Econometric model of energy consumption and generation in Ecuadorian households with the integration of photovoltaic systems and electric vehicles

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***Abstract*—This paper analyzes the structural determinants of provincial electricity consumption in Ecuador using a cross-sectional econometric framework for 2024. Because official provincial demand data are unavailable, consumption is constructed by allocating the national total from the Energy Balance 2024 according to historical provincial shares. Climate variables come from NASA POWER, while population and Gross Value Added are taken from official national statistics. A parsimonious log-linear OLS model with HC3 standard errors is estimated for 23 mainland provinces. Results show that electricity demand is primarily driven by structural economic factors: the elasticity with respect to VAB is about 0.74 and the elasticity for population is about 0.51, both significant. The model explains roughly 95% of the cross-sectional variation, whereas annual-average climate indicators exhibit limited explanatory power in a single-year cross-section. These findings highlight the dominance of economic scale effects over contemporaneous climatic conditions in shaping provincial electricity demand. The study contributes to understanding subnational demand drivers in developing economies and offers a replicable approach for contexts with limited provincial data availability.**

***Index Terms*—electricity demand, climate variables, cross-sectional data, regression analysis, econometric modeling, Ecuador.**

I. Introduction

Today, the world agrees that the energy transition has shifted the focus of the electrical system from large centralized generation plants toward distributed and highly dynamic environments, where households play an active role through the adoption of photovoltaic (PV) generation and the acquisition of electric vehicles (EVs). This process significantly increases the temporal variability of consumption and generation, introduces nonlinear behaviors, and amplifies the influence of exogenous factors such as weather, electricity tariffs, and usage habits [1–4]. Several studies highlight that, in residential scenarios, the simultaneity between PV generation and EV charging can produce demand peaks, bidirectional power flows, and self-consumption patterns that are highly dependent on time of day, making efficient planning and operation of electrical systems more difficult [5–7]. In this context, residential demand ceases to behave as a stable process and instead acts as a complex stochastic system, especially in regions with high penetration of distributed energy resources.

To address this complexity, multiple approaches have been proposed for modeling residential electricity consumption, ranging from classical econometric models to data-driven techniques based on time series and statistical learning. Regression models, ARIMA/ARIMAX, and multivariate variants have been widely used to capture relationships among consumption, climatic variables, and socioeconomic factors [8–11]. In parallel, data-driven approaches have gained relevance by enabling the estimation of system behavior from historical data without requiring explicit physical models. However, numerous studies point out that these methods often assume ideal conditions such as Gaussian noise, incomplete datasets, or temporal stability, which limits their performance in real-world scenarios characterized by corrupted measurements, structural changes, and high uncertainty [12–14]. In particular, when alternative energy systems are incorporated, many existing models tend to underestimate uncertainty, providing point estimates that do not adequately reflect the real variability of the system [15, 16].

Given these limitations, this study employs a parsimonious econometric model to examine the structural factors of electricity consumption. The analysis is based on a cross-sectional regression framework that relates demand to economic and demographic factors, complemented with climatic indicators. This approach prioritizes interpretability and robustness under data constraints. [17–20]. However, most of these developments have focused on industrial or control systems, while their application to residential energy systems integrating PV–EV remains limited, especially in Latin American contexts where data are scarce and local conditions differ from standard assumptions [21, 22].

In the Ecuadorian context, existing studies have mainly on technological and economic feasibility analyses, offering valuable contributions on scenarios, consumption profiles, and local energy conditions. However, a gap remains in the development of parsimonious econometric models capable of identifying the structural determinants of electricity consumption. In a data-constrained environment, this approach provides a transparent, interpretable, and replicable framework to understand how economic and demographic factors shape electricity demand among the provinces of Ecuador. [23].

II. Data and Reseach Context

A. Study Area

The study works with 2024 provincial data for Ecuador. The 24 provinces are included. The provinces are in the Costa, Sierra, Amazonia, and the insular region (Galápagos), so the sample captures clear differences in terrain and local climate within a single national setting. The provincial boundaries used to define the study area are shown in Figure 1.

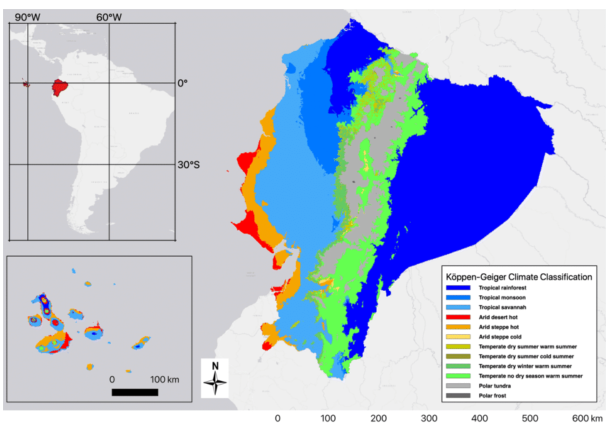

Figure 1: Provincial division of Ecuador.

The analysis uses a provincial cross-section for 2024 because that year has data for both electricity consumption and climate variables. Using a single-year snapshot used to compare provinces under the climatic conditions observed in the same year.

B. Electricity Demand

Given the absence of publicly available official statistics for annual electricity consumption disaggregated by province for 2024, provincial consumption was estimated using a proportional disaggregation procedure. Specifically, the national consumption for 2024 (35,640 GWh)—according to Energy Balance 2024 (national total) + ARCONEL distribution reports (historical shares) was allocated across provinces using historical real shares from the period 2015–2021, as reported by sectoral sources (ARCONEL / distribution reports). This approach allows the reconstruction of annual provincial consumption while maintaining consistency with the national total, under the assumption of relative stability in provincial shares over time [24].

C. Climatic Variables and Solar Resource Data

NASA POWER provides daily weather and solar data for 2024. The daily records are condensed to a single annual value per province since electricity consumption is only available as an annual provincial total. Three indicators are kept:

- Mean of daily series of Air temperature is 2 m(°C)
- Mean of daily series of Surface downward shortwave radiation (kWh/m^2/day).
- Total daily value for Precipitation (mm)

Table I summarizes definitions, units, and data sources.

D. Construction of the Dataset

The final dataset covers the 24 provinces in 2024. Electricity consumption and climate indicators are combined at the province level, and the resulting file is checked to ensure that each province appears only once.

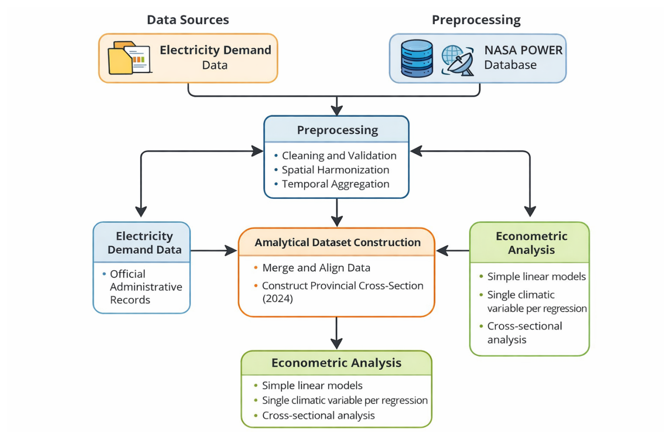

Figure 2: Steps used to integrate climate data and electricity demand information into a provincial cross-sectional dataset (2024).

After, the dataset is used as a provincial cross-section for the econometric analysis. Figure 2 shows the workflow used to integrate climate indicators and electricity demand. In addition to climate indicators, the analytical dataset incorporates structural provincial covariates to reduce omitted-variable bias: population and gross value added [23]. All datasets were harmonized at the province level using standardized province identifiers (upper-case and hyphen/spacing normalization) to ensure a one-to-one merge across sources. The final dataset includes 24 provinces, and the main estimation excludes Galápagos (insular outlier) as a robustness strategy.

E. Data Limitations and Methodological Motivation

The cross-sectional design imposes inherent limitations, as the lack of temporal variation restricts the identification of dynamic effects and limits causal inference regarding climate–demand relationships. Climate indicators are highly correlated across provinces and display minimal cross-sectional variation in 2024, reducing their explanatory power and requiring separate regressions. For these reasons, the analysis prioritizes structural economic determinants—population and GVA—while climate variables serve only as a benchmark.

Table I: Variables used in the empirical analysis

Variable	Description	Unit	Source
Electricity consumption (C_i)	Total annual electricity consumption by province (2024, estimated using historical shares)	GWh	Energy Balance 2024 + ARCONEL historical reports
Log electricity consumption ($\ln C_i$)	Natural logarithm of provincial electricity consumption	–	Authors' calculation
Population (Pop_i)	Provincial population (2022)	Persons	INEC
Log population ($\ln Pop_i$)	Natural logarithm of provincial population	–	Authors' calculation
Gross Value Added (VAB_i)	Provincial gross value added (2022)	Million USD	Banco Central del Ecuador (BCE)
Log VAB ($\ln VAB_i$)	Natural logarithm of provincial gross value added	–	Authors' calculation
Average temperature (T_i)	Annual mean air temperature at 2 m	$^\circ$C	NASA POWER
Solar radiation (S_i)	Annual mean surface downward shortwave radiation	kWh/m^2/day	NASA POWER
Precipitation (P_i)	Total annual precipitation	mm	NASA POWER
Log precipitation ($\ln(1+P_i)$)	Log-adjusted annual precipitation	–	Authors' calculation

III. Econometric Methodology

A. Notation

The analysis is based on Ecuadorian provincial data for 2024. Since electricity consumption is measured annually, the dependent variable is defined as $y_i = \ln(C_i)$, where C_i denotes electricity consumption in GWh. To match this annual scale, daily climate observations are summarized as annual values: mean temperature, mean shortwave radiation, and total precipitation. Population and an indicator of economic scale are also included as control variables.

B. Dependent Variable and Consumption Construction

Because official public statistics of *provincial* annual electricity consumption for 2024 are not available, provincial consumption is estimated by proportional allocation (Option A). Let [C^{nat}_{2024}] denote national electricity consumption in 2024 (GWh), and let π_i denote the historical provincial participation share (computed from reliable historical distributions). Provincial consumption is constructed as:

$$C_{i,2024} = \pi_i \, C^{\text{nat}}_{2024}, \tag{1}$$

with $\sum_i \pi_i = 1$. The dependent variable is then defined as:

$$y_i = \ln(C_{i,2024}). \tag{2}$$

C. Climatic Variables Variables

Three climatic indicators are considered as baseline explanatory variables: average air temperature at 2 meters (T_i, °C), average surface downward shortwave radiation (S_i, kWh/m^2/day), and total annual precipitation (P_i, mm). To mitigate skewness in precipitation, the transformed precipitation variable is:

$$P_i^* = \ln(1 + P_i). \tag{3}$$

Baseline single-variable benchmark models are:

$$y_i = \alpha + \beta_T T_i + \varepsilon_i, \tag{4}$$

$$y_i = \alpha + \beta_S S_i + \varepsilon_i, \tag{5}$$

$$y_i = \alpha + \beta_P P_i^* + \varepsilon_i. \tag{6}$$

These climate-only models are reported as descriptive benchmarks and should be interpreted as correlational.

D. Extended Structural Specification

Province-to-province variations in electricity use are caused by scale. The specification takes into account each climate indicator independently after including population and value added as control:

$$y_i = \alpha + \beta X_i + \gamma_1 \ln(\text{Pop}_i) + \gamma_2 \ln(\text{VAB}_i) + u_i. \tag{7}$$

Here $y_i = \ln(C_i)$, with C_i measured in GWh. Population (Pop_i) is taken from INEC and gross value added (VAB_i) from the BCE provincial accounts. X_i stands for a single climate measure (T_i, S_i, or P_i). Using logs keeps coefficients comparable across provinces and makes γ_1 and γ_2 interpretable as elasticities.

