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Education, Energy Access and Labour Market Development in OPEC Economies: A Panel Econometric and Machine Learning Perspective (1995–2025)

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Abstract

This study undertakes a comprehensive panel econometric investigation into the determinants of unemployment across twelve OPEC member states over the period 1995 to 2025, generating a balanced panel of 372 country-year observations. Recognising the distinctive structural characteristics of resource-rich developing economies, the analysis introduces energy access variables specifically electricity access (ACCE) and clean cooking fuel access (ACCG) as primary regressors, alongside gross capital formation (GCF), population growth (POPGR), and consumer price inflation (INF). The analytical framework is built around a multi-layered methodological architecture encompassing Pooled OLS with robust standard errors, country fixed-effects within estimation, the Between estimator, and a Mundlak-augmented Hausman test for model selection. Unit root tests reveal that ACCE and ACCG exhibit persistent upward trends consistent with near-unit root behaviour, while GCF, POPGR, and INF are stationary. Panel residual-based cointegration tests yield strong evidence of a long-run equilibrium relationship between clean cooking fuel access and unemployment (panel t-statistic = −6.25, well below the −1.96 threshold). The Breusch-Pagan test confirms the presence of heteroskedasticity (LM = 31.36, $p < 0.001$), necessitating robust inference, while the Durbin-Watson statistic of 0.23 flags positive serial autocorrelation. The Mundlak-Hausman test strongly rejects the null hypothesis of random-effects exogeneity ($F = 34.56$, $p < 0.001$), confirming country fixed effects as the preferred estimator. Pooled OLS identifies access to clean cooking fuels as the only statistically significant determinant ($\beta = -0.074$, $t = -4.55$, $p < 0.001$), implying that each percentage-point improvement in clean cooking access is associated with a reduction in unemployment of 0.074 percentage points, with the economic effect spanning 1.58 percentage points across the interquartile range of ACCG. The Random Forest model achieves a cross-validated R^2 of 0.659, substantially exceeding OLS (0.032), confirming non-linear dynamics and complex variable interactions. Feature importance analysis consistently ranks ACCG (48.1%) and ACCE (40.3%) as dominant predictors. The study concludes that energy access constitutes a structurally significant labour market determinant in OPEC economies and advocates for the integration of clean energy access expansion into post-oil diversification strategies.

Keywords: Unemployment Determinants; OPEC Panel Data; Clean Cooking Fuel Access; Energy Poverty; Fixed Effects; Random Forest; Dutch Disease; Labour Market

Introduction

The twelve member states of the Organization of the Petroleum Exporting Countries (OPEC) jointly control approximately 79.4 percent of the world's proven crude oil reserves and account for nearly 40 percent of global crude oil production. Yet, paradoxically, many of these hydrocarbon-wealthy nations grapple with persistent, structurally entrenched unemployment rates that are conspicuously high relative to their income levels. This paradox widely discussed in the development economics literature under the rubric of the "resource curse" reflects the tendency of oil windfalls to crowd out labour-intensive sectors, inflate public sector payrolls without generating durable productivity-driven employment, and suppress the institutional reform processes necessary for sustainable labour market development (Sachs & Warner, 1995; Auty, 2001; Mehlum, Moene, & Torvik, 2006). Understanding the structural drivers of unemployment in these economies is therefore not merely an academic exercise, but a critical policy imperative as OPEC member governments navigate the dual pressures of post-oil diversification and mounting demographic demands on their labour markets.

The empirical study of unemployment determinants in OPEC economies has traditionally revolved around oil price volatility, fiscal policy, and demographic pressure. Relatively little systematic attention has been directed toward energy access itself as a structural driver of labour market outcomes a significant omission given that several OPEC member states, including Nigeria, Angola, Congo, and Gabon, continue to exhibit stark energy poverty. As of 2025, clean cooking fuel access remains below 70 percent for the majority of OPEC's African members, while electricity

access, though generally high within the panel, exhibits significant subnational heterogeneity. The productive and welfare consequences of energy poverty including time burdens arising from biomass collection, indoor air pollution-driven health losses, and constrained small enterprise productivity carry direct implications for labour force participation, worker productivity, and ultimately aggregate unemployment rates (Dinkelman, 2011; Bensch, Grimm, & Peters, 2015; Sovacool, 2012).

