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Disentangling Structural Breaks from Nonlinearity in the Energy–Growth Nexus: A Regime-Based Panel Analysis for Service Economies

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Abstract. Energy and electricity are foundational inputs for logistics networks, digital services, and production systems, making accurate modelling of the energy–growth nexus essential for service-system planning and infrastructure investment. This study revisits the energy–growth relationship in six Middle Eastern economies over 1970–2022 and examines whether widely reported nonlinearities reflect intrinsic economic dynamics or instead arise from unmodelled structural breaks. Adopting a sequential empirical strategy, the analysis combines baseline panel estimators (pooled OLS, fixed effects, and random effects), quadratic-form diagnostics, and Bai–Perron multiple structural break tests. The results show that apparent nonlinear patterns in the full-sample panel largely disappear once multiple breaks are endogenously identified and regime-specific models are estimated. Break selection based on the Bayesian Information Criterion reveals four statistically significant breakpoints, partitioning the sample into five regimes. Within these regimes, the relationship between energy use and economic output is well approximated by linear specifications with time-varying coefficients. Regime-wise estimates indicate that per capita energy use has a statistically significant and economically meaningful positive effect on output only during the 2003–2011 period, associated with rapid demand expansion and investment cycles. In contrast, per capita electricity consumption exhibits a consistently positive association with GDP across baseline and regime-specific models, underscoring the critical role of reliable power infrastructure for logistics, services, and digital activities. The findings caution against interpreting nonlinear energy–GDP relationships without explicitly accounting for structural instability. By demonstrating how unmodelled breaks can generate false nonlinearity, the study contributes a transparent, regime-aware empirical workflow that is well suited for energy, logistics, and service-system analytics and supports more adaptive, context-sensitive policy and infrastructure planning.

Keywords: Energy–Growth Nexus, Structural Breaks, False Nonlinearity, Regime-Dependent Panel Models, Electricity Infrastructure, Logistics- and Service-Intensive Economies

1. Introduction

Energy and electricity are foundational inputs into modern production systems, public services, and logistics-intensive sectors. Global supply chains, transport networks, warehousing, and digital service platforms all depend on reliable, cost-effective energy, making the energy–growth nexus highly relevant to logistics, informatics, and service science. Consequently, the empirical relationship between energy consumption and economic activity has been a long-standing theme in applied econometrics (Kraft & Kraft, 1978; Stern, 2000; Ozturk, 2010). However, this literature often yields contradictory findings, including mixed signs, unstable magnitudes, and competing claims about linear versus nonlinear effects, which complicate strategic planning in energy-intensive logistics and service systems.

Many empirical models in economics and management science are built on the simplifying assumption that relationships between variables are linear and stable over time (Fuxiao Li, Xiao, & Chen, 2025). This assumption facilitates estimation, interpretation, and implementation in decision-support systems and analytics platforms. However, real-world macroeconomic and sectoral data—exceptionally long time series and panel data—are rarely generated by a single, stable regime. They are exposed to major external shocks, including commodity price cycles, financial crises, regulatory reforms, global pandemics, and geopolitical conflicts. These episodes induce what the statistical literature terms structural breaks: points in time at which key parameters of the data-generating process (means, variances, or regression coefficients) change markedly. When such breaks are ignored, empirical models may yield biased and inconsistent estimates, misleading inference, and poor predictive performance—outcomes that are particularly problematic when these models inform logistics planning, infrastructure investment, and service system design.

A key methodological issue is that structural breaks can induce parameter instability that masquerades as nonlinearity. When the actual data-generating process exhibits multiple regime shifts, fitting a single, stable-parameter model can mistakenly create patterns that appear to exhibit curvature (or "nonlinearity"), even if each regime is approximately linear. In other words, the relationship between variables may not be globally linear over long horizons yet may display piecewise linearity within relatively stable subperiods (Fuxiao Li et al., 2025). This study, therefore, asks whether apparent nonlinearity in the energy–growth nexus is intrinsic, or instead a by-product of unmodelled structural change—a phenomenon we refer to as "false nonlinearity."

The research problem is sharpened by common empirical practice. When standard tests reject linearity for the full sample, many researchers immediately adopt complex nonlinear frameworks (such as threshold autoregressive (TAR) models, smooth transition autoregressive (STAR) models, or Markov-switching specifications). While these models are robust and appropriate for genuinely nonlinear dynamics, their use may be unwarranted if the instability in the data is primarily due to structural breaks rather than intrinsic nonlinearity (Fuxiao Li et al., 2025). In applications to logistics and service systems—where model transparency, interpretability, and computational tractability are important for integration into information systems—unnecessarily complex nonlinear models can also hinder practical uptake. This study proposes an intermediate and operationally useful solution: modelling the process as a multi-regime linear system whose parameters change at endogenously determined breakpoints (Baltagi, 2021).

Empirically, we focus on six Middle Eastern economies over 1970–2022, a setting that plausibly features repeated breaks due to oil-market dynamics, regional conflicts, and major policy reforms. Using World Development Indicators series for GDP (current US$), energy use (kg of oil equivalent per capita), and electric power consumption (kWh per capita), we first estimate baseline panel models and conduct conventional specification tests, which suggest rejection of global linearity. We then apply Bai–Perron multiple structural break procedures (Bai & Perron, 1998, 2003) to endogenously identify breakpoints and partition the sample into distinct regimes. Estimating regime-wise models reveals that within each subperiod the energy–growth relationship is well approximated by a stable linear specification with regime-specific parameters, indicating that multiple structural breaks can generate the illusion of a long-run nonlinear relationship when the underlying process is better characterised as a sequence of distinct linear systems.

