Market Structures*

After calculating efficiency scores, the study compares utility performance across different power market structures and institutional features. To do so, utilities are grouped by the characteristics of the electricity sector in their respective countries. Using box plots, I visualize the distribution of DEA scores across key institutional variables, including power market structure type, presence of a sector regulator, existence of an independent power producer (IPP), and whether the system has undergone any form of unbundling reform. These visual comparisons help identify whether certain structural or regulatory arrangements are more consistently associated with higher utility efficiency.

3. Linking Utility Efficiency to Electricity Access

Finally, I assess whether utility efficiency is associated with improved national electricity access. I estimate a cross-sectional regression with electricity access in 2022 (percentage of the population) as the dependent variable and DEA efficiency scores as the main explanatory variable. Control variables include the natural logarithm of GDP per capita (averaged from 2012–2022) and population density in 2022, to account for differences in economic development and geographic service delivery complexity. Box plots are also used to visually support the regression findings.

Data Sources

The study draws on three primary datasets, each offering complementary insights at the utility and country levels.

1. Utility Performance and Behavior Today (UPBEAT) Dataset

The UPBEAT database, developed by the World Bank, compiles standardized financial and operational performance indicators for 190 electric utilities across 93 countries between 2012 and 2022. It includes 44 indicators covering areas such as tariffs, cost recovery, losses, billing, debt levels, and profitability. Data are primarily sourced from utility financial statements, regulator reports, and ministry publications. The dataset provides cleaned and harmonized values that ensure comparability across jurisdictions and time periods (World Bank, 2024).

Utilities in UPBEAT are classified by their function—generation (G), transmission (T), distribution (D), or vertically integrated (VIU)—with some combining multiple roles. For this study, I focus on utilities that perform distribution operations, whether as standalone distributors or as part of vertically integrated firms. I extract key input and output variables from the latest available year for each utility to calculate DEA efficiency scores.

2. Global Power Market Structure Database

To characterize national power market structures, I use the Global Power Market Structure Database, which tracks institutional and structural reforms across 230 countries between 1989 and 2024. The database defines power market structure as the overarching institutional, financial, and regulatory design used to organize the provision of electricity in a country (Akcura, 2024). For this analysis, I group countries into one of three broad categories:

i. **Vertically Integrated Utility (VIU)**: A single entity controls all major segments of the supply chain—generation, transmission, and distribution.
ii. **Single Buyer Model (SBM)**: While generation may be opened to private producers, a legally designated single buyer—usually a national utility or transmission operator—holds exclusive rights to purchase all electricity and resell it to distributors or consumers.
iii. **Wholesale–Retail Competition (WRC)**: Markets where competition exists in both generation and retail. Generators compete to sell power through organized markets or bilateral contracts, and end-users (residential, commercial, industrial) can choose their electricity supplier. In this study, I consolidate wholesale and retail models into a single WRC category, as they typically operate in tandem (Akcura, 2024).

In addition to market structure, the database provides information on three other institutional characteristics:

i. **Unbundling Status**: I record a binary "Yes/No" value indicating whether any form of unbundling has occurred in the national power sector. The types of unbundling considered include:

- *Accounting unbundling*: Separate financial records for different utility segments.
- *Functional unbundling*: Operational independence across segments (e.g., different teams or units).
- *Legal unbundling*: Creation of legally distinct companies within the same holding structure.
- *Independent Transmission Operator (ITO)* and *Independent System Operator (ISO)*: Independent entities manage transmission operations, either with or without asset ownership.
- *Ownership unbundling*: Complete separation of ownership between network and competitive segments (Akcura, 2024).

For this exercise, a country is coded as "unbundled" if any of these forms of structural separation are implemented in the electricity sector by the year corresponding to the utility performance data.

ii. **IPP Presence:** I create a binary indicator reflecting whether an independent power producer (IPP) is operational in the country as of the year observed in the UPBEAT utility data. IPPs are private or semi-private firms that own and operate generation assets independently of the regulated utility (Akcura, 2024).

iii. **Sector Regulator Presence**: These variable captures whether an independent electricity regulator has been established in the country by the year of observation. These agencies are typically responsible for tariff-setting, licensing, infrastructure planning oversight, and monitoring utility behavior (Akcura, 2024). A binary "Yes/No" coding is applied based on whether a functioning regulator was in place.

These institutional features provide a framework for assessing how structural and regulatory designs shape the behavior and performance of utilities across different national contexts.

3. *Electricity Access Data*

National electricity access is measured using World Bank data on the percentage of the population with access to electricity in 2022. This indicator reflects the availability of grid-based or off-grid electricity services and is collected from household surveys, national energy ministries, and development agencies. It serves as a consistent and widely used proxy for energy poverty (World Bank, 2023). In this study, the variable is used as the dependent variable in the regression analysis linking utility efficiency to broader development outcomes, and in descriptive box plots that compare access rates across different utility efficiency groups.

By integrating performance data from utilities with rich institutional context and national access metrics, this study provides a multi-level analysis of how governance and market structure affect outcomes in the electricity sector. It also revisits questions about the effectiveness of power sector reforms, offering new empirical insights two decades after the height of liberalization efforts in many developing economies.

In the next section, I outline the methodological foundations of the study—explaining the logic of Data Envelopment Analysis (DEA), the use of box plots, and the structure of the regression models. The section that follows then details how these methods were applied in practice, including the specific model specifications tested, the process for selecting input and output variables, and the rationale for the analytical choices made during implementation.

Methodology

Comparing the performance of electric utilities across countries is inherently complex. Utilities differ in size, operating context, and data availability. Some perform well on certain indicators but poorly on others, while many lack complete records across key metrics. As such, conventional one-to-one comparisons risk obscuring the multidimensional nature of utility performance. To streamline comparison and produce a standardized performance indicator, this study applies Data Envelopment Analysis (DEA), a well-established benchmarking method that has been widely used in infrastructure sectors, including electricity distribution (Susanty, Purwanggono, & Al Faruq, 2022).

DEA enables the construction of a single, composite efficiency score for each utility based on how well it transforms inputs into outputs relative to its peers. This serves as the foundational performance metric for the analysis. The study then builds on this benchmark in two additional steps: first, by examining how performance varies across market structure categories using visual tools; and second, by evaluating whether utility efficiency is associated with electricity access outcomes through regression analysis. The specific implementation of these methods—model specifications, input/output choices, and estimation procedures—is described in the following section.