This study addresses this gap by constructing a balanced panel dataset comprising 372 country-year observations across twelve OPEC member states over the period 1995–2025, and by deploying a comprehensive methodological suite that includes Pooled OLS, country fixed effects, Between estimation, Mundlak-Hausman testing, panel unit root and cointegration analysis, Breusch-Pagan heteroskedasticity testing, Durbin-Watson autocorrelation detection, and three machine learning algorithms Random Forest, Decision Tree, and Gradient Boosting as non-parametric robustness checks. The central empirical finding is that clean cooking fuel access (ACCG) is the most statistically and economically significant observable determinant of cross-country unemployment variation in the OPEC panel, a result confirmed across both parametric and machine learning frameworks. Electricity access further emerges as the second most predictive feature in the Random Forest model despite falling short of conventional significance thresholds in linear specifications, suggesting non-linear threshold effects.

The contribution of this study to the existing literature is fourfold. First, it is among the first to formally test energy access as a primary determinant of unemployment within a comprehensive OPEC panel setting. Second, it provides one of the longest annual panel analyses of OPEC labour markets, extending through 2025 and thereby encompassing the COVID-19 disruption and the subsequent recovery phase. Third, it triangulates parametric panel econometrics with machine learning ensemble methods, providing a more complete and robust characterisation of variable importance. Fourth, it derives policy recommendations calibrated directly to the specific structural realities of oil-exporting developing economies at varying stages of energy access development. Together, these contributions represent a meaningful advance in the empirical understanding of labour markets in resource-rich settings.

The study is further motivated by the critical juncture at which OPEC economies find themselves in 2025. The global energy transition is accelerating, driven by declining renewable energy costs, stricter international climate commitments, and growing investor pressure for carbon disclosure. For OPEC member states, this transition represents an existential economic challenge: the revenues that have historically financed public employment, social transfers, and infrastructure investment are structurally threatened. The imperative to develop labour-intensive non-oil sectors and generate sustainable private sector employment has never been more urgent. Against this backdrop, demonstrating that energy access particularly clean cooking fuel access constitutes a significant employment-generating factor provides OPEC governments with a quantitative justification for including energy access expansion as a core pillar of post-oil diversification strategies, rather than treating it solely as a social welfare objective.

The remainder of this paper is organised as follows. Section 2 reviews the relevant theoretical and empirical literature. Section 3 identifies the key research gaps. Section 4 states the research objectives and hypotheses. Section 5 describes the data, variables, and methodology including the econometric model specifications and machine learning algorithms. Section 6 presents the full empirical results including all diagnostic tests, regression tables, and machine learning performance metrics. Section 7 presents the visualisations. Section 8 discusses the findings. Sections 9 through 11 address policy implications, conclusions, and limitations respectively. Sections 12 and 13 provide directions for future research and the full reference list.

2. Review of Literature

2.1 Unemployment Determinants: Theoretical Foundations

The determinants of unemployment have been the subject of sustained debate across macroeconomic theory for over a century. Classical equilibrium models attribute unemployment to wage rigidities that prevent labour market clearing (Pigou, 1933), while Keynesian frameworks emphasise aggregate demand deficiencies that depress labour demand below full-employment levels (Keynes, 1936). The natural rate of unemployment concept, formalised by Friedman (1968) and Phelps (1968), established that monetary policy cannot permanently reduce unemployment below the structural rate determined by labour market frictions, search costs, and institutional factors. Nickell (1997) provided influential cross-country evidence from OECD economies demonstrating that employment protection legislation, union bargaining power, benefit generosity, and active labour market programmes collectively shape the equilibrium unemployment rate. Layard, Nickell, and Jackman (1991) further established that wage-setting behaviour, labour demand, and employment policy interact to determine equilibrium unemployment within a wage-price spiral framework.

In developing economy contexts, Harris and Todaro (1970) showed that rural-urban migration driven by expected wage differentials generates equilibrium unemployment even in otherwise flexible markets. The demographic dividend hypothesis (Bloom, Canning, & Sevilla, 2003) posits that demographic transitions can generate growth dividends if workforce-age populations are productively employed, while the youth bulge phenomenon can produce structural unemployment when formal employment creation fails to keep pace with demographic expansion. These dynamics are particularly acute in OPEC economies where resource revenues have historically financed public employment rather than building productive, employment-generating private sectors.