With only N provinces.The 2024 climate measures are annual aggregates, and they do not differ much from one province to another, so their coefficients come out noisy in this single-year cross-section. The specification focuses on population and GVA, and the climate-only regressions are shown as descriptive baselines.

E. Estimation and Robust Inference (HC3)

Coefficients are estimated by OLS. Since the cross-section is small and residual variance may differ across provinces, standard errors are computed using the HC3 heteroskedasticity-consistent correction. In matrix form,

$$\widehat{\text{Var}}(\hat{\theta}) = (X'X)^{-1}\left(X'\widehat{\Omega}_{\text{HC3}}X\right)(X'X)^{-1}. \tag{8}$$

F. Diagnostic Checks

A small set of standard checks is reported to support the linear specification:

1) **Multicollinearity:** Variance Inflation Factors (VIFs).
2) **Heteroskedasticity:** Breusch–Pagan test (HC3 standard errors are used in all cases given the small cross-section).
3) **Normality of residuals:** Jarque–Bera test on the residuals.

G. Sensitivity Analyses

Simple sensitivity checks are reported:

1) The baseline results use the 23 mainland provinces; Galápagos is excluded as a special case.
2) **Alternative measure of economic activity.** $\ln(\text{VAB}_i)$ is replaced with $\ln(\text{Employment}_i)$ (formal employment):

$$y_i = \alpha + \beta X_i + \gamma_1 \ln(\text{Pop}_i) + \gamma_2 \ln(\text{Employment}_i) + u_i. \tag{9}$$

3) **Per-capita outcome.** Electricity consumption is also expressed per person:

$$\ln\left(\frac{C_{i,2024}}{\text{Pop}_i}\right) = \alpha + \beta X_i + \gamma_2 \ln(\text{VAB}_i) + u_i. \quad (10)$$

H. Identification Scope

The results are descriptive and should not be read as causal effects. In this cross-section, the goal is simply to see how much of the cross-province differences in electricity consumption can be accounted for by population and economic activity, and whether the annual climate indicators add any explanatory power on top of those controls.

In the 2024 annual-aggregate dataset, climate indicators exhibit limited cross-sectional variation, which can induce collinearity in the extended specification; therefore, climate-only models are retained as benchmarks and the structural specification is emphasized as the main model.

IV. Results and Discussion

Present the main estimation and robustness results.

A. Results

The baseline sample includes the 23 mainland provinces, excluding Gal'apagos. The dependent variable is defined as $y_i = \ln(C_i)$, where C_i denotes electricity consumption in 2024. Since province-level electricity consumption totals are not available for that year, C_i is approximated by allocating the 2024 national total across provinces using historical consumption shares.

The HC3 standard errors for the OLS estimates are in Table II. The results suggest that the scale variables are the main determinants of electricity consumption. The elasticity of gross value added (VAB) is around 0.74 (HC3 $p < 0.001$), which implies that a 1% difference in economic activity across provinces is associated with about a 0.74% difference in electricity consumption. Population is also positive and statistically significant with elasticity close to 0.51 (HC3 $p = 0.010$).

Table II: Main structural model results (mainland provinces, HC3 robust standard errors)

	Estimate	HC3 Std. Error	p-value
Intercept	-5.8716	1.2027	0.00009
ln(Population)	0.5125	0.1812	0.01039
ln(VAB)	0.7400	0.1858	0.00073
Observations	23 (Galápagos excluded)		
R^2 / Adj. R^2	0.9461 / 0.9408		
F-statistic (OLS)	175.7 (p $<$ 0.001)		

The model displays very high explanatory power for cross-sectional variation in electricity consumption ($R^2 \approx 0.946$, Adj. $R^2 \approx 0.941$), highlighting that provincial demand differences in 2024 are primarily explained by structural economic size rather than annual-average climatic conditions. This has implications for planning future distributed energy systems, as demand growth will likely follow economic expansion rather than short-term climate variability.