Data Envelopment Analysis (DEA)

Data Envelopment Analysis (DEA) is a non-parametric linear programming method used to evaluate the efficiency of comparable entities—referred to as decision-making units (DMUs)—by comparing their input-output ratios to a best-practice production frontier. In this study, each electric utility is treated as a DMU. Those that lie on the efficiency frontier receive a score of 1.00 and are deemed fully efficient; those below it have room for improvement (Pahwa, Feng, & Lubkeman, 2002).

In this analysis I apply the Constant Returns to Scale (CRS) model developed by Charnes, Cooper, and Rhodes (1978)—commonly referred to as the CCR model. The CRS assumption implies that outputs increase proportionally with inputs, an appropriate assumption when comparing utilities operating under broadly similar cost structures and technical conditions. The study also uses an input-oriented specification, which emphasizes minimizing inputs (e.g., labor, capital) while maintaining output levels (e.g., customers served, revenue). This orientation is particularly relevant in the context of electric utilities, where operational efficiency and cost control are key policy concerns (Pahwa, Feng, & Lubkeman, 2002).

A critical step in DEA is the selection of input and output variables. While there is no universally agreed-upon standard for this selection, there is a well-established body of literature offering guiding principles and empirical precedents. The most influential sources reviewed include:

i. Santos et al. (2011) and Jamasb and Pollitt (2001), which suggest that typical inputs for electricity distribution utilities include workforce size, total assets, transformer capacity, and network length, while outputs often include the number of customers, units of energy delivered, and size of service area (Santos, Armando, & Rosado, 2011) (Jamasb & Pollit, 2000). These studies stress the importance of avoiding ratio variables (e.g., cost per customer), which can distort DEA outcomes.

ii. Dashti et al. (2013) and Giannakis et al. (2005), which emphasize the relevance of including system losses and capacity indicators, and caution that DEA performance deteriorates when the number of variables exceeds the discriminatory power of the model (Dashti, Yousefi, & Moghaddam, 2013) (Giannakis, Jamasb, & Pollit, 2005).

iii. Dyson et al. (2001), which provides the frequently cited rule-of-thumb that the number of DMUs (utilities) should be at least three times the total number of input and output variables ($n \geq 3[m + s]$) to maintain valid comparisons and prevent oversaturation (Dyson, et al., 2001).

iv. The super-efficiency DEA study published in Springer (2018) and the Soft Systems Methodology approach in Elsevier (2022), both of which guided the methodological choices made in this research (Bongo, Ocampo, Magallano, Manaban, & Ramos, 2018) (Susanty, Purwanggono, & Al Faruq, 2022). These papers reinforce the use of physical infrastructure, expenditure, and customer coverage metrics, and support the use of DEA for benchmarking utilities with varied service conditions and cost structures.

This study closely follows the model design proposed in *Performance Evaluation of Electric Distribution Utilities Based on Data Envelopment Analysis* (IEEE, 2004), which serves as the core methodological reference. The paper demonstrates how DEA can benchmark utility performance across countries using financial and operational data, justifying the input-oriented CRS model given the comparable nature of utilities as production units (Pahwa, Feng, &

Lubkeman, 2002). The structure of this model—its objective function, constraints, and benchmarking interpretation—is replicated here using the UPBEAT dataset.

Visual Analysis: Box Plots by Market Structure

Following the calculation of DEA scores, utilities are grouped according to key market structure and institutional characteristics. To examine how utility efficiency varies across different governance environments, box plots are used to visually represent the distribution of DEA scores across Market Structure Type (Vertically Integrated, Single Buyer Model, Wholesale–Retail Competition); Regulator Presence (Yes/No); Independent Power Producer (IPP) Operational (Yes/No); and Unbundling of Sector (Yes/No). Each plot summarizes DEA scores by group, offering a visual starting point to explore links between institutional structures and utility performance.

Regression Analysis: Linking Efficiency and Electricity Access

The final component of the methodology involves testing whether utility performance, as measured by DEA, is associated with broader development outcomes—specifically, electricity access at the national level. For this, DEA efficiency scores are aggregated from the utility level to the country level. In countries with multiple utilities, a weighted average is computed using each utility's share of total customers as the weight. This ensures that larger utilities contribute proportionally more to the country's aggregate efficiency score.

The empirical strategy involves estimating an ordinary least squares (OLS) regression where the dependent variable is access to electricity (% of the population, 2022). DEA-based efficiency scores serve as the key explanatory variable. Additional control variables include log GDP per capita (average 2012–2022) to account for income effects and population density

(2022) to control for geographic service complexity. In one specification, the urban population share is also included to further isolate urban–rural differences in electrification.

To complement the regression, the study also creates box plots that group countries by efficiency quartiles—ranging from fully efficient utilities (score = 1.00) to lower-performing groups. These visualizations provide an intuitive representation of the relationship between utility performance and electricity access.

Implementation of the Methodology

This section details how I selected and refined input-output variables, applied the DEA model, and constructed the final dataset to explore its association with electricity access and market structure.

Data Envelopment Analysis (DEA)

1. Adjusting the Model

The selection of input and output variables is critical in DEA, as they determine how utilities are compared in transforming resources into outcomes. Based on the literature reviewed on DEA applications in the electricity sector, consultations with experts, and constraints posed by data availability in the UPBEAT dataset, I developed an approach grounded in best practice. The study "Input-Output Performance Efficiency Measurement of an Electricity Distribution Utility Using Super-Efficiency Data Envelopment Analysis" explicitly notes that there is no definitive standard for variable selection in DEA (Bongo, Ocampo, Magallano, Manaban, & Ramos, 2018). Instead, it identifies guiding principles that I applied throughout this analysis.

In my first application of the model, I followed the approach used by Pahwa, Feng, and Lubkeman (2003) in their study “Performance Evaluation of Electric Distribution Utilities Based on Data Envelopment Analysis”. Like their approach, I implemented a DEA CCR model using linear programming to solve an optimization problem for each utility. However, while Pahwa et al. focused on capital and O&M expenses as inputs and total electricity sales as output, I used different inputs and outputs that better reflected the UPBEAT dataset and cross-country data availability.

Following recommendations from Jamasb and Pollitt (2001), Santos et al. (2011), and Dashti et al. (2013), I ensured that the number of utilities analyzed was at least three times the total number of inputs and outputs, preventing overfitting and maintaining meaningful efficiency rankings. Additionally, Omrani et al. (2015) cautioned against using too many variables, which could distort efficiency scores, while Giannakis et al. (2005) advised avoiding ratio-based inputs with composite indicators that complete inputs and outputs.

I initially selected three inputs—number of employees, total system length, and total assets—and three outputs—operating and debt service cost recovery (excluding subsidies), revenue, and number of customers. However, further testing showed that total system length was highly correlated with total assets (r = 0.64), and cost recovery indicators between cash basis and billed basis presented tradeoffs. Based on both conceptual and empirical considerations, these were revised in subsequent models.