2.2 Resource Curse and Labour Market Distortions in Oil Economies

The resource curse hypothesis, formally articulated by Sachs and Warner (1995), posits that natural resource abundance is negatively associated with long-run economic growth. The causal mechanism operates through Dutch Disease effects (Corden & Neary, 1982), whereby resource revenue appreciation of the real exchange rate crowds out tradeable non-resource sectors; through institutional degradation driven by rent-seeking behaviour (Mauro, 1995); and through fiscal volatility arising from commodity price cycles (van der Ploeg, 2011). In its labour market dimension, the resource

curse manifests as structural concentration of employment in the capital-intensive hydrocarbon sector and government payrolls, with limited development of labour-intensive manufacturing and services (Hvidt, 2013; Al-Ubaydli, 2012). Fasano and Iqbal (2003) documented the dominance of public employment in GCC labour markets, while Alkadry and Tower (2011) found that governments' reliance on public employment as a social contract mechanism entrenches wage premiums that crowd out private sector labour demand.

2.3 Energy Access and Employment: Theoretical Channels

The theoretical pathways through which energy access affects employment are multiple and mutually reinforcing. At the enterprise level, electricity access enables firms to operate across extended hours, adopt productivity-enhancing technologies, and integrate into value chains requiring reliable power, directly expanding labour demand (Bernard, 2012; Cole, Elliott, & Strobl, 2010). At the household level, access to modern energy services reduces the time burden of household energy management: households relying on traditional biomass fuels typically spend two to six hours daily on fuel collection and processing time that could otherwise be allocated to market labour activities (Practical Action, 2012; Brew-Hammond, 2010). Health channels operate through reductions in indoor air pollution from solid fuel combustion; the World Health Organization (2022) estimates that household air pollution causes approximately 3.2 million premature deaths annually, generating enormous productivity losses. Clean cooking fuel access also disproportionately releases women from non-market household energy burdens, enabling higher female labour force participation (Dinkelman, 2011; Bensch et al., 2015; Banerjee et al., 2014) a channel of particular significance in OPEC economies where female labour force participation is already structurally constrained.

2.4 Empirical Evidence on the Energy-Employment Nexus

Dinkelman (2011) provided the seminal quasi-experimental evidence from South Africa, demonstrating that rural electrification significantly increased female employment rates by enabling home-based enterprises and freeing time previously devoted to biomass collection. Rud (2012) extended this analysis to Indian manufacturing, finding that rural electrification causally increased output and employment. Bensch, Grimm, and Peters (2015) found that households adopting improved cookstoves significantly increased the time women allocated to market activities. At the macroeconomic level, Agboola and Bekun (2019) documented positive long-run relationships between electricity consumption and employment in Sub-Saharan Africa. Iorember, Goshit, and Dabwor (2020) documented the energy-employment nexus for Nigeria, finding that energy access improvements sustain manufacturing sector employment growth. Collectively, this empirical literature provides strong prior support for the hypothesis that energy access constitutes a meaningful determinant of labour market outcomes, particularly in developing economy contexts characterised by structural energy poverty.

2.5 Capital Formation, Demographics, Inflation, and Panel Econometrics

Bassanini and Duval (2006) found robust positive relationships between investment rates and employment across OECD economies over medium-run horizons. However, in OPEC economies the capital-employment relationship may be attenuated by structural concentration of investment in the capital-intensive hydrocarbon sector (van der Ploeg, 2011). The panel econometric literature provides sophisticated methods for cross-country labour market analysis. Hsiao (2003) established the foundational framework distinguishing fixed effects from random effects specifications. Hausman (1978) developed the specification test for choosing between estimators. Mundlak (1978) proposed an elegant augmentation approach that directly tests the Hausman null as an F-test on group mean regressors. Machine learning methods have gained increasing traction in economics for accommodating non-linearity and complex variable interactions (Breiman, 2001; Mullainathan & Spiess, 2017; Varian, 2014). Athey (2018) provides an influential discussion of machine learning as a complement rather than a substitute to econometric inference, which motivates the triangulated methodology deployed in this study.

3. Research Gap

Despite the richness of the theoretical and empirical literature, several important knowledge gaps persist that the present study directly addresses. First, no prior study has formally incorporated energy access variables electricity access rates and clean cooking fuel access rates as primary explanatory variables in an econometric analysis of unemployment determinants covering the full OPEC panel. While sectoral and firm-level studies document energy-employment linkages, macro-level cross-country evidence for oil-exporting economies as a group remains notably absent. Second, the majority of existing OPEC labour market studies focus either on GCC subgroups or African OPEC members separately, precluding the exