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When Darkness Pollutes: Grid Electricity Deficits, Dirty Energy Substitution, and Carbon Emissions in West Africa

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Abstract

West Africa confronts one of the world's most acute electricity crises, yet its environmental consequences remain poorly understood. Where grid electricity is absent or unreliable, households and firms substitute towards private diesel generators and solid biomass fuels, both markedly dirtier than grid supply. This paper introduces and formally tests the dirty substitution hypothesis for 13 West African countries (2000-2022), using a constructed electricity deficit index (the gap between installed capacity and output per capita) to test whether larger deficits raise CO2 emissions through dirty substitution. We apply a three-layer empirical strategy: CS-ARDL and Augmented Mean Group (AMG) estimators for cross-sectional dependence and slope heterogeneity; method-of-moments quantile regression (MMQR) of Machado and Santos Silva to test whether the effect varies across the emissions distribution; and a machine learning ensemble (Random Forest, Gradient Boosting) validating variable importance out of sample. Results reveal a bounded rather than uniform relationship: the deficit index is significantly and negatively associated with emissions at the lower and median quantiles, consistent with severe deficits being met by rationed energy consumption, but this weakens and loses significance toward the upper quantiles, where income and generator capacity are highest. Granger causality tests indicate emissions lead the deficit index rather than the reverse, consistent with economic growth jointly driving both. Renewable energy share carries the expected negative sign throughout but never reaches conventional significance. These findings reframe West Africa's electricity access challenge as conditional rather than uniformly climate-relevant, with the emissions consequences of grid failure concentrated among the region's poorest-served economies, with implications for how ECOWAS energy transition targets and multilateral climate finance are sequenced.

Keywords: Electricity deficit, Dirty substitution, Carbon emissions, West Africa, CS-ARDL, MMQR, Machine learning, Energy transition.

1 | Introduction

Access to reliable electricity is not merely a convenience; it is a structural prerequisite for economic productivity, health, and environmental sustainability. Yet across West Africa, chronic grid failure has become

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the defining feature of everyday energy experience. Nigeria, the region's largest economy, operates with an installed generation capacity that consistently falls short of demand, leaving households and enterprises without reliable power for the majority of each day [1–3]. Ghana, Senegal, Côte d'Ivoire, and their neighbours face variants of the same structural problem: grids that are underfunded, undertransmitted, and unable to meet rising demand from growing urban populations and expanding industrial activity [2].

The conventional framing of this crisis, in academic literature, policy discourse, and multilateral development strategies alike, treats electricity deficits as a poverty and development problem [4], [5]. Expanding access, the argument runs, raises productivity, reduces household energy expenditure, and supports human capital formation. The environmental dimension, when it appears at all, is typically framed as a trade-off: more electricity access implies more energy consumption, which implies more emissions [6]. This framing is not wrong, but it is critically incomplete. It ignores what people actually do when the grid fails.

Without reliable grid electricity, West African households and firms do not simply go without energy. They substitute. The substitution is not clean: it takes the form of private diesel generators, petrol-powered inverters, kerosene lamps, and solid biomass combustion. In Nigeria alone, it is estimated that over 15 million diesel generators are in active use, producing CO2 emissions equivalent to approximately 60 per cent of the country's entire formal electricity sector annual emissions [7]. These generators operate at the lowest efficiencies of any fossil fuel combustion technology, and their proximity to residential and commercial spaces makes their particulate and toxic emissions a direct and severe public health threat [8], [9]. The Nigeria Energy Transition Plan [10] identified diesel self-generation as an 'urgent priority for decarbonisation', recognising at the highest level of policy that the generator economy is an environmental emergency, not merely an inconvenience.

Despite this, no econometric panel study has formally modelled the electricity deficit-CO2 emissions nexus through the lens of dirty energy substitution for West Africa. Existing empirical literature on the region addresses renewable energy adoption [11], financial development and environmental quality [6], urbanisation and emissions [12], and general energy-growth-environment relationships [4]. None of these papers constructs an electricity deficit variable or tests the substitution mechanism directly. The present paper fills this gap.

We introduce and empirically test the dirty substitution hypothesis: that larger electricity supply deficits in West African economies systematically increase CO2 emissions by forcing households and firms into higher-emitting energy alternatives. We construct a panel dataset for 13 ECOWAS member states from 2000 to 2022, derive a country-level electricity deficit index from World Bank World Development Indicators (WDI) and International Energy Agency (IEA) data, and examine the deficit-emissions nexus using a three-layer empirical strategy that combines state-of-the-art heterogeneous panel econometrics, distributional quantile analysis, and machine learning validation.

The paper makes four specific contributions to the literature. First, it introduces the electricity deficit as an explicit explanatory variable in the environmental economics of West Africa, shifting the analytical focus from supply-side access rates to the demand-side consequences of supply failure. Second, it provides the first panel quantile evidence on whether the deficit-emissions relationship is uniform across the conditional distribution of emissions or concentrated at a particular part of it, a question the paper's results answer in a direction that itself carries substantive meaning (Section 5.4). Third, it tests the moderating role of renewable energy share, examining whether countries with higher renewable penetration are less exposed to the dirty substitution dynamic. Fourth, it employs a machine learning ensemble as an independent, non-parametric check on the relative importance and directional consistency of the econometric results, consistent with the hybrid econometric-machine learning approach advocated by Magazzino and Odonkor [13] and Magazzino [14].