2. *Evolution to Model 2 and Model 3*

To enhance the robustness of the analysis, I developed two additional versions of the DEA model beyond the initial specification. In Model 2, rather than relying on the latest available year for each utility, I calculated the average value of each input and output variable over the 2012–2022 period. This approach enabled a more stable representation of utility performance, reducing sensitivity to annual fluctuations, and allowed for a cleaner cross-sectional comparison. To maintain temporal consistency, I aligned this model with each country's market structure as of 2012, under the premise that structural reforms may require time to affect operational outcomes.

Building on insights from both previous specifications, the final and preferred version—Model 3—reflected a set of methodological refinements and practical trade-offs. The model retained two inputs—Number of employees and Total assets—and selected three outputs: Net profit margin, Number of customers, and Transformed system losses. I excluded Total system length in this version due to its high correlation with Total assets (correlation coefficient ≈ 0.64). Since the physical size of a utility's infrastructure is already embedded within the valuation of its assets, including both variables would have introduced redundancy without adding explanatory value.

For financial performance, I replaced the cost recovery metrics used in earlier models with Net profit margin. While the UPBEAT dataset includes several cost recovery indicators, each presented limitations. The operating and debt service cost recovery (cash basis) measure showed high inter-annual variability and was unavailable for many utilities, making it unreliable for cross-country analysis. The billed basis version, on the other hand, does not adequately capture whether utilities are effectively collecting revenues or sustaining operations, particularly in lower-income contexts. In contrast, net profit margin offers a more comprehensive, stable, and consistently reported indicator, capturing both revenue sufficiency and cost management. It also facilitates better comparability across utilities operating under different tariff structures and subsidy regimes.

The inclusion of system losses as an output variable is rooted in its widespread use in energy sector literature as a proxy for operational efficiency. High losses—whether technical (e.g., outdated infrastructure) or non-technical (e.g., theft, inaccurate metering)—are symptomatic of weak utility performance (Dashti, Yousefi, & Moghaddam, 2013). Since DEA requires outputs to be represented as desirable quantities to be maximized, I transformed the indicator using the formula (1 - losses), a standard technique in DEA applications to convert undesirable outputs into efficiency-enhancing metrics.

This final configuration struck a practical balance between data availability, methodological rigor, and alignment with sector best practices, enabling efficiency scores to be calculated for 49 utilities across 37 countries, using 10-year averages for all inputs and outputs. Importantly, results across all three models—despite minor variation in individual scores—were broadly consistent. The relative ranking of high- and low-performing utilities remained stable, underscoring the robustness of the DEA methodology when applied to a diverse global sample.

3. DEA Implementation in R

I implemented the final model using the `Benchmarking` package in R. The selected inputs and outputs were converted to numeric matrices, and an input-oriented CRS DEA was run using the `dea()` function. The resulting efficiency scores were merged with each utility's profile in the UPBEAT dataset to enable further analysis alongside governance and access indicators.

To allow for further analysis, I harmonized country names and merged DEA results with governance features (market structure, IPP presence, unbundling, regulator) for the year 2012. Subsequently, I combined this dataset with national electricity access data for 2022, enabling regression analysis of the link between utility efficiency and access outcomes. This process resulted in a final dataset (Efficiency_Markets_Access.csv) that includes standardized performance metrics, governance variables, and development outcomes—allowing for both benchmarking and policy inference. For replicability, the cleaned dataset and an accompanying codebook—detailing variable definitions, data sources, and transformation procedures—are included in the GitHub repository referenced in the *Acknowledgments and Additional Materials* section of this paper.

Exploring Institutional and Developmental Patterns Using Box Plots

To visually analyze how institutional characteristics and efficiency outcomes relate across electric utilities, I used box plots as a diagnostic tool at two stages of the analysis. This approach allowed for a straightforward yet powerful comparison of efficiency distributions across policy environments and across performance tiers.

1. Box Plots by Market Structure and Governance Characteristics

The first set of box plots examined the relationship between utility efficiency scores and various market structure features. After calculating DEA efficiency scores for each utility, I grouped utilities by the institutional characteristics of the countries where they operate, using data from the 2012 Global Power Market Structure database. The box plots displayed the distribution of efficiency scores across the following key policy variables:

i. **Market Structure Type** (Vertically Integrated, Single Buyer Model, Wholesale-Retail Competition)
ii. **Unbundling** (Yes/No, capturing any form of unbundling applied, from account to full ownership unbundling)
iii. **Sector Regulator Presence** (Yes/No)
iv. **Private Independent Power Producer (IPP) Participation** (Yes/No)

Each box plot showed the median, interquartile range, and the full range of DEA scores within each category, enabling an intuitive comparison of whether utilities operating under specific institutional configurations tend to exhibit higher or lower operational efficiency. This method offered a clear visualization of the possible associations between regulatory and structural reforms and performance, though causality was not inferred at this stage.

2. Box Plots Linking Efficiency and Electricity Access

In the second stage, I examined the connection between utility performance and electricity access outcomes using country-level box plots. Here, I first aggregated utility-level DEA scores to the national level. In cases where multiple utilities existed within a country, I applied a weighted average based on the number of customers served by each utility. This approach ensured that larger utilities carried more weight in the national performance estimate. To visualize the relationship with electricity access, I grouped countries into four performance buckets:

i. **Bucket 1**: Fully efficient (DEA score = 1.00)
ii. **Bucket 2**: DEA score between 0.66 and 0.99
iii. **Bucket 3**: DEA score between 0.33 and 0.66

iv. **Bucket 4**: DEA score between 0.00 and 0.33

I then plotted box plots showing the distribution of national electricity access rates (as of 2022) across these four performance groups. This allowed for a direct, non-parametric visualization of how varying levels of utility efficiency might be associated with differing levels of electricity access. These visualizations were later complemented by regression analysis, which formally tested the statistical association between performance and access while controlling for GDP per capita and population density.

These box plot explorations provided a valuable first step in revealing potential patterns and heterogeneity in the data—both in terms of institutional settings and developmental outcomes—and helped guide the interpretation of subsequent quantitative results.

Regression Analysis: Assessing the Link Between Utility Efficiency and Electricity Access

The final stage of the analysis investigates whether countries served by more efficient utilities are also those with higher rates of electricity access. To assess this relationship, I implemented a cross-sectional Ordinary Least Squares (OLS) regression using country-level data. The dependent variable is each country's electricity access rate in 2022, while the key explanatory variable is the average utility efficiency score, derived from the DEA model. By combining these variables, the regression empirically tests whether micro-level utility performance—measured by operational and financial efficiency—is associated with macro-level development outcomes such as universal energy access.

The dependent variable in this analysis is Access to Electricity (2022), defined as the percentage of a country's population with access to electricity, as reported by the World Bank's

World Development Indicators. This indicator serves as a key benchmark for Sustainable Development Goal 7 (SDG 7) and captures both grid-connected and off-grid service coverage. It reflects a country's ability to deliver basic infrastructure services and is widely used in global energy access assessments.

The main explanatory variable is the efficiency score obtained from DEA, which was aggregated to the country level by calculating a customer-weighted average of utility-level scores. This aggregation method gives proportionally greater weight to larger utilities, better reflecting their role in shaping national outcomes. The DEA scores represent how effectively utilities convert core inputs—namely labor and assets—into desirable outputs such as customer coverage, profitability, and reduced technical losses.

To account for structural and economic differences across countries that might also influence electricity access, I included three control variables:

i. **Log of GDP per Capita (2012–2022 Average)**: This variable serves as a proxy for national wealth and institutional capacity to finance infrastructure investments. The logarithmic transformation helps normalize its distribution and enables a linear relationship in the regression model. Countries with higher average incomes are typically better positioned to expand electricity networks and manage service provision effectively (Li, Yang, Huang, Liu, & Guo, 2023).

ii. **Population Density (2022)**: Expressed as the number of people per square kilometer, population density captures the spatial feasibility of service expansion. Densely populated countries often face lower infrastructure costs per capita, while those with dispersed populations may struggle to achieve economies of scale in grid expansion (Muzayanah, Lean, Hartono, Indraswari, & Partama, 2022).

iii. **Urban Population Share (2022)**: This variable reflects the proportion of the population living in urban areas. Since grid infrastructure is typically more concentrated and accessible in cities, a higher share of urban population generally facilitates greater electricity access (Li, Yang, Huang, Liu, & Guo, 2023).

Two regression models were estimated to compare the robustness and parsimony of specifications:

- **Model 1 (Full model with all controls)**

$$Access_{(2022)} = \beta_0 + \beta_1 \cdot \text{Efficiency Score} + \beta_2 \cdot \log(\text{GDP per Capita}) + \beta_3 \cdot \text{Population Density}_{(2022)} + \beta_4 \cdot \text{Urban Population Share}_{(2022)} + \varepsilon$$

- **Model 2 (Preferred)**

$$Access_{(2022)} = \beta_0 + \beta_1 \cdot \text{Efficiency Score} + \beta_2 \cdot \log(\text{GDP per Capita}) + \beta_3 \cdot \text{Population Density}_{(2022)} + \varepsilon$$

While Model 1 includes an additional control for urbanization, its inclusion modestly increased multicollinearity among independent variables and did not significantly improve explanatory power. Given the sample size of 37 countries, I ultimately favored Model 2 for its parsimony, interpretability, and statistical stability.

This regression analysis complements the earlier descriptive box plot comparisons by quantifying the relationship between utility efficiency and electricity access. By controlling for key economic and geographic characteristics, the model isolates the role of utility performance in explaining cross-country variation in access. The results support the broader policy relevance of benchmarking utility efficiency—not only for internal reforms but for its potential impact on national development outcomes.

Results and Discussion

This study evaluated the relative efficiency of 49 electricity utilities operating in 37 countries using an input-oriented DEA model with constant returns to scale. The analysis was based on two input variables—number of employees and total assets—and three output variables—net profit margin, number of customers, and transformed distribution losses (1 – losses). These inputs and outputs were averaged over the period 2012–2022 to reflect long-run performance while ensuring methodological consistency across utilities.

Overall Results and Spread

Out of the 49 utilities analyzed, 7 achieved an efficiency score of 1.00, indicating that they lie on the DEA production frontier. These utilities are:

- CESSA and ELFEC S.A. (Bolivia)
- ELECTROCENTRO (Peru)
- CPFL Paulista (Brazil)
- MEPCO (Pakistan)
- Marshalls Energy Company (Marshall Islands)
- Pohnpei Utilities Corporation (Micronesia)

The distribution of efficiency scores was right-skewed, with values ranging from 0.04 to 1.00 and a mean of 0.576. While just under 15% of utilities were classified as fully efficient, over half scored below 0.60, reflecting significant operational gaps across much of the sample. The table below summarizes the efficiency score, along with key operational indicators—net profit margin, distribution losses, and customer-to-employee ratio—which provide insight into each utility's underlying performance. These characteristics are often associated with efficiency, and their correlation with the DEA results offers a useful check on the model's face validity.

Table 1: Summary of DEA Efficiency Scores and Key Operational Metrics

No	Utility and Country	Efficiency	Net Profit Margin	Distribution Losses	Costumers per Employee
1	CESSA, Bolivia	1.00	4.84%	7.66%	848
2	ELFEC S.A, Bolivia	1.00	9.95%	9.20%	677
3	ELECTROCENTRO, Peru	1.00	15.64%	10.70%	1884
4	CPFL PAULISTA, Brazil	1.00	4.31%	8.86%	13754
5	MEPCO, Pakistan	1.00	-8.01%	15.79%	348
6	MEC, Marshall Islands	1.00	13.53%	34.00%	21
7	PUC_M, Federated States of Micronesia	1.00	-12.07%	27.00%	46
8	Severelectro, Kyrgyzstan	0.97	-2.49%	14.91%	182
9	WZPDCL, Bangladesh	0.91	-0.09%	9.78%	497
10	AFINIA, Colombia	0.87	-0.50%	28.03%	1397
11	SEDC, Sudan	0.84	-0.73%	15.50%	401
12	CENORED, Namibia	0.84	2.63%	12.29%	150
13	UMEME, Uganda	0.83	7.17%	19.35%	716
14	CEDENAR, Colombia	0.82	3.13%	19.11%	735
15	EDENOR, Argentina	0.82	-2.65%	16.49%	666
16	LESCO, Pakistan	0.81	-7.80%	13.33%	307
17	LUCELEC, Saint Lucia	0.79	11.17%	7.45%	267
18	DOMLEC, Dominica	0.72	4.74%	7.94%	134
19	ENA, Armenia	0.70	6.86%	9.88%	135
20	PEA, Thailand	0.69	4.08%	5.37%	659
21	ESSA, Colombia	0.66	10.51%	12.26%	871
22	CIENERGIES, Ivory Coast	0.62	1.87%	13.49%	4412
23	CENTROSUR, Ecuador	0.61	19.30%	6.66%	800
24	PESCO, Pakistan	0.55	-29.30%	35.76%	224
25	SBEE, Benin	0.54	-2.89%	24.57%	342
26	CIE, Ivory Coast	0.54	1.85%	15.34%	459
27	ErongoRED, Namibia	0.50	5.78%	6.80%	124
28	KUS, Kazakhstan	0.45	-13.58%	10.27%	123