This study contributes to both the energy–growth literature and to empirical work in logistics in three ways. First, it provides an explicit test for false nonlinearity by contrasting global nonlinear behaviour with regime-wise linearity in a structurally unstable panel. Second, it delivers regime-specific estimates that are directly interpretable for policy makers concerned with the evolution of energy-intensive logistics and service infrastructures across different macroeconomic environments. Third, it offers a transparent empirical workflow—combining standard panel estimators with Bai–Perron structural break detection—that can be replicated with widely available software and readily adapted to other logistics and service-oriented panel datasets.

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2. Literature Review

2.1. Energy–Growth Nexus and Its Relevance for Logistics and Services

The relationship between energy use and economic activity has been widely studied across countries, time periods, and econometric frameworks. Early contributions such as Kraft and Kraft (1978) sparked debate on the direction of causality between energy consumption and output, while subsequent multivariate cointegration work emphasised energy as a key production input rather than a mere by-product of growth (Stern, 2000). Survey articles show that empirical conclusions about the energy–growth nexus are highly sensitive to sample choice, measurement of energy variables, and econometric methodology (Payne, 2010; Ozturk, 2010).

For logistics, informatics and service science, this nexus is more than a macroeconomic curiosity. Energy and electricity underpin transport networks, warehousing, cold chains, digital service infrastructure, and data centres. Mischaracterising the energy–growth relationship can therefore distort the design of energy-intensive logistics systems, the planning of service capacity, and the evaluation of efficiency gains from digital transformation.

2.2. Structural Breaks and Multi-Break Panel Econometrics

In response to the mixed evidence in the energy–growth literature, recent research has increasingly turned to nonlinear and regime-switching models to capture asymmetries, thresholds, or time-varying elasticities. However, nonlinear specifications can be highly sensitive to unmodelled parameter instability. Structural-break econometrics offers a principled way to detect and model shifts at unknown dates, avoiding the conflation of genuine nonlinearity with regime changes.

Bai and Perron (1998, 2003) developed widely used least-squares estimators and tests for multiple structural breaks in linear models. Their framework provides tools to determine both the number and location of breaks based on objective functions and sequential testing. It has become the cornerstone for analysing macroeconomic series subject to repeated shocks. Building on this foundation, Ditzen, Karavias, and Westerlund (2025) extend break detection to interactive-effects panel models, allowing the unobserved common component to vary over time and across units while accommodating cross-sectional dependence. This improves the estimation of slope coefficients in environments with strong temporal and cross-sectional correlation—conditions typical for regional energy, logistics, and service data.

In parallel, Li, Xiao, and Chen (2025) propose an estimation procedure for "common breaks" in linear panel models, assuming synchronised break dates across units that reflect shared institutional shifts or macroeconomic cycles. This common-break perspective enhances the power to detect structural change when multiple economies or sectors experience the same shock and reduces biases associated with unit-by-unit break estimation. At the algorithmic level, Li, Xiao, and Chen (2023) develop a screening-and-ranking approach to estimate multiple breaks efficiently in large panels, balancing statistical accuracy with computational cost and automatically determining the number of breaks. These advances are highly relevant for high-dimensional datasets that arise in logistics informatics, where many locations, corridors, or service nodes are observed over long horizons.

2.3. Structural Breaks in Energy and Sectoral Applications

Empirical applications that explicitly incorporate structural breaks demonstrate how crucial they are for interpreting the energy–growth nexus and related sectoral dynamics. Bazán Navarro, Morocho Ruiz, and Castillo Alvarado (2024) analyse the relationship between economic growth and electricity consumption in Latin American and Caribbean countries using panel models and causality tests over extended time horizons. By allowing for country heterogeneity and structural shifts, they show that estimates of the energy–growth linkage are fundamentally shaped by the presence and timing of breaks; ignoring these shifts can lead to misleading causal inferences. This has direct implications for planning energy-intensive logistics and service infrastructures in emerging economies.

Similarly, Guliyev (2023) examines renewable energy and economic growth in European countries using a panel framework that accounts for structural breaks. The contribution of renewable energy is found to be regime-dependent: it increases during periods of supportive policies and price stability and weakens during market disruptions or regulatory uncertainty. These results underscore that assuming a single stable relationship over the entire sample can mask regime-specific effects that matter for energy policy, transport decarbonisation, and sustainable logistics strategies. Empirical evidence from other emerging economies suggests that political stability and macroeconomic conditions have substantial effects on investment flows and structural dynamics (Khudari, Sapuan, & Fadhil, 2023), reinforcing the expectation that macro and institutional shocks in the Middle East generate significant structural breaks in the energy–growth relationship.

Adopting an "episodic" perspective, Bartak, Jabłoński, and Jastrzębska (2021) propose decomposing economic history into structurally distinct episodes before conducting causal analysis. This reframes the question from "Does energy cause growth?" to "When, where, and under which institutional system does this causal relationship hold?" By making structural regimes the primary organising principle, their approach is directly transferable to the study of energy-intensive logistics and service systems that operate across shifting regulatory, technological, and geopolitical environments.

2.4. Identified Gap

Despite these advances, two gaps remain particularly salient for macro panels in the Middle East and for applications relevant to logistics, informatics and service science. First, many studies adopt nonlinear or regime-switching models without explicitly testing whether the observed curvature is intrinsic or instead driven by structural breaks—leaving open the possibility of "false nonlinearity" generated by unmodelled parameter shifts. Second, even when structural breaks are identified, relatively few contributions translate them into regime-specific estimates that can inform energy infrastructure planning, demand-management strategies, or logistics and service-system design.