The remainder of the paper proceeds as follows. Section 2 reviews the theoretical framework and related empirical literature. Section 3 presents the data, variable definitions, and preliminary diagnostics. Section 4 describes the econometric and machine learning methodology. Section 5 reports and discusses the results. Section 6 concludes with policy implications.

2 | Theoretical Framework and Literature Review

2.1 | Theoretical Underpinnings: The Dirty Substitution Mechanism

The theoretical foundation of this paper draws on three interrelated strands of economic theory. The first is energy substitution theory, which holds that energy commodities are imperfect substitutes and that the relative cost and reliability of different energy sources determine the household and firm energy mix [15], [16]. When grid electricity supply is unreliable or unavailable, the effective price of grid electricity, inclusive of outage costs, lost productivity, and spoilage, rises sharply, inducing substitution toward alternative energy carriers. In the West African context, these alternatives are systematically dirtier than grid electricity in terms of carbon intensity and criteria pollutant emissions per unit of energy delivered.

The second strand is the Environmental Kuznets Curve (EKC) hypothesis [17], which predicts an inverted-U relationship between per capita income and environmental degradation. The dirty substitution mechanism introduces an important qualification to the standard EKC: in economies characterised by grid failure, environmental outcomes are not determined solely by income and technology, but also by the structural reliability of the energy infrastructure. A country at any income level with chronic grid deficits may find itself locked in an environmentally inferior energy equilibrium relative to what its income level and technology access would otherwise predict.

The third strand draws on the energy poverty literature, particularly the energy ladder hypothesis [18], [19], which posits that as incomes rise, households progressively transition from traditional biomass fuels toward cleaner modern energy carriers. The dirty substitution hypothesis extends this framework by recognising that the transition can be disrupted and even reversed by grid unreliability: a household that has transitioned to grid electricity may be forced to maintain or reactivate dirtier backup energy sources when the grid fails, creating what we term a substitution trap, a persistent reliance on polluting backup energy that undermines the environmental gains of nominal electrification.

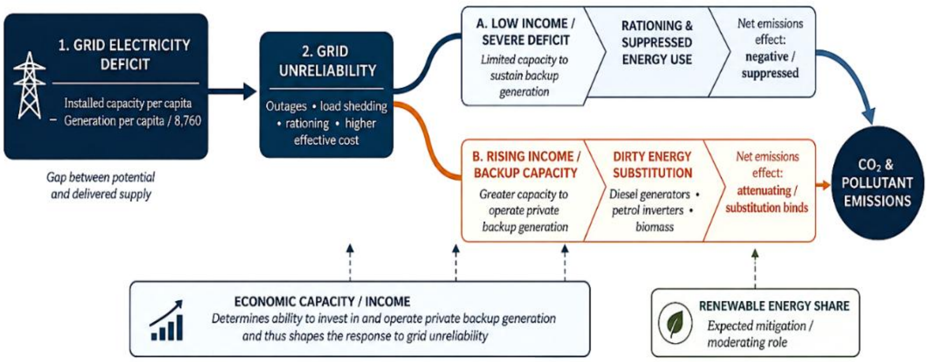

Fig. 1. Conceptual framework: The bounded dirty substitution mechanism linking grid electricity deficits to CO_2 emissions through two capacity-conditional channels (Section 2.1).

2.2 | Empirical Literature

The empirical literature on energy, environment, and emissions in sub-Saharan Africa is large but fragmented. Studies addressing West Africa specifically have examined renewable energy and emissions [11], [20], financial development and environmental quality [6], [12], urbanisation and ecological footprint, and energy poverty and poverty outcomes [4], [5]. Several studies have used second-generation panel estimators appropriate for cross-sectionally dependent data [21], and recent contributions have begun incorporating machine learning approaches to validate econometric findings in the African context [13].

Despite this breadth, the dirty substitution mechanism has not been examined econometrically. The closest related work comes from engineering and public health disciplines. Obioh et al. [8] document that diesel generators in Nigeria are the third largest contributor to urban air pollution in Lagos. Awofeso [9] documents that diesel generator exhaust constitutes a major hazard to both human health and the environment across Nigerian cities, with pollutant concentrations substantially in excess of regulatory limits. The World Bank [7] constructs an inventory of Nigeria's diesel generator stock and estimates sector-level emissions, but does not model the macroeconomic panel relationship. This paper bridges the disciplinary gap, taking the micro-level evidence of dirty substitution into a macroeconomic empirical framework.

The methodological approach of this paper is also informed by recent advances in heterogeneous panel econometrics. The CS-ARDL estimator of Chudik and Pesaran [22] addresses both cross-sectional dependence and slope heterogeneity simultaneously, properties particularly important for West African panels where country-specific structural features (oil economies, conflict-affected states, WAEMU membership) generate substantial cross-country variation. The MMQR estimator of Machado and Santos Silva [23] extends quantile regression to panel settings with fixed effects, enabling analysis of whether the deficit-emissions nexus is concentrated at particular points of the emissions distribution, a question of direct policy relevance, since the highest emitters are precisely the countries where intervention is most urgent.