29	PLN, Indonesia	0.42	1.50%	7.27%	1332
30	ECG, Ghana	0.41	-10.29%	23.72%	526
31	Eneo, Cameroon	0.37	-0.10%	31.35%	304
32	EDM_Moz, Mozambique	0.36	-6.34%	19.30%	462
33	Senelec, Senegal	0.34	2.24%	17.35%	500
34	EDN, Peru	0.33	11.72%	8.34%	2
35	DPDC, Bangladesh	0.32	1.57%	7.87%	219
36	SONABEL, Burkina Faso	0.30	-3.29%	13.22%	336
37	ENDE, Angola	0.30	-47.44%	13.93%	325
38	NIGELEC, Niger	0.30	2.92%	11.39%	199
39	MEA, Thailand	0.29	4.80%	3.49%	390
40	ENERCA, Central African Republic	0.26	-23.55%	33.00%	43
41	ARD, Kazakhstan	0.25	1.15%	11.46%	43
42	ANDE, Paraguay	0.24	8.76%	20.38%	311
43	EPBiH, Bosnia and Herzegovina	0.16	1.55%	8.32%	164
44	ZETDC, Zimbabwe	0.16	-14.66%	13.10%	142
45	QESCO, Pakistan	0.14	-76.64%	24.39%	94
46	TNB, Malaysia	0.13	12.08%	6.31%	262
47	ZESCO, Zambia	0.11	-1.73%	12.63%	125
48	ESKOM, South Africa	0.07	-2.78%	7.79%	143
49	SNEL, Democratic Republic of the Congo	0.04	-35.83%	19.52%	95

Patterns Across Key Characteristics

The DEA efficiency scores show clear patterns across different regions, income levels, and types of utilities.

Sub-Saharan Africa had the largest number of utilities in the sample, with 19 in total. However, this region also had the lowest average efficiency score—around 0.39—and many of its utilities scored below 0.5, indicating significant performance challenges. Latin America and the Caribbean included 13 utilities and had several of the top performers, such as CPFL Paulista in Brazil and Electrocentro in Peru. East Asia and Pacific, along with South Asia, each had six utilities, with a mix of both high- and low-efficiency cases. Europe and Central Asia had five utilities, which also showed a wide range of efficiency outcomes.

When looking at income groups, utilities in upper middle-income countries generally had higher efficiency scores. These utilities often benefit from stronger financial performance and lower distribution losses. In contrast, utilities in lower middle-income and low-income countries showed more variation, with many falling in the middle or lower end of the efficiency distribution.

In terms of ownership and structure, most of the utilities in the sample were publicly owned—38 out of 49. These public utilities had a wider spread of efficiency scores, while the 11 private utilities tended to score higher on average. Functionally, 25 utilities operated only in distribution, while 20 were vertically integrated and 4 combined distribution with other roles. These differences in operational scope likely influenced their efficiency scores, especially in cases where vertically integrated utilities carried additional costs or assets not fully reflected in the outputs used in the DEA model.

Overall, the patterns suggest that both country-level context and utility-specific characteristics matter for performance. Regional differences, income levels, ownership type, and the role of the utility all help explain why some utilities are more efficient than others.

Interpreting Patterns—and Their Limits

Some high-scoring utilities align well with conventional performance indicators. For example, CPFL Paulista (Brazil) combined low distribution losses (8.86%), positive profit margins, and an exceptionally high customer-to-employee ratio (13,754). Likewise, Electrocentro (Peru) and CESSA (Bolivia) paired financial health and technical efficiency, offering strong validation of their DEA scores.

However, not all efficient utilities performed strongly across all metrics. Utilities such as MEPCO (Pakistan), MEC (Marshall Islands), and PUC (Micronesia) received a score of 1.00 despite:

- **Negative or modest net profit margins**
- **High distribution losses** (above 25% in MEC and PUC)
- **Very low customer-to-employee ratios** (below 50 in MEC and PUC)

These cases demonstrate that DEA efficiency scores are relative—utilities are benchmarked against each other, and can appear efficient if they perform better than others with similar profiles, even if their absolute performance is weak. In systems with limited peers (e.g., island utilities), a utility may score highly simply by being the best of a poor-performing group.

Thus, while DEA provides a valuable standardization framework, results must be interpreted in context. Technical, financial, and institutional conditions vary significantly across utilities, and DEA does not account for non-commercial mandates, differences in operating environments, or limitations in available data. These issues are explored further in the next subsection on model limitations and interpretation.

Caveats and Interpretation of DEA Results

While the DEA model provides a useful lens to benchmark relative utility efficiency, interpreting the results requires caution and contextual nuance. The utilities analyzed span 37 countries, diverse institutional models, and vastly different operating environments. The following caveats are especially important for understanding the implications of the efficiency scores presented.

1. Diverse Operating Contexts

Utilities in this dataset serve very different geographies, customer bases, and institutional environments. For instance, MEPCO (Pakistan) and QESCO (Pakistan) operate under the same national policy framework, yet MEPCO achieves a perfect efficiency score (1.0), while QESCO ranks among the least efficient (0.14). This contrast highlights how differences in regional load density, theft rates, and bill collection can shape performance even within a single country (GEPCO). Similarly, PUC (Micronesia) and MEC (Marshall Islands) operate in island systems with unique infrastructure and cost challenges. While both score 1.0, their small size and limited customer base (serving just a few thousand people) mean they face different performance expectations than large urban utilities like CPFL Paulista (Brazil) (CPFL Energia, n.d.).

2. DEA Model Assumptions and Output Choices

The DEA model applied is input-oriented and assumes constant returns to scale (CRS), meaning it assumes utilities can scale inputs and outputs proportionally. While CRS allows for consistent cross-country comparisons, it may disadvantage smaller utilities that cannot achieve the same economies of scale as large ones. Additionally, the choice of Net Profit Margin, Number of Customers, and Transformed Losses as outputs reflects a commercial efficiency focus. These metrics do not capture service quality, reliability, or the full range of development outcomes. For instance, utilities tasked with expanding rural access may have high costs per customer, which can reduce their measured efficiency despite strong policy contributions.

3. Utility Mandates and Objectives

Not all utilities are designed or expected to operate as profit-maximizing entities. Many public utilities fulfill social mandates—like expanding access to unserved populations or providing subsidized electricity to low-income households (International Trade Administration, 2024). These objectives may result in lower revenue or higher staffing levels, which the DEA model interprets as inefficiency. For example, SNEL (DR Congo) has among the lowest efficiency scores (0.04) and extreme financial losses, yet it serves one of the world's most challenging electrification environments and may be fulfilling critical social functions not fully captured by the model.

4. Vertical Integration and Input Mismatches

The inclusion of both distribution-only (D) and vertically integrated utilities (VIU) introduces additional complexity. In principle, the DEA model assesses how well a utility transforms inputs (employees, assets) into outputs related to customer service and technical performance. However, vertically integrated utilities like TNB (Malaysia) and Eskom (South Africa) include assets and staff related to generation and transmission that are not reflected in the output metrics, which focus on distribution performance. As a result, these utilities may appear less efficient not due to poor performance, but due to mismatches in model specification. For example, TNB scores only 0.13 despite a 12% net profit margin and losses below 7%, likely because its large asset base supports functions not reflected in the model outputs.

5. *Outlier Effects and Frontier Distortion*

DEA is sensitive to outliers because it constructs an “efficiency frontier” based on the best performers. Utilities like CPFL Paulista, with an extremely high 13,754 customers per employee, set a high bar that few others can match. While such utilities offer valuable benchmarks, they may not be representative or replicable in all contexts. Similarly, MEC and PUC achieve perfect efficiency scores despite high losses or low labor productivity—suggesting that small utilities may reach efficiency by excelling in one or two dimensions, rather than across the board.

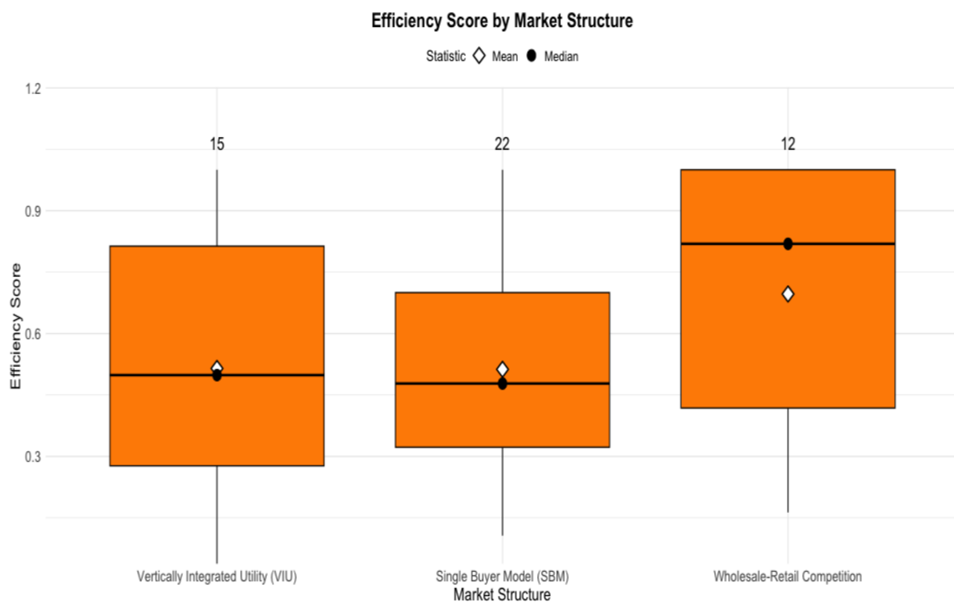
Efficiency and Market Structure

Having analyzed the overall efficiency distribution, the next step is to examine how these performance scores relate to institutional and structural features of the power sector. The following subsections explore patterns in efficiency scores across key dimensions of market structure: the degree of vertical integration, presence of a regulator, status of private IPP participation, and whether unbundling reforms have been implemented.

1. *Efficiency by Market Structure Type*

The box plot in Figure 1 presents the distribution of efficiency scores across three types of market structures: Vertically Integrated Utilities (VIU), Single Buyer Models (SBM), and Wholesale-Retail Competition models. The median and mean scores are visibly higher in markets with Wholesale-Retail Competition, with a median efficiency score around 0.85, compared to about 0.52 for VIUs and 0.49 for SBMs. Among the 12 utilities in competitive markets, several—including CPFL Paulista (Brazil) and PEA (Thailand)—are highly efficient and benefit from clear commercial mandates, high customer-to-employee ratios, and relatively low distribution losses. In contrast, utilities in Single Buyer markets tend to exhibit more performance variability and generally lower average scores.

Figure 1: Efficiency Score by Market Structure

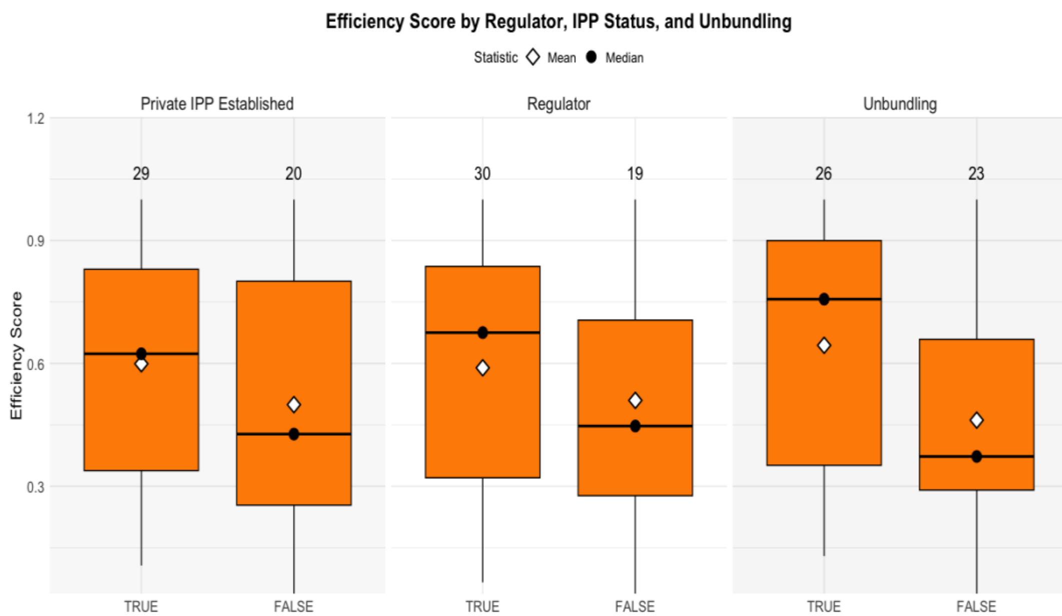


These patterns suggest that markets with a clearer separation of roles and stronger competition may be better positioned to support operational efficiency. However, the performance of VIUs is also heterogeneous, with several scoring at or near the efficiency frontier. For example, MEC (Marshall Islands) and PUC_M (Micronesia) emerge as DEA-efficient despite relatively poor performance indicators—reflecting the model's sensitivity to context and input-output combinations, as discussed earlier.