Given that energy and electricity systems in Middle Eastern economies are tightly linked to industrial upgrading, transport corridors, and public service delivery, policy responses are likely to be regime-contingent rather than time-invariant. There is therefore a need for empirical frameworks that (i) integrate modern multi-break detection procedures into standard panel models, (ii) discriminate between intrinsic nonlinearity and false nonlinearity caused by structural change, and (iii) provide transparent, regime-wise estimates that can guide decisions in energy-intensive logistics and service contexts. The present study addresses this gap by applying Bai–Perron-type multi-break analysis to the energy–growth nexus in six Middle Eastern economies and interpreting the resulting regimes from the perspective of logistics and service-system policy.

3. Research Design and Methodology

3.1. Methodological Positioning and Research Hypothesis

Recent panel econometric developments emphasise modelling structural breaks as an inherent feature of longitudinal data rather than as statistical anomalies. Multi-break frameworks in interactive-effects panels (Ditzen, Karavias, & Westerlund, 2025) and common-break models in linear panels (Li, Xiao, & Chen, 2025) show that ignoring synchronised structural shifts can severely bias coefficient estimates and distort inference, especially in settings with strong time and cross-sectional dependence. These methodological advances are particularly relevant for energy–growth studies in regions exposed to recurrent geopolitical and policy shocks, such as the Middle East, and for empirical work informing energy-intensive logistics and service systems.

Against this background, the central null hypothesis of this study is:
H0: The relationship between the economic variables under study is *piecewise linear* with multiple structural breaks induced by external shocks; apparent global nonlinearity in the full sample arises from unmodelled parameter shifts rather than an intrinsically nonlinear data-generating process.

Under this hypothesis, the appropriate empirical specification is not a complex nonlinear model but a sequence of linear models whose parameters change at endogenously determined breakpoints (Ditzen et al., 2025; Rodríguez-Caballero, 2022). Testing H0 therefore involves (i) comparing standard panel estimators against multi-break specifications and (ii) assessing whether regime-wise linear models deliver a statistically adequate description of the data.

3.2. Data, Sample, and Variables

The empirical analysis uses an unbalanced panel of six Middle Eastern economies that are both energy-rich and central to regional logistics and service activity: Iraq, Kuwait, Saudi Arabia, Syria, United Arab Emirates, and Iran.

These countries have experienced repeated political and regional shocks—with direct implications for energy markets, infrastructure investment, and service delivery—which makes them a natural laboratory for studying structural breaks in the energy–growth nexus.

The study period spans 1970–2022 (52 years), subject to data availability for each country. This horizon encompasses major oil price cycles, wars, sanctions, and policy reforms that plausibly generate multiple structural breaks in macroeconomic and energy variables.

All macroeconomic and energy series are drawn from the World Development Indicators (WDI) and related World Bank databases (World Bank, 2024). These sources provide harmonised, internationally comparable statistics suitable for panel modelling and policy analysis in logistics- and service-intensive sectors.

The core variables are:

- Gross domestic product (GDP_{it})Aggregate economic output for the country $i$in year t. In line with the original dataset, GDP is measured in current US dollars. For the econometric analysis, GDP is transformed to logarithms to reduce heteroskedasticity and interpret coefficients as elasticities where appropriate.
- Per capita energy use ($\mathrm{energy\_pc}_{it}$)Total primary energy use in kilograms of oil equivalent per capita. This indicator captures overall energy intensity and is directly relevant for energy-intensive logistics and service operations (transport, warehousing, digital infrastructure).
- Per capita electric power consumption ($\mathrm{elec\_pc}_{it}$)Electric power consumption in kilowatt-hours per capita. This variable proxies the availability and use of electricity, a critical input for service sectors, digital platforms, and logistics facilities.

Following standard practice in spatial and panel econometrics (Rodríguez-Caballero, 2022; Le Gallo & Patuelli, 2023), the panel is cleaned for missing values, checked for outliers, and transformed into a country–year structure suitable for panel regression and structural break analysis.

3.3. Baseline Panel Model Specification

The starting point is a conventional linear panel model relating economic output to energy and electricity use:

$$\mathrm{GDP}_{it} = \beta_0 + \beta_1\,\mathrm{energy\_pc}_{it} + \beta_2\,\mathrm{elec\_pc}_{it} + u_{it},$$

where GDP_{it} is the (log) gross domestic product of the country i in year t, $\mathrm{energy\_pc}_{it}$ is per capita energy use, $\mathrm{elec\_pc}_{it}$ is per capita electricity consumption, and u_{it} is the composite error term.
To account for unobserved country-specific heterogeneity, three standard panel estimators are considered: Pooled OLS, Fixed Effects Model (FE), and Random Effects Model (RE)(Croissant & Millo, 2008; Baltagi, 2021; Le Gallo & Patuelli, 2023).

The pooled ordinary least squares (OLS) model assumes no unobserved country-specific effect:

$$\mathrm{GDP}_{it} = \beta_0 + \beta_1\,\mathrm{energy\_pc}_{it} + \beta_2\,\mathrm{elec\_pc}_{it} + u_{it}.$$

This specification treats all observations as coming from a single pooled sample, which is restrictive but provides a benchmark for subsequent models.

The fixed effects model (FE) allows for time-invariant unobserved heterogeneity across countries:

$$\mathrm{GDP}_{it} = \alpha_i + \beta_1\,\mathrm{energy\_pc}_{it} + \beta_2\,\mathrm{elec\_pc}_{it} + u_{it},$$

where α_i captures country-specific intercepts that absorb factors such as geography, long-run institutional characteristics, and relatively stable structural features of national logistics and service systems. The slope coefficients β_1 and β_2 are assumed to be homogeneous across countries.