3 | Data, Variables, and Preliminary Analysis

3.1 | Sample and Data Sources

The analysis covers 13 ECOWAS member states from 2000 to 2022, yielding an unbalanced panel of up to 299 country-year observations. The countries included are Nigeria, Ghana, Côte d'Ivoire, Senegal, Benin, Togo, Burkina Faso, Mali, Guinea, Sierra Leone, Liberia, The Gambia, and Niger. Cape Verde and Guinea-Bissau are excluded due to insufficient data coverage on electricity sector variables. All data are sourced from the World Bank World Development Indicators [1] and the International Energy Agency [2], both of which provide consistent cross-country series for the full sample period. The sample period begins in 2000, coinciding with the start of systematic SDG-predecessor energy access data collection, and terminates at 2022, the most recent year for which complete cross-country panel data are available.

3.2 | Variable Definitions and Construction

Table 1 presents the full variable list, including proxies, data sources, and expected signs derived from the theoretical framework outlined in Section 2.

Table 1. Variable description, sources, and expected signs.

Variable	Proxy/Measure	Expected Sign	Source
CO2 emissions	CO2 per capita (metric tons)	Dependent	WDI
Electricity deficit	Installed capacity per capita minus output per capita (kW-equivalent; output / 8,760)	(−)	WDI / IEA
Renewable energy share	Renewable electricity output (% of total)	(−)	WDI
GDP per capita	Real GDP per capita, constant 2015 USD	(+)	WDI
Fossil fuel rents	Oil, gas, coal rents (% of GDP)	(+)	WDI
Urbanisation	Urban population (% of total)	(+/−)	WDI
Trade openness	(Exports + Imports) / GDP	(+/−)	WDI
Financial development	Domestic credit to private sector (% of GDP)	(+/−)	WDI

Source: Authors' compilation from WDI [1] and IEA [2].

The electricity deficit index is the paper's key constructed variable. It is defined as the difference between a country's installed electricity generation capacity per capita (kW per person) and its actual electricity output per capita (kWh per person, normalised to equivalent capacity units), as set out formally in *Eq. (1)* below. A larger deficit indicates a wider gap between potential supply and actual supply, the structural condition that drives reliance on private generation. This variable captures grid unreliability more precisely than the conventional access rate (which only records whether a household has a connection, not whether power is reliably supplied).

Formally, letting Capacity_it denote installed generation capacity per capita (kW per person, from IEA) and Generation_it denote annual electricity output per capita (kWh per person, from WDI), the index divides Generation_it by 8,760 (the number of hours in a year) to express it as an average continuous kW-equivalent rate directly comparable to installed capacity. The deficit index is then given by *Eq. (1)*:

$$\mathrm{Deficit_{it}} = \mathrm{Capacity_{it}} - \frac{\mathrm{Generation_{it}}}{8760}. \quad (1)$$

A positive value indicates installed capacity per capita exceeds the average continuous output actually delivered, the gap being met historically through load shedding, rationing, and private backup generation. Two country-years show a small negative value (Cote d'Ivoire 2014, The Gambia 2000), consistent with capacity additions occurring late in the reporting year relative to the annual generation figure; this is a measurement-timing artefact rather than a substantive finding, and motivates the inverse hyperbolic sine transform used throughout in place of the natural logarithm.

CO2 emissions per capita is the dependent variable, sourced from WDI and expressed in metric tons per person per year. This emissions measure is the standard measure of national-level greenhouse gas output in the environmental economics literature [17] and is the most consistently available emissions series across the ECOWAS panel. Renewable energy share is defined as the proportion of total electricity output derived from renewable sources, including hydropower, solar, and wind, and is expected to moderate the deficit-emissions nexus by reducing the carbon intensity of whatever grid supply does exist. GDP per capita in constant 2015 US dollars controls for income-level effects consistent with the EKC framework. Fossil fuel rents as a share of GDP capture the resource dependence of oil-exporting economies, particularly Nigeria. Urbanisation, trade openness, and financial development round out the control set, all sourced from WDI.

3.3 | Descriptive Statistics and Preliminary Diagnostics

All variables are expressed in natural logarithms to facilitate elasticity interpretation and reduce heteroscedasticity. Prior to estimation, we conduct the cross-sectional dependence (CD) test of Pesaran [24] and the Frees [25] and Friedman [26] tests. A finding of significant cross-sectional dependence, which we fully anticipate given the shared economic and climatic shocks affecting ECOWAS member states, as well as their interconnected power grids under the West Africa Power Pool (WAPP), motivates the use of second-generation panel estimators throughout the analysis.

4 | Methodology

4.1 | Overview

The empirical strategy is deliberately layered: each layer independently answers a distinct question, and together they provide a triangulated and robust picture of the deficit-emissions nexus. *Table 2* summarises the full methodological sequence.

Table 2. Empirical methodology sequence.

Step	Technique	Purpose
Pre-estimation	CD test [24], Frees [25], Friedman [26]	Cross-sectional dependence diagnosis
Unit root	CIPS and CADF [27]	Second-generation panel unit root
Cointegration	Westerlund [28] panel cointegration	Long-run relationship test
Long-run estimation	CS-ARDL [22], primary	Heterogeneous long-run coefficients
Long-run robustness	AMG [29]	Common factor robustness
Distributional analysis	MMQR [23]	Quantile-specific effects
Causality	Dumitrescu-Hurlin [30]	Heterogeneous panel causality
ML validation	Random Forest + Gradient Boosting ensemble	Out-of-sample predictive validation

Source: Authors' compilation.