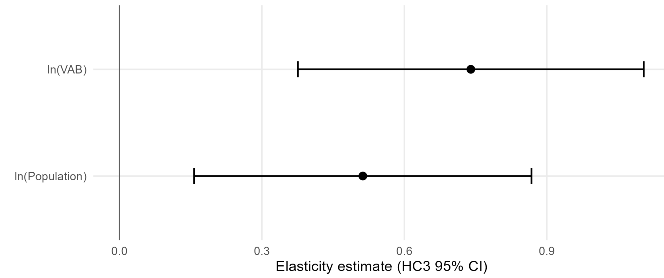

Figure 3: Estimated structural elasticities with HC3 95% intervals.

Figure 3 presents the elasticity estimates with 95% intervals. Figure 4 shows that, for provinces, the observed and fitted values lie near the 45-degree line.

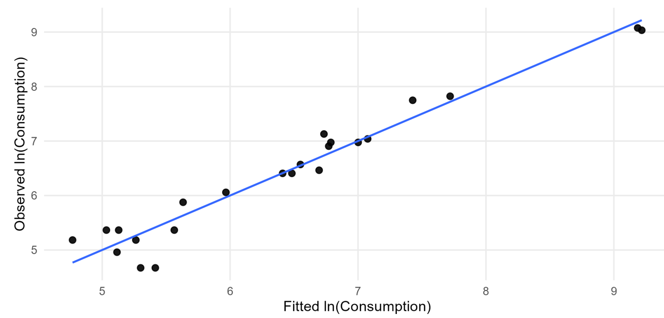

Figure 4: Observed versus fitted values for the main structural model (mainland provinces).

B. Interpretation and Implications

Taken together, the results point to a simple scale story across provinces. GVA (VAB) explains most of the cross-province variation in electricity consumption, and population adds a smaller but still relevant contribution. This pattern matches the idea that electricity use rises with economic output and the size of local activity. In Fig. 5, residuals are centered around zero with no clear systematic pattern.

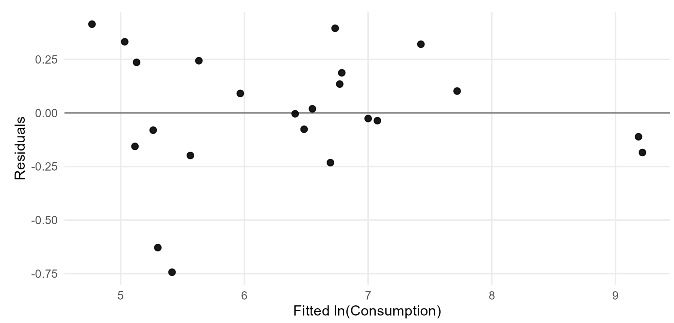

Figure 5: Residuals and fitted values for the structural specification.

C. Limitations

Two caveats are worth keeping in mind. Provincial electricity consumption for 2024 is not published as a subnational series, so it is approximated by allocating the national total using historical provincial shares. Climate enters only through annual provincial summaries for a single year, which leaves limited variation across provinces and makes the climate coefficients noisy. A next step is to use more information of differents levels of frequency, multi-year data to study seasonal patterns and short-run weather effects more directly.

V. Conclusion

This study looks at the differences in electricity use in Ecuador's provinces in 2024. The national total reported in the Energy Balance is distributed using historical provincial shares to approximate consumption, as provincial totals are not published. Galápagos is not included in the analysis, which is limited to the 23 provinces.

The results mainly reflect scale effects. Provinces with more economic activity and larger populations tend to consume more electricity. In this model, the population elasticity is about (0.51), while the elasticity with respect to Gross Value Added is about (0.74). Together, these two variables explain around (95%) of the differences in electricity consumption across provinces in 2024.

The extent of these results is limited by two points. The 2024 provincial electricity consumption has to be reconstructed and should be regarded as an estimate because it is not officially reported as a series. Additionally, climate only enters through yearly summaries at the province level for a single year, leaving little variation between provinces. It would be simpler to distinguish between short-term weather impacts and seasonal patterns if higher-frequency data were collected over a number of years.

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