The random effects model (RE) treats the country-specific effect as stochastic:

$$\mathrm{GDP}_{it} = \beta_0 + \beta_1\,\mathrm{energy\_pc}_{it} + \beta_2\,\mathrm{elec\_pc}_{it} + \alpha_i + u_{it},$$

where α_i is a country-specific random effect, assumed to be uncorrelated with the regressors, and u_{it} is the idiosyncratic error term. This formulation yields efficiency gains when the orthogonality assumption holds.

The choice between FE and RE is guided by the Hausman test (Baltagi, 2021):

$$H = (\hat{\beta}_{FE} - \hat{\beta}_{RE})'\left[\mathrm{Var}(\hat{\beta}_{FE}) - \mathrm{Var}(\hat{\beta}_{RE})\right]^{-1}(\hat{\beta}_{FE} - \hat{\beta}_{RE}),$$

where $\hat{\beta}_{FE}$ and $\hat{\beta}_{RE}$ are the vectors of slope coefficients from the fixed and random effects estimators, respectively. Rejection of the null hypothesis (that RE is consistent) indicates that FE is preferred; otherwise, RE is adopted as the baseline panel specification.

3.4. Structural Break Detection: Bai–Perron Multi-Break Procedure

To test the “false nonlinearity” hypothesis and identify regime-wise linear relationships, the study applies the Bai–Perron (1998, 2003) multiple structural break framework. In its canonical form, a linear regression with $m$breaks (and thus $m + 1$regimes) can be written as:

$$y_t = x_t'\beta_j + u_t, t = T_{j-1} + 1, \dots, T_j, j = 1, \dots, m + 1,$$

where:

$y_t$is the dependent variable at time t,

$x_t$is the vector of regressors,

$\beta_j$is the regime-specific vector of coefficients in regime j,

$T_j$denotes the break dates (with $T_0 = 0$and $T_{m+1} = T$), and

$u_t$is the error term.

In the panel context, we treat the estimated panel model (e.g., the preferred FE or RE specification) as the baseline and use Bai–Perron procedures to identify common breakpoints that segment the time dimension into regimes. For each candidate number of breaks m, the algorithm estimates break dates that minimise the residual sum of squares (RSS), subject to minimal segment-length constraints.

3.5. Model Selection Criterion: Bayesian Information Criterion (BIC)

To select the optimal number of breaks, the study employs the Bayesian Information Criterion (BIC), which balances fit and parsimony (Ditzen et al., 2025; Feng Li, Xiao, & Chen, 2024; Karavias, Tzavalis, & Zhang, 2022). For a candidate model with $n$observations, residual sum of squares RSS, and $k$free parameters, the BIC is defined as:

$$\mathrm{BIC} = n \cdot \ln\left(\frac{RSS}{n}\right) + k \cdot \ln(n),$$

with

$$RSS = \sum_{i=1}^{n} (y_i - \hat{y}_i)^2.$$

Lower BIC values indicate a better trade-off between model fit and complexity. In the context of multi-break models, increasing the number of breaks m improves fit (reduces RSS) but increases k. BIC penalises overfitting by favouring models that achieve substantial reductions in RSS relative to the additional complexity. This is particularly important for policy-relevant applications in logistics and service systems, where overly complex models can be challenging to interpret and implement (Feng Li et al., 2024; Karavias et al., 2022; Lee et al., 2023; Zhang et al., 2023).

For the practical implementation of the Bai–Perron multiple-break framework in R, we rely on the m breaks package, which provides efficient routines for estimating and testing linear models with multiple structural changes (CRAN, 2025).

All data preparation, panel estimation, and structural-break analysis are implemented in R, an open-source statistical programming environment. R is chosen for several reasons:

Availability of specialised packages for panel data (e.g., PLM) and structural break analysis (e.g., strucchange, fixest, or Bai–Perron implementations), Strong support for reproducible workflows, enabling transparent replication and extension of the empirical strategy, and Cross-platform availability and active community support, which facilitate adoption by researchers and practitioners working with logistics, energy, and service-related datasets (Qin & Al Amin, 2023).

The combination of standard panel methods, Bai–Perron structural break detection, and BIC-based model selection yields an empirical workflow that is both methodologically rigorous and practically implementable for analysing regime-dependent energy–growth relationships in Middle Eastern economies and for drawing implications for energy-intensive logistics and service systems.

4. Empirical Results

4.1. Descriptive Patterns and Scatterplots

Figures 1 and 2 provide an initial visual assessment of the bivariate relationships between GDP and the two energy variables.

Figure 1 plots GDP against per capita energy use (energy_pc) for all country–year observations. The scatter (diffusion) diagram shows a clear upward pattern: countries and years with higher energy use per capita tend to exhibit higher GDP levels. In the underlying graph, logarithmic scales compress extreme values and allow the core cloud of observations to be seen more clearly despite differences in levels across countries and over time. This visual evidence is consistent with a positive association between energy intensity and economic scale in energy- and logistics-intensive economies.