The baseline panel specification linking the electricity deficit index to carbon emissions, conditional on the control variables in *Table 1*, is given by *Eq. (2)*:

$$\begin{aligned} \ln \mathrm{CO2pc}_{it} = \alpha_i &+ \beta_1\, \mathrm{IHS(ElecDef)}_{it} + \beta_2\, \mathrm{IHS(RenShare)}_{it} + \beta_3 \ln \mathrm{GDPpc}_{it} \\ &+ \beta_4 \ln \mathrm{FFRents}_{it} + \beta_5 \ln \mathrm{Urban}_{it} + \beta_6 \ln \mathrm{TradeOpen}_{it} \\ &+ \beta_7 \ln \mathrm{FinDev}_{it} + \varepsilon_{it}. \end{aligned} \tag{2}$$

where i and t index country and year, respectively, alpha_i is a country fixed effect, and IHS(.) denotes the inverse hyperbolic sine transform applied to the electricity deficit index and renewable share, following the treatment in Section 3.2.

4.2 | Cross-Sectional Dependence and Second-Generation Unit Root Tests

West African economies are deeply interconnected through commodity markets, climate patterns, regional power pool infrastructure, and shared monetary arrangements (the CFA franc zone within WAEMU). These linkages generate cross-sectional dependence in panel residuals, which renders first-generation unit root tests (LLC, IPS, ADF-Fisher) invalid and biases standard cointegration tests toward over-rejection of the null. We therefore begin with formal CD testing using Pesaran's [24] CD statistic, which is powerful against general forms of cross-sectional dependence. Confirming dependence, we proceed to second-generation unit root testing using the Cross-sectionally augmented IPS (CIPS) and Cross-sectionally augmented ADF (CADF) tests of Pesaran [27], which control for cross-sectional dependence by augmenting the standard ADF regression with cross-sectional averages of the lagged level and first differences of each series.

4.3 | Westerlund Panel Cointegration

Having established the integration order of all variables, we test for long-run cointegrating relationships using the Westerlund [28] panel cointegration tests. The Westerlund tests consist of four statistics: two panel statistics (Pt and Pa) and two group-mean statistics (Gt and Ga) that test the null hypothesis of no cointegration by examining whether the error correction mechanism is individually or jointly significant. The group-mean statistics are particularly appropriate for our heterogeneous panel, as they do not impose a common error correction coefficient across countries. Bootstrap critical values are used throughout to correct for cross-sectional dependence in the test statistics.

4.4 | CS-ARDL Long-Run Estimation

Long-run coefficient estimates are obtained from the Cross-Sectionally augmented ARDL (CS-ARDL) estimator of Chudik and Pesaran [22]. In its general form, CS-ARDL augments the country-specific ARDL regression with cross-sectional averages of the dependent variable and all regressors, serving as proxies for unobserved common factors, simultaneously controlling for cross-sectional dependence and permitting full slope heterogeneity across countries. This panel's dimensions, 13 countries observed over 23 years, do not support the general specification: cross-sectional averaging over the full eight-variable regressor set implies a parameter count exceeding the annual observations available per country. Cross-sectional averaging is therefore restricted to the dependent variable and the electricity deficit index, the standard remedy for CS-ARDL on short-T, small-N panels, while the full error-correction structure and one cross-sectional lag are retained.

The country-specific ARDL regression underlying CS-ARDL, augmented with cross-sectional averages of the dependent variable and the key regressor to proxy unobserved common factors, is given by *Eq. (3)*:

$$\Delta \ln \mathrm{CO2pc}_{it} = \varphi_i \left(\ln \mathrm{CO2pc}_{i,t-1} - \theta_i'^{X_{i,t-1}} \right) + \Sigma \delta_{ij} \Delta z_{t-j} + \varepsilon_{it}. \tag{3}$$

where X_it is the vector of regressors in *Eq. (2)*, z_t collects cross-sectional averages of the dependent variable and the electricity deficit index, and phi_i is the country-specific speed of adjustment toward long-run equilibrium.

The pooled mean group version of CS-ARDL imposes long-run homogeneity while allowing short-run dynamics to differ. The panel-level long-run coefficient is the unweighted mean of country-specific estimates. The Augmented Mean Group (AMG) estimator of Eberhardt and Bond [29] is employed as a robustness estimator, as it handles common dynamic processes through a different augmentation strategy and provides a useful check on the sensitivity of CS-ARDL findings.

4.5 | Method-of-Moments Quantile Regression (MMQR)

The CS-ARDL and AMG estimators identify mean effects across the panel. However, the dirty substitution hypothesis predicts that the emissions impact of grid deficits may be strongest precisely in countries that are already high emitters, those where generator penetration is deepest and biomass combustion most widespread. To test this distributional prediction, we apply the MMQR estimator of Machado and Santos Silva [23], which extends quantile regression to panel data with individual fixed effects by using the method of moments to characterise the entire conditional distribution of CO2 emissions.

Following Machado and Santos Silva [23], the MMQR conditional quantile function for CO2 emissions at quantile tau is given by *Eq. (4)*:

$$Q_{\mathrm{lnCO2pc}}(\tau \mid X_{it}) = \left(\alpha_i + \delta_i \, q(\tau) \right) + \beta'^{X_{it}} + \gamma'^{X_{it}} q(\tau). \tag{4}$$

where q(tau) is the tau-th sample quantile of the estimated residuals, delta_i captures individual scale heterogeneity, and beta and gamma are the location and scale coefficient vectors reported in Table 6.