2. *Efficiency by Presence of Regulator, IPPs, and Unbundling*

Figure 2 disaggregates efficiency scores by three key governance variables: whether a regulator is present, whether private independent power producers (IPPs) are established, and whether the market has undergone any form of unbundling.

Figure 2: Efficiency Score by Regulator, IPP Status, and Unbundling



i. **Regulator Presence:** Utilities operating in countries with a power sector regulator (30 out of 49) tend to have higher median and mean efficiency scores. The median score is approximately 0.60 with a regulator, compared to 0.45 without one. This supports the view that regulatory oversight may encourage better performance through clearer accountability, tariff setting, and enforcement of service obligations.

ii. **IPP Participation:** Utilities in countries with established IPPs (29 cases) also exhibit slightly higher average efficiency scores. This likely reflects the broader enabling environment for private participation and cost discipline that often accompanies IPP frameworks.

iii. **Unbundling:** A similar trend is visible with unbundling. Utilities operating in unbundled systems (26) show higher median scores than those in vertically bundled systems (23). However, the spread within each group is substantial, suggesting that unbundling alone does not guarantee efficiency gains unless accompanied by supportive institutional and market conditions.

3. What Drives Efficiency?

Across these governance features, a consistent pattern emerges: utilities embedded in more liberalized, well-regulated, and functionally unbundled environments tend to perform better. These market and institutional arrangements are thought to enhance efficiency through several channels. First, regulatory oversight introduces clearer performance benchmarks and greater transparency, which can reduce political interference and ensure cost-recovery tariff structures—both of which are critical for financial sustainability (Ngulube, 2023). Second, unbundling separates generation, transmission, and distribution functions, thereby reducing coordination inefficiencies and allowing managers to focus on operational performance in their specific segment (Mulder, 2000). Third, the presence of private IPPs can promote efficiency indirectly by creating a more competitive procurement environment and exposing utilities to commercial discipline (Hoskote, 1995).

However, these structural reforms are not sufficient on their own. The wide variation in efficiency within each governance group suggests that utility-specific factors—such as managerial capacity, operational practices, legacy infrastructure, and even political economy constraints—play an equally important role in shaping performance outcomes. In some countries, utilities may operate in partially reformed markets where legal mandates and regulatory independence exist on paper but are undermined by weak enforcement or fiscal pressures. Similarly, reforms may be implemented unevenly, producing hybrid market structures that fall short of delivering full efficiency gains.

These observations point to the need for more nuanced research that examines how sector-wide reforms interact with firm-level conditions. For instance, the positive effects of unbundling or regulation may only materialize when accompanied by capable leadership, adequate investment, or customer engagement strategies. In future work, linking DEA-based efficiency scores with qualitative case studies or panel datasets could help disentangle these interacting drivers of performance.

Ultimately, while the results suggest that market structure and governance matter, they should be interpreted as part of a broader system of incentives and constraints shaping utility behavior. The findings provide a useful starting point, but further empirical work is needed to determine the conditions under which structural reforms translate into improved operational performance and service delivery.

Efficiency and Electricity Access

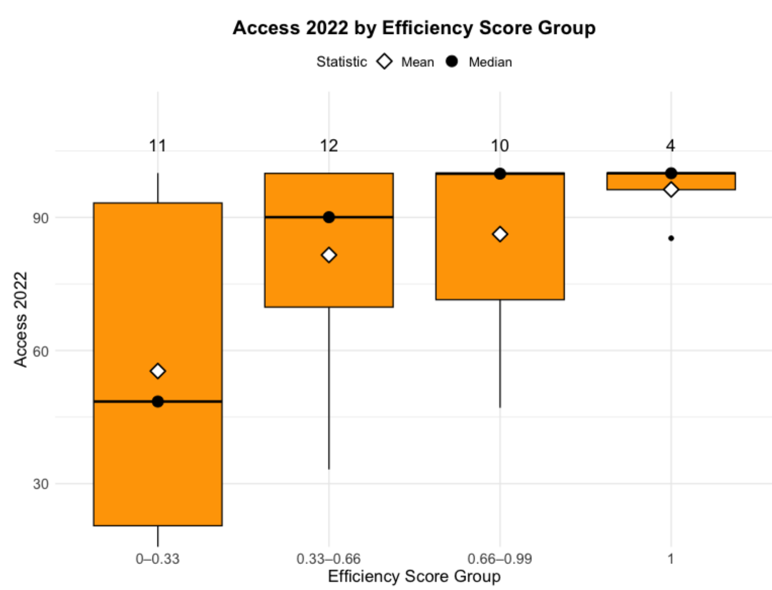
The final component of this analysis examines whether utility efficiency—as benchmarked through DEA—is linked to broader development outcomes, specifically national access to electricity. This relationship is explored through both descriptive and econometric techniques using data from 37 countries.

1. Descriptive Patterns: Access Across Efficiency Groups

To begin, Figure 3 presents a box plot of 2022 electricity access rates across four efficiency score groups. These groups are constructed as follows: (1) utilities with DEA scores between 0–0.33, (2) scores between 0.33–0.66, (3) scores between 0.66–0.99, and (4) fully efficient utilities (score = 1.00). Countries are grouped by the efficiency score among their distribution utilities, weighted by customer base.

The figure reveals a clear upward trend. Median access rates increase with utility efficiency: countries in the lowest efficiency group have a median access rate below 50%, while those in the top two efficiency groups consistently achieve medians near or above 90%. Notably, all countries with fully efficient utilities had access levels above 90%, suggesting that operational excellence and service reach often go hand-in-hand. However, variation within the mid-efficiency groups highlights that while efficiency may be a necessary condition for access, it is not sufficient on its own—other institutional and structural factors remain influential.

Figure 3: Access 2022 by Efficiency Score Group



2. Econometric Results: Linking Efficiency and Access

To quantify this relationship, I estimate two cross-sectional OLS regression models, where the dependent variable is the national electricity access rate in 2022. Table 2 summarizes the results. The analysis includes 37 countries for which complete information on utility efficiency, GDP per capita, and demographic variables was available.