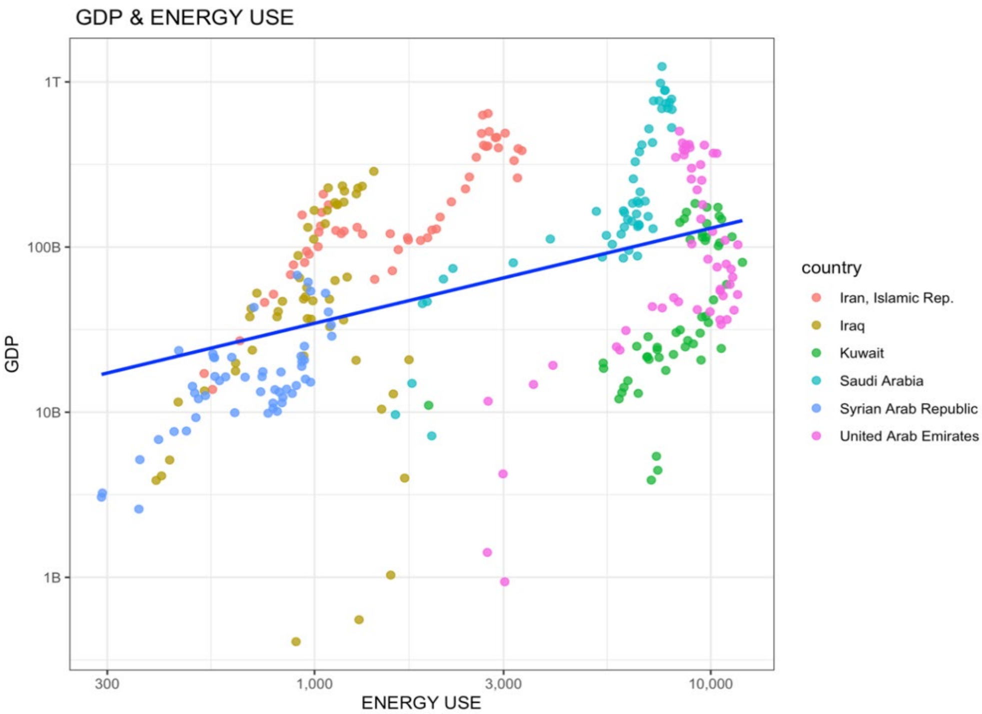

Fig.1: The Relationship between GDP and Energy Consumption

Figure 2 plots GDP against per capita electricity consumption (elec_pc). Similar to energy use, the scatter reveals a strong positive correlation: higher electricity consumption per capita is systematically associated with higher GDP. Again, the log transformation makes the relationship easier to detect by reducing the influence of observations with very high income and consumption. Taken together, Figures 1 and 2 motivate a formal panel-data analysis in which GDP is modelled as a function of per capita energy and electricity use, controlling for unobserved country effects and possible structural breaks.

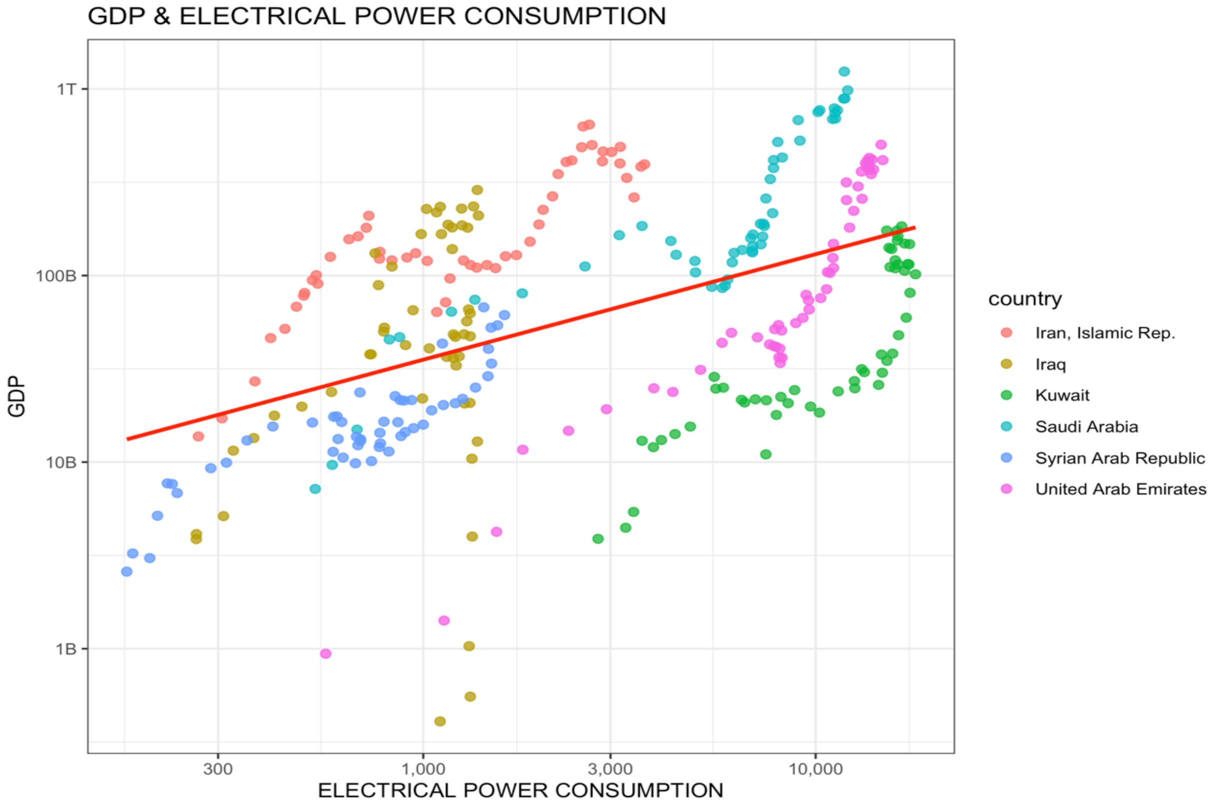

Fig.2: The relationship between electricity consumption per capita and GDP

4.2. Baseline Panel Estimates for the Full Sample (1970–2022)

Similar to energy consumption, there is a strong positive correlation between per capita electricity consumption and GDP. This is to be expected, as economic and industrial growth require more electricity. Table 1 reports the baseline panel regressions estimated over the whole period 1970–2022 under three standard specifications: pooled OLS, fixed effects (FE), and random effects (RE).