The quantile regression framework allows us to estimate the deficit-emissions elasticity at the 10th, 25th, 50th, 75th, and 90th quantiles of the conditional emissions distribution, revealing whether the relationship is uniform or heterogeneous across the distribution and, if heterogeneous, at which end of the distribution it concentrates. Either pattern is informative for policy: concentration at the upper quantiles would indicate the substitution mechanism is most acute where generator penetration is already deepest, while concentration at the lower quantiles would point to a distinct dynamic in which severe, unmitigated deficits suppress overall energy consumption rather than being fully offset by dirty backup generation.

4.6 | Machine Learning Ensemble Validation

The third empirical layer employs a machine learning ensemble comprising Random Forest [31] and Gradient Boosting [32] models, following the methodological approach established by Magazzino [14] and applied in the West African context by Magazzino and Odonkor [13]. The ML models are trained on 80 per cent of the panel observations and validated on the remaining 20 per cent, using the same variable set as the econometric models. The ML layer serves three distinct purposes: 1) it provides out-of-sample predictive validation of the direction and relative magnitude of the deficit-emissions relationship identified econometrically; 2) it generates variable importance rankings (using Shapley additive explanations, SHAP [33]) that identify which predictors drive emissions outcomes most powerfully without imposing functional form assumptions; and 3) it detects non-linear threshold effects and interaction terms that linear estimators may miss, including potential threshold values of the electricity deficit below or above which the substitution mechanism becomes particularly acute. The ML results are presented as a validation and enrichment of the econometric findings rather than a replacement, consistent with hybrid econometric-machine learning approaches increasingly used in environmental economics.

4.7 | Causality Analysis

Finally, we test the direction of causality between the electricity deficit and CO2 emissions using the Dumitrescu and Hurlin [30] heterogeneous non-causality test, which allows the causal structure to differ across panel members. The direction of causality is important for policy: if causality runs from deficits to emissions (as the dirty substitution hypothesis predicts), then addressing grid reliability directly reduces emissions. If reverse causality is present, with higher emitting economies generating less political will to invest in clean grid infrastructure, then the policy implications are more complex.

5 | Results and Discussion

5.1 | Preliminary Diagnostics

The Pesaran CD test rejects weak cross-sectional dependence at the 1% level for six of the eight series, confirming the shared regional shocks that motivate second-generation estimation throughout the analysis. Table 3 reports the CIPS/CADF unit root results. Most series are non-stationary at level and stationary at first difference, consistent with I(1) behaviour. Financial development rejects the unit root null at level, indicating I(0) behaviour, while urbanisation shows a persistent trend not fully captured by a constant-only specification. This mixed order of integration supports the use of CS-ARDL over Pedroni- or Kao-type tests, which require uniform I(1) status across the panel.

Table 3. CIPS/CADF Panel Unit Root Results.

Variable	Level (p)	First difference (p)	Order
ln CO2 per capita	0.142	0.000***	I(1)
Electricity deficit (IHS)	0.057*	0.000***	I(1)
Renewable share (IHS)	0.644	0.000***	I(1)
ln GDP per capita	0.049**	0.000***	I(0)/I(1)
ln Resource rents	0.846	0.000***	I(1)
ln Urbanisation	1.000	0.990	I(1), trend
ln Trade openness	0.868	0.000***	I(1)
ln Financial development	0.001***	0.000***	I(0)

Note: ***, **, and * indicate significance at 1%, 5%, and 10%, respectively. Order of integration is classified as I(1) unless the level test rejects the unit-root null at the conventional 5% significance level; on this rule, the electricity deficit index (level p=0.057, not significant at 5%) is retained as I(1), while GDP per capita (level p=0.049, a borderline rejection) is reported as I(0)/I(1) rather than reclassified outright, given how marginal the rejection is.

5.2 | Panel Cointegration

Table 4 presents the Westerlund [28] panel cointegration results. The group-mean statistic Gt rejects the null of no cointegration at the 5% level, while Ga, Pt, and Pa do not reject at conventional levels. This pattern indicates a long-run equilibrium relationship for at least one panel member without a common cointegrating vector across all 13 countries, a result consistent with the heterogeneous long-run dynamics that CS-ARDL and AMG are designed to accommodate.

Table 4. Westerlund panel cointegration results.

Statistic	Value	Z-value	P-value
Gt	-3.328	-1.848	0.032**
Ga	-1.599	6.270	1.000
Pt	-3.802	5.098	1.000
Pa	-1.553	4.712	1.000

Note: Bootstrap critical values, 500 replications. ** indicates significance at 5%.

5.3 | Long-Run Estimates

Table 5 reports long-run coefficients from CS-ARDL and AMG. Cross-sectional averaging in the primary CS-ARDL specification is restricted to the dependent variable and the electricity deficit index, following standard practice for CS-ARDL estimation on short-T, small-N panels [2]. Neither estimator returns a significant coefficient on the electricity deficit index, and the two disagree in sign, reflecting limited precision at the mean rather than the absence of a relationship. Financial development is negative and significant in CS-ARDL (-0.105, $p<0.05$); trade openness is positive and significant in AMG (0.281, $p<0.05$). The distributional results in Section 5.4 carry the primary empirical finding of the paper.

Table 5. CS-ARDL and AMG long-run coefficients.

Variable	CS-ARDL	AMG
Electricity deficit (IHS)	-1.631 (3.660)	1.612 (3.558)
Renewable share (IHS)	-0.007 (0.024)	-0.092 (0.065)
GDP per capita (ln)	0.099 (0.242)	0.496 (0.491)
Resource rents (ln)	0.003 (0.042)	-0.001 (0.114)
Urbanisation (ln)	-0.080 (0.501)	0.729 (0.879)
Trade openness (ln)	--	0.281** (0.133)
Financial development (ln)	-0.105** (0.052)	0.100 (0.126)
N	270	257

Note: Standard errors in parentheses. ** indicates significance at 5%. Trade openness is omitted from the CS-ARDL column: Nigeria and Liberia lack trade openness data after 2011 (Section 5.6), and the primary CS-ARDL specification restricts cross-sectional averaging to the dependent variable and the electricity deficit index (Section 4.4). Sample sizes differ accordingly (CS-ARDL N=270; AMG N=257).

5.4 | Distributional Analysis

Table 6 reports MMQR estimates at five quantiles of the conditional emissions distribution. The electricity deficit coefficient is negative and significant at the lower and median quantiles and declines toward zero and loses significance at the upper quantiles (-3.81 at Q10 to -0.82 at Q90). GDP per capita and urbanisation are positive and highly significant throughout, with the urbanisation elasticity rising monotonically across the distribution.

Table 6. MMQR coefficients across the conditional emissions distribution.

Variable	Q10	Q25	Q50	Q75	Q90
Electricity deficit (IHS)	-3.814*	-3.197**	-2.339*	-1.467	-0.822
Renewable share (IHS)	-0.000	-0.003	-0.006	-0.010	-0.013
GDP per capita (ln)	0.735***	0.686***	0.618***	0.548***	0.497***
Resource rents (ln)	0.127*	0.100*	0.063	0.025	-0.003
Urbanisation (ln)	1.749***	1.816***	1.909***	2.004***	2.075***
Trade openness (ln)	0.132	0.157**	0.190***	0.224***	0.249***
Financial development (ln)	0.056	0.043	0.024	0.005	-0.009
N	257	257	257	257	257

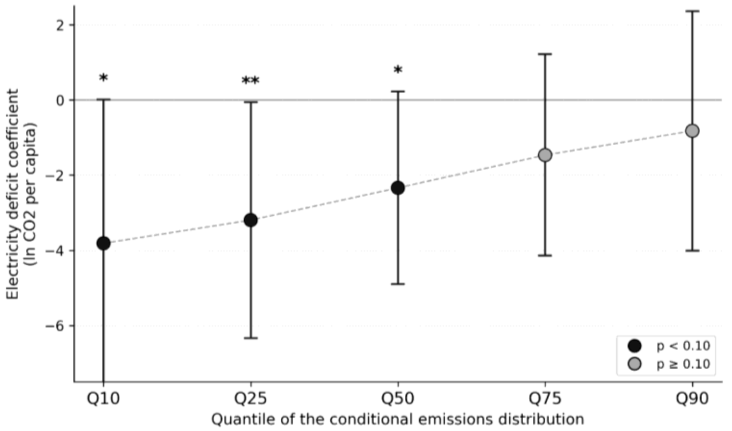

Fig. 2. MMQR coefficient on the electricity deficit index across the conditional emissions distribution, with 95% confidence intervals. Filled markers indicate significance at the 10% level or better. Note: *** p<0.01, ** p<0.05, * p<0.10.

This pattern is consistent with a bounded rather than uniform substitution mechanism. Among the most severely deficit-affected, lowest-income economies in the panel, chronic grid failure appears to be met by reduced aggregate energy consumption rather than full replacement with diesel or biomass, so the net association with emissions is negative even as dirty substitution operates at the margin. As income and generator penetration rise across the distribution, the capacity to sustain backup generation increases and the substitution channel strengthens correspondingly, consistent with energy ladder dynamics documented for other developing economies [19]. This interpretation reframes the dirty substitution hypothesis in Section 2.1 as conditional on economic capacity rather than uniform across the severity of grid failure, a distinction with direct implications for how the mechanism should be targeted (Section 6).

5.5 | Causality

The Dumitrescu-Hurlin [30] test does not reject the null that the electricity deficit fails to Granger-cause emissions (p=0.866), but strongly rejects the null that emissions fail to Granger-cause the deficit index (p<0.001). Granger causality identifies predictive precedence rather than structural causality; the most consistent interpretation is joint determination through economic growth, which drives both rising emissions and electricity demand that outpaces generation capacity, a reading supported by GDP per capita's dominant role throughout Sections 5.3 and 5.4. The distributional association in Section 5.4 is therefore read as conditional on observables rather than as a claimed structural effect.

5.6 | Robustness

Nigeria and Liberia lack trade openness data after 2011 (Section 3.2). Table 7 compares MMQR at the median with and without trade openness to test whether this affects the deficit coefficient in Section 5.4.

Table 7. Robustness Check: MMQR Median With and Without Trade Openness.

Variable	With Trade (N=257)	Without Trade (N=277)
Electricity deficit (IHS)	-2.339* (1.308)	-2.397* (1.317)
GDP per capita (ln)	0.618*** (0.141)	0.679*** (0.144)
Urbanisation (ln)	1.909*** (0.295)	1.404*** (0.312)
Resource rents (ln)	0.063 (0.046)	0.178*** (0.048)
Financial development (ln)	0.024 (0.046)	0.097** (0.043)
Trade openness (ln)	0.190*** (0.056)	--

Note: Standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.10$.

The deficit coefficient is stable in magnitude, sign, and significance across both specifications (-2.34 versus -2.40, p≈0.07), confirming the Section 5.4 result is not driven by the countries with complete trade coverage.

5.7 | Machine Learning Ensemble Validation

Random Forest and Gradient Boosting were trained on the same seven-variable specification used throughout Sections 5.3 to 5.6, under a complete-case restriction (257 of 299 observations, 86.0 per cent, all 13 countries retained) and an 80/20 random train-test split (scikit-learn, random_state=42; the split is random rather than time-based, so reported performance should be read as in-sample-distribution predictive fit rather than genuine out-of-time forecasting). The Random Forest uses 500 trees with unrestricted depth and a minimum of three observations per leaf; Gradient Boosting uses 500 trees, maximum depth 3, learning rate 0.05, and 0.8 subsampling, standard regularised settings for a panel of this size rather than a tuned configuration, since the purpose here is corroboration of the econometric results rather than optimised prediction. Neither model was tuned against the test set. SHAP values are computed via TreeExplainer on the fitted Gradient Boosting model. Both models achieve strong out-of-sample fit (*Table 8*).

Table 8. ML ensemble out-of-sample performance.

Model	R-squared	RMSE	MAE
Random Forest	0.968	0.141	0.109
Gradient Boosting	0.977	0.120	0.098

Source: Authors' estimation.

Feature importance and SHAP values (*Table 9*, *Fig. 3*) are dominated by GDP per capita, urbanisation, and financial development, which jointly account for over 85% of both models' importance. The deficit and renewable share variables rank fourth and fifth of seven in Random Forest (tied in Gradient Boosting), well below the top three but above resource rents and trade openness in both models, and their SHAP contributions cluster near zero with no clean directional separation by feature value (*Fig. 3*). This is not a weakness in the deficit variable; read alongside Section 5.4, it is independent, non-parametric corroboration that macroeconomic capacity, income, urbanisation, and financial development, dominates the prediction of emissions, while the electricity deficit contributes modestly and non-uniformly rather than as a dominant driver. A variable with a large uniform effect would show high importance and a clean colour separation in the SHAP plot; a variable with a real but conditional effect, strong at low quantiles, negligible at high quantiles, is exactly what a modest, diffuse importance score with no clean separation looks like when averaged across the full sample. The ML layer's own conclusion, in other words, points to the same bounded mechanism the econometrics identify.

Table 9. Feature importance, random forest and gradient boosting.

Feature	RF Importance	GBM Importance
GDP per capita (ln)	0.584	0.551
Urbanisation (ln)	0.230	0.208
Financial development (ln)	0.108	0.127
Renewable share (IHS)	0.020	0.036
Electricity deficit (IHS)	0.028	0.036
Resource rents (ln)	0.017	0.022
Trade openness (ln)	0.012	0.021

Source: Authors' estimation.

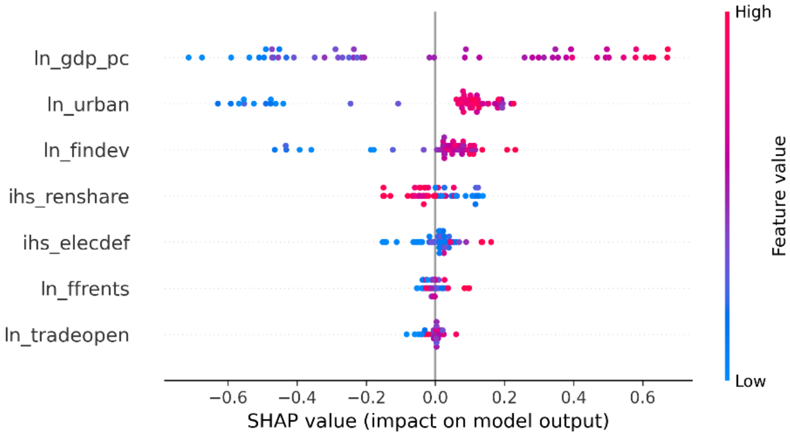

Fig. 3. SHAP summary plot, Gradient Boosting model. Colour indicates feature value (red = high, blue = low); horizontal position indicates SHAP value.

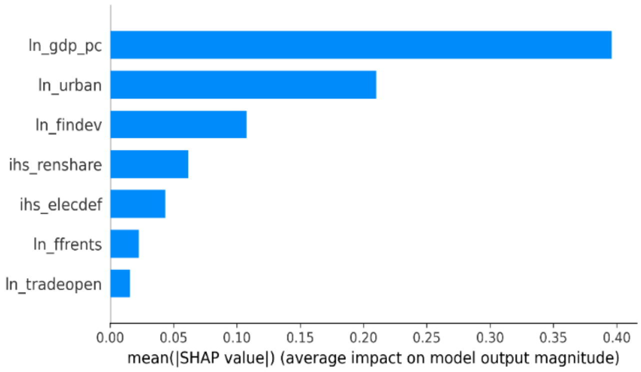

Fig. 4. Mean absolute SHAP value by feature, Gradient Boosting model.