Table 2: Regression Results

	Baseline	Model 2
(Intercept)	-149.01***	-153.19***
	(21.59)	(19.74)
Efficiency	24.47**	24.64**
	(7.10)	(7.01)
Log_GDP_per_capita	23.44***	24.37***
	(2.97)	(2.31)
Population.density.2022	0.03*	0.03*
	(0.01)	(0.01)
Urban.Population.2022	0.07	
	(0.14)	
R^2	0.83	0.83
Adj. R^2	0.81	0.81
Num. obs.	37	37

***$p < 0.001$; **$p < 0.01$; *$p < 0.05$

Statistical models

In both the baseline and extended models, utility efficiency is positively and significantly associated with electricity access. In the preferred Model 1, a one-point increase in the DEA score (on a 0–1 scale) is associated with a 24.5 percentage point increase in electricity access ($p < 0.01$). This result holds even when controlling for national income levels and population distribution. Specifically:

i. **Log GDP per capita** (averaged 2012–2022) is strongly and positively associated with access, as expected. Higher-income countries typically have the fiscal space and institutional capacity to expand grid infrastructure.

ii. **Population density** (2022) also has a significant, albeit smaller, positive effect. Denser populations allow infrastructure investments to reach more customers at lower per capita cost.

iii. **Urban population share** (2022), included in Model 1, was not statistically significant and introduced mild multicollinearity. As such, Model 2 is preferred for its parsimony and interpretability.

Together, the models explain over 80% of the variation in access outcomes across 37 countries. These results support the hypothesis that utility-level performance, particularly in distribution efficiency, plays a crucial role in enabling universal energy access—complementing broader economic and spatial enablers.

3. Interpreting the Link

The positive association between DEA efficiency scores and electricity access is intuitive: efficient utilities are more likely to manage resources effectively, maintain reliable service, and invest in grid expansion. However, causality should be interpreted with caution. Higher access levels may also feed back into utility efficiency by improving economies of scale, customer revenues, and planning predictability.

Moreover, the regression focuses on national access, which may mask important subnational disparities. In some countries, a single utility's performance may not be fully representative of broader sector outcomes. Nonetheless, the consistency between descriptive and statistical results reinforces the relevance of benchmarking utility efficiency as part of the broader development agenda.

Conclusion and Policy Implications

This study applied a benchmarking framework to assess the operational efficiency of electric utilities in low- and middle-income countries and explored how these performance metrics relate to broader development outcomes—specifically, electricity access. Using an input-oriented, constant returns to scale (CRS) Data Envelopment Analysis (DEA) model, I calculated efficiency scores for 49 utilities in 37 countries based on core input and output indicators. These scores were then linked to governance structures and national access rates, producing insights into the operational and institutional factors that shape energy service delivery.

The analysis revealed substantial variation in efficiency across utilities. While a small subset of utilities operated on the efficient frontier—typically characterized by low system losses, strong financial performance, and lean staffing—many others exhibited considerable inefficiencies. Notably, utilities in Sub-Saharan Africa tended to have lower efficiency scores, while those in Latin America and Asia were more likely to approach the frontier. However, these results must be interpreted in context: DEA scores are sensitive to data availability, the choice of input/output variables, and differences in utility mandates and operating environments. For example, some utilities flagged as highly efficient serve isolated systems with limited scale, such as those in island countries, while others operate in competitive or corporatized environments that incentivize performance.

The comparative analysis across market structures showed that utilities in more liberalized, unbundled, and better-regulated settings tend to perform better on average. While these relationships are not necessarily causal, they suggest that structural reforms can support efficiency when paired with sound institutional frameworks. This aligns with broader research highlighting how regulatory clarity, accountability mechanisms, and independent power producer (IPP) participation can strengthen incentives and discipline in the electricity sector.

Regression results reinforce the significance of utility performance. Controlling for income and demographic factors, DEA efficiency scores were positively and significantly associated with national electricity access rates in 2022. Countries with more efficient utilities tend to have broader service reach, suggesting that operational reforms and performance benchmarking should be integral to energy access strategies.

These findings point to three core policy takeaways:

i. **Performance benchmarking should guide utility reform**. DEA and similar tools offer practical methods for comparing utilities across contexts and identifying those that excel despite constraints. These insights can inform peer learning, capacity-building, and technical assistance programs.

ii. **Institutional features matter**. Utilities embedded in coherent, rules-based environments—where regulators are empowered, private participation is well-structured, and functional roles are clearly defined—tend to perform better. This highlights the importance of sequencing reform not just around market design, but also around governance quality.

iii. **Efficiency is necessary but not sufficient for access**. While efficiency correlates with electricity access, it is only one part of the equation. Expanding access also requires fiscal commitment, targeted subsidies, planning for last-mile delivery, and mechanisms to reach underserved populations.

While DEA provides a robust and replicable approach to benchmarking, it also carries important limitations. The CRS input-oriented model used in this study evaluates utilities relative to top performers within the sample, not against an external standard. Results are heavily influenced by the choice of inputs and outputs—meaning that service quality, reliability, and equity remain unmeasured unless explicitly incorporated. Utilities serving remote or low-income populations may therefore appear inefficient despite fulfilling essential policy objectives. Additionally, combining distribution-only utilities with vertically integrated utilities (VIUs) introduces structural inconsistencies, as VIUs manage broader asset portfolios that are not fully captured in the output metrics. Future applications would benefit from benchmarking distribution utilities separately to ensure more accurate comparisons. DEA is also sensitive to outliers and data gaps, which can distort the efficiency frontier. These limitations point to the value of complementing DEA with additional performance metrics, longitudinal trends, and second-stage analysis to better understand the drivers of efficiency.

This study underscores the value of combining performance metrics with governance diagnostics and development indicators. By building cross-national datasets like UPBEAT and applying transparent analytical frameworks, researchers and policymakers can better understand what works—and where the sector still falls short. Ultimately, aligning utility performance with equitable, universal access remains a critical challenge for achieving Sustainable Development Goal 7. This paper contributes to that agenda by offering empirical tools and evidence to support smarter reform strategies.

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Acknowledgements and Additional Material

I would like to thank Professor Daniel Bernhofen for his invaluable guidance and support as my faculty advisor throughout this project. I am also grateful to Professor Austin Hart for his thoughtful feedback and encouragement during the research and data analysis process. Special thanks to the experts at the World Bank and the International Finance Corporation (IFC) who provided input and insights that helped define and refine the methodology and interpretation of results.

For further details on the dataset construction, variable definitions, and methodology, please refer to the accompanying codebook available at: https://github.com/eaguilar-git/codebook.