Table 1: Model values for the first methodology that takes the data as a complete batch

Model	Estimate energy_pc	p-value energy_pc	Estimate elec_pc	p-value elec_pc	R^2	Adj. R^2	N	Test
Pooled OLS	-15,513,278	0.017	22,671,606	≈1.5e-6	0.136	0.130	312	F=24.32 (p<1e-9)
Fixed Effects (within)	-4,399,681	0.540	34,388,814	<2e-16	0.367	0.353	312	F=88.19 (p<2e-16)
Random Effects (Swamy–Arora)	-7,785,379	0.265	34,376,598	<2e-16	0.351	0.347	312	Chi^2=167.21 (p<2e-16)

- **Pooled OLS** yields a negative and statistically significant coefficient on energy_pc ($p \approx 0.017$), while elec_pc is positive and highly significant ($p \approx 1.5\times10^{-6}$). The model explains about 13.6% of the variation in GDP ($R^2 = 0.136$).
- **Fixed effects** absorb time-invariant country heterogeneity. In this specification, the coefficient on energy_pc becomes statistically insignificant ($p = 0.540$), while elec_pc remains very strongly significant ($p < 2\times10^{-16}$). The explanatory power improves substantially ($R^2 = 0.367$).
- **Random effects (Swamy–Arora)** produce results very similar to FE: the coefficient on energy_pc is again insignificant ($p = 0.265$), while elec_pc remains highly significant ($p < 2\times10^{-16}$), with $R^2 = 0.351$.

Taken together, these estimates indicate that, over the full sample, electricity consumption is a robust predictor of GDP. At the same time, the effect of per capita energy use is weak once country-specific unobservables are controlled.

To determine whether the FE or RE specification should be preferred as the baseline for subsequent analysis (including the structural break procedure), we apply the Hausman test. The test compares the FE and RE estimators under the null that the RE estimator is consistent and efficient. Table 2 summarises the Hausman results.

Table 2. Hausman test comparing fixed-effects and random-effects panel models

Test	χ^2 statistic	df	p-value	Decision ($\alpha = 0.05$)	Preferred model
FE vs. RE (GDP on energy_pc, elec_pc)	4.20	2	0.1223	Do not reject H_0 (RE consistent)	Random effects

The χ^2 statistic of 4.20 with 2 degrees of freedom yields a p-value of 0.1223, which is above the conventional 5% significance level. Thus, we do not reject the null hypothesis that the RE estimator is consistent. The random-effects model is therefore adopted as the preferred baseline specification for the full sample, and it serves as the starting point for the subsequent structural break analysis.

4.3. Testing for Multiple Structural Breaks

To relax the assumption of parameter stability, the Bai–Perron multiple structural break procedure is applied to the panel model. Table 3 summarises the candidate break structures (m = 0,…,5) along with the associated residual sum of squares (RSS) and Bayesian Information Criterion (BIC) values.

Table 3: Bai-Perron Test Results

M	Breakpoints at observation number	Corresponding to break dates
1	212	0.666666666666667
2	165, 212	0.518867924528302, 0.666666666666667
3	53, 165, 212	0.166666666666667, 0.518867924528302, 0.666666666666667
4	53, 165, 212, 271	0.166666666666667, 0.518867924528302, 0.666666666666667, 0.852201257861635
5	53, 106, 165, 212, 271	0.166666666666667, 0.333333333333333, 0.518867924528302, 0.666666666666667, 0.852201257861635

The BIC monotonically improves as breaks are added up to m = 4 (BIC = 17,341), after which the criterion worsens slightly for m = 5 (BIC = 17,352). This indicates that a four-break specification (and hence five regimes) provides the best balance between fit and parsimony. The estimated breakpoints corresponding to the following calendar years are shown in Table 4.

Table 4: Comparison of the results to determine the significant value based on the Bayesian criterion

m (number of change points)	RSS	BIC
0	1136540539806022908248064O	17428
1	10913002672652402940706816	17426
2	8851782884192879888039936	17371
3	8110752768978508541067264	17355
4	7486998345632580330586112	17341
5	7471861516186935854366720	17352

These dates align well with significant regional and global events affecting energy markets and economic activity, including oil price shocks, conflict episodes, and the post-2011 political transitions. They partition the sample into five distinct economic regimes.

4.4. Regime-Wise Panel Estimates

Following breakpoint identification, the panel model is re-estimated separately for each of the five regimes, allowing coefficients to differ across periods while maintaining a linear structure within each regime, as shown in Table 5.

Table 5 summarises the regime-specific.

Period	Span	R^2	Adj. R^2	Estimate (energy_pc)	p-value (energy_pc)	Significance	Notes on year dummies
1	≤ 1978	0.628	0.486	3,839,195	0.235	n.s.	Late-1970s dummies significantly positive
2	1979–1995	0.133	−0.109	3,443,438	0.232	n.s.	No clear pattern; 1990 marginal
3	1996–2002	0.611	0.450	−3,296,031	0.266	n.s.	2000–2002 dummies strongly positive
4	2003–2011	0.728	0.631	48,190,072	0.021	*	2006–2011 dummies strongly positive
5	> 2011	0.293	0.062	−22,809,885	0.358	n.s.	2020 dummy negative; others mostly insignificant

n.s. = not statistically significant at conventional levels.

The key findings are:

- Periods 1–3 (≤1978, 1979–1995, 1996–2002): The coefficient on energy_pc is not statistically significant, although time dummies capture important period-specific shocks (e.g., late-1970s and early-2000s positive dummies).
- Period 4 (2003–2011, the oil-boom era): The coefficient on energy_pc becomes large, positive, and statistically significant ($p \approx 0.021$). This is the only regime in which per capita energy consumption shows a clear, robust positive association with GDP.
- Period 5 (post-2011): The coefficient on energy_pc is again statistically insignificant, with some evidence of negative shocks (e.g., 2020).