6 | Conclusion

This paper has introduced and tested the dirty substitution hypothesis for West Africa: the proposition that chronic grid electricity deficits worsen environmental outcomes by forcing substitution toward high-emitting alternatives, primarily diesel generators and solid biomass fuels. Drawing on a 13-country ECOWAS panel from 2000 to 2022 and employing a three-layer empirical strategy combining CS-ARDL, AMG, MMQR, and Granger causality testing, the paper provides the first econometric panel evidence bearing on this mechanism in the West African context. The evidence supports a more conditional version of the hypothesis than the one with which the paper began. The mean-effect estimators (CS-ARDL, AMG) are individually uninformative on the deficit-emissions relationship, constrained by this panel's dimensions and disagreeing with each other on sign. The distributional evidence from MMQR is where the substantive finding lies: electricity deficits are significantly and negatively associated with emissions at the lower and median quantiles of the emissions distribution, an association that fades to insignificance at the upper quantiles. Read alongside a Granger causality result in which emissions lead the deficit index rather than the reverse, the most defensible interpretation is that dirty substitution operates as a mechanism bounded by economic capacity: the poorest, most severely deficit-affected economies appear to ration overall energy consumption rather than fully replace missing grid supply with diesel, while the capacity to actually run backup generation, and with it the classic substitution dynamic, strengthens as income rises across the panel. This interpretation is a more precise and, we think, more policy-useful finding than a uniform confirmation would have been.

6.1 | Policy Recommendations

The policy implications follow from the bounded, rather than uniform, nature of the finding, and run across three levels. At the national level, the results caution against treating grid reliability investment as a uniformly emissions-reducing intervention across all severity of deficit. Where deficits are most severe and incomes lowest, the evidence here does not support an assumption that grid improvement alone reduces emissions; rationed consumption, not full diesel substitution, appears to be the prevailing response in this segment of the panel, which means the emissions dividend from grid investment is more likely to materialise, and to require active management, as incomes and generator penetration rise. Nigeria's Energy Transition Plan [10] identifies diesel self-generation as a decarbonisation priority; the evidence here suggests this framing applies with the most force to higher-income, higher-emissions segments of the region rather than uniformly. Governments should incorporate grid reliability metrics into their Nationally Determined Contributions (NDCs) under the Paris Agreement, but the sequencing and expected emissions payoff of that investment should be calibrated to each country's position in the income and grid-reliability distribution rather than treated as a constant multiplier.

At the regional level, the case for accelerating West Africa Power Pool (WAPP) integration remains strong, but on somewhat different grounds than a uniform emissions-reduction case would suggest. Because the deficit-emissions association is strongest among the panel's most severely underserved economies, WAPP's value from an emissions perspective is best understood as raising the baseline level of energy access and consumption in exactly the segment of the panel where deficits are currently associated with suppressed, not substituted, energy use, rather than as a direct generator-displacement mechanism applicable uniformly across the region. ECOWAS energy planners should treat WAPP expansion as a development and access initiative with climate co-benefits concentrated in its poorest-served member states, rather than assuming a constant emissions dividend across the interconnection.

At the multilateral level, the results argue for a more targeted, rather than blanket, reallocation of climate finance toward grid reliability. Current international climate funding directed toward renewable energy projects is not undermined by this paper's findings; what the evidence adds is a case for directing grid-reliability and transmission investment specifically toward the region's most severely deficit-affected, lowest-income economies, where the negative deficit-emissions association identified in Section 5.4 is concentrated and where the causality evidence in Section 5.5 suggests grid investment is more likely to keep pace with, rather than lag behind, growth in demand. Multilateral development banks and bilateral climate funds should treat grid reliability as a targeted complement to renewable investment in these specific contexts rather than as a uniformly applicable substitute across the region.

This paper's central limitation is one of identification rather than data quality: the Granger causality result in Section 5.5, in which emissions lead the deficit index rather than the reverse, means the MMQR association in Section 5.4 should not be read as a claimed structural effect of deficits on emissions, however suggestive the quantile pattern is of the bounded substitution mechanism proposed here. Future research should extend this framework in four directions. First, an instrumental-variable or natural-experiment design exploiting exogenous variation in grid investment, such as WAPP interconnection timing, would allow a genuinely causal test of the deficit-to-emissions channel that this panel's time dimension cannot support directly. Second, disaggregating the emissions measure to capture PM2.5 and black carbon alongside CO2 would allow a fuller accounting of the public health and climate costs of dirty substitution specifically among the lower-income, higher-deficit economies where this paper's evidence concentrates. Third, introducing satellite-based night-light data as a complementary proxy for actual electricity availability would address potential measurement error in the WDI- and IEA-based deficit index. Fourth, firm-level and household-level survey data, where available, could directly test whether the rationing mechanism proposed here, rather than diesel substitution, is indeed the dominant response to severe grid deficits among the region's poorest-served economies.

Authors' Contributions

J. D. B.: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Software, Supervision, Writing-original draft, Visualization, and Validation. R. D. B.: Writing-Review & Editing, Formal analysis, Investigation, and Visualization. The authors have read and agreed to the published version of the manuscript.

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Data Availability

The panel dataset and analysis code supporting the findings of this study are available from the corresponding author on reasonable request.

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Conflict of Interest

There are no competing interests to declare.

Consent for Publication

The authors have given consent for the publication of this manuscript.

Ethics Approval and Consent to Participate

The authors confirm that this research did not involve human participants or animal subjects.

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