Thus, the regime-wise analysis reveals that the energy–growth relationship is not time-invariant: energy use per capita matters for GDP only during the 2003–2011 boom, while in other regimes its effect is weak or negligible once common shocks and country heterogeneity are accounted for.

4.5. Specification Tests for Regime-Wise Linearity

To assess whether the linear model is adequate within each regime or whether additional nonlinearity remains, the Ramsey RESET test is applied to each regime-specific regression.

Table 6 summarises the results.

Time Period	Period	RESET statistic	df (1, 2)	p-value	Decision ($\alpha = 0.05$)	Conclusion
≤ 1978	1	0.53	(2, 43)	0.5928	Do not reject H_0	Linear model adequate
1979–1995	2	1.17	(2, 97)	0.3140	Do not reject H_0	Linear model adequate
1996–2002	3	1.17	(2, 37)	0.3209	Do not reject H_0	Linear model adequate
2003–2011	4	0.11	(2, 49)	0.8991	Do not reject H_0	Linear model adequate
> 2011	5	32.94	(2, 61)	< 0.0001	Reject H_0	Evidence of nonlinearity

For periods 1–4, the RESET p-values are well above 0.05, indicating no evidence against the linear specification within each regime. For period 5 (post-2011), the RESET statistic is large and highly significant, suggesting that the linear model is misspecified and that nonlinearities or additional omitted dynamics may be important in the most recent regime.

4.6. Diagnostic Plots

Residual–fitted plots for the preferred RE specification show residuals randomly scattered around zero with no strong patterns in the early regimes, consistent with homoskedastic errors and adequate specification. At the same time, deviations are more pronounced in the post-2011 period. As shown in Figure 3. the dots should be randomly scattered around the red horizontal line at zero, without any obvious pattern. This suggests that error variance is a constant (homoskedasticity).

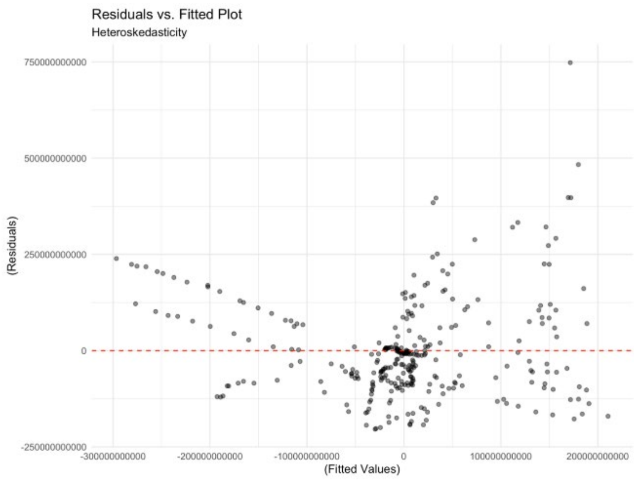

Fig.3: Residuals versus fitted values (diagnostic)

Actual–fitted plots indicate that the models fitted within regimes 1–4 track observed GDP reasonably well, whereas predictive performance is weaker in regime 5. As shown in Figure 4. the dots should cluster close around the dashed blue line (45° line). The closer the points are to this line, the better the model's predictive performance, indicating that it explains a large percentage of the variance in the dependent variable.

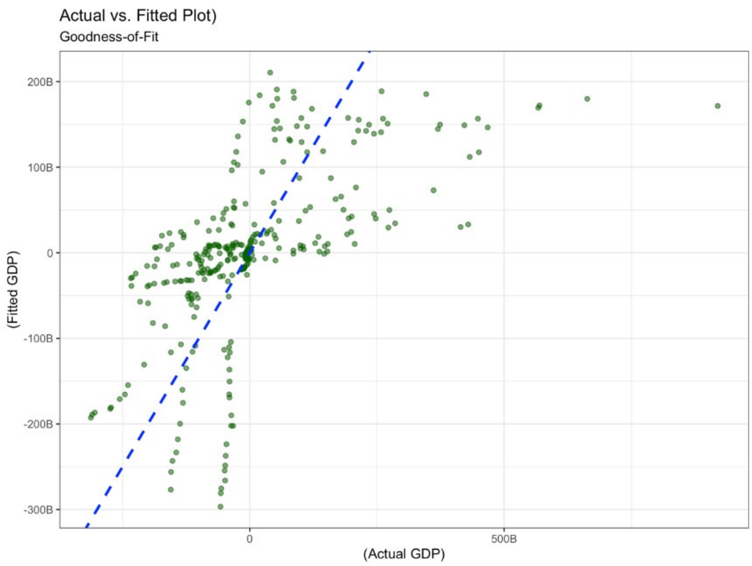

Fig.4: Actual versus fitted values (diagnostic).

Coefficient plots with confidence intervals make clear which coefficients are precisely estimated and which are not, reinforcing the regime-dependent nature of the energy effect. As shown in Figure 7, the chart indicates that the confidence intervals for both energy_pc and elec_pc lie entirely to the right of zero, confirming that their impact on GDP is positive and statistically significant.

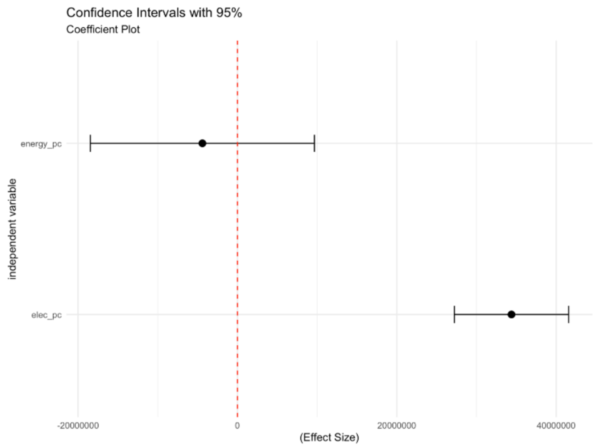

Fig.5: Coefficient plot with 95% confidence intervals (baseline model)

5. Discussion

When estimated over the full 1970–2022 period and augmented with quadratic terms in energy_pc and elec_pc, the baseline panel models suggest that the relationship between energy variables and GDP is nonlinear, with evidence of curvature in the energy–growth nexus. Taken at face value, this could justify the use of more complex nonlinear models (e.g., threshold or Markov-switching specifications). However, the structural break analysis reveals that this apparent nonlinearity is largely a false nonlinearity. Once the sample is partitioned into endogenous break regimes, linear specifications provide an adequate fit in four out of five regimes, as confirmed by the RESET tests. The pronounced curvature observed in the full-sample model is therefore driven by pooling structurally distinct regimes into a single equation, rather than by intrinsic nonlinear behaviour within the regimes.

The regime-wise results show that per capita energy use has a statistically significant positive effect on GDP only in the 2003–2011 oil-boom period, and is insignificant in all other regimes. This pattern is consistent with the region's economic history: during the boom, high oil prices and expanded energy production directly translated into higher output and investment, including in logistics and service infrastructure. Outside that period, the marginal contribution of additional energy use to GDP appears weak or muted, possibly due to inefficiency, saturation effects, or structural constraints.

Electricity consumption, by contrast, displays a robust positive association with GDP in the full-sample models, highlighting its critical role as a complementary input for production, logistics, and digital services. The contrast between the unstable effect of energy_pc and the more stable role of elec_pc suggests that the composition and efficiency of energy use, rather than aggregate volume alone, is crucial for supporting sustainable growth in logistics-intensive economies.

From a methodological perspective, the comparison between the “single-regime” and “multi-regime” approaches is instructive. The first approach (full-sample, time-invariant coefficients) yields a single, misleading average effect—no significant role for energy_pc—which does not reflect the underlying economic history. The second approach, combining Bai–Perron structural break detection with regime-wise estimation, recovers a richer, more nuanced dynamic story of how the energy–growth relationship evolves across distinct economic episodes.

This supports the view that structural breaks should be treated as a central modelling feature rather than a nuisance, particularly in regions and sectors subject to recurrent shocks.

6. Conclusion

This study set out to examine whether the apparent nonlinearity in the energy–growth relationship in six Middle Eastern economies is intrinsic or mainly a consequence of unmodelled structural breaks. Using panel data for 1970–2022, we first estimated standard pooled, fixed-effects, and random-effects models, then applied Bai–Perron multiple structural break tests to identify common break dates, and finally re-estimated models within each structurally stable regime.

The main conclusions are:

1. Full-sample panel models suggest that per capita energy use does not have a stable, statistically significant effect on GDP once country heterogeneity is controlled for, while per capita electricity consumption has a robust positive effect.
2. Structural break analysis identifies four statistically significant breakpoints (1978, 1995, 2002, 2011), partitioning the sample into five regimes that correspond to distinct economic and political episodes.
3. Regime-wise estimations reveal that the effect of energy_pc on GDP is significantly positive only during the 2003–2011 oil-boom period and insignificant in all other regimes. In contrast, linear models are adequate within the first four regimes.
4. RESET tests indicate that linearity holds within regimes 1–4, while the post-2011 regime exhibits residual nonlinearity, suggesting that more complex dynamics may characterise the recent period.

Taken together, these findings demonstrate that what appears to be nonlinear behaviour in long-horizon panel data can be explained mainly by structural instability. The energy–growth nexus in the region is better characterised as a sequence of regime-dependent linear relationships than as a stable nonlinear function over the entire sample.

The results carry several implications:

1. Regime-contingent planning of energy-intensive logistics systems. The strong, statistically significant impact of energy use on GDP during the 2003–2011 boom, contrasted with its insignificance in other periods, implies that the effectiveness of energy-intensive investments in transport corridors, warehousing, and port infrastructure is highly regime-dependent. Planning frameworks should therefore incorporate scenario analysis aligned with structural regimes rather than extrapolating from full-sample averages.
2. Prioritising electricity reliability for service and digital platforms. The consistent importance of electricity consumption as a predictor of GDP underscores the central role of reliable power supply for modern service systems and digital logistics platforms. Investments in electricity infrastructure, grid stability, and renewable integration can have broad productivity effects, particularly for logistics, e-commerce, and information services.
3. Model choice for decision-support and analytics. For practitioners building decision-support tools and analytics systems, the findings caution against automatically adopting complex nonlinear models whenever full-sample tests reject linearity. Instead, structural break diagnostics and regime-wise linear models may offer a more interpretable and operationally useful basis for forecasting and policy evaluation, especially when models need to be embedded in information systems used by non-specialist decision makers.

4. Design of adaptive, regime-aware policies. Policymakers should recognise that energy policies that worked effectively during one regime (e.g., the oil boom) may not be appropriate in others (e.g., post-2011). Adaptive, regime-aware strategies—such as adjusting fuel subsidies, investing in logistics efficiency, or diversifying energy sources—are more likely to succeed than uniform, time-invariant policy rules.

Overall, the transition from static, single-regime analysis to dynamic, regime-aware panel modelling is not merely a technical refinement; it is a necessary step toward a more realistic and policy-relevant understanding of energy-driven growth processes in logistics- and service-intensive economies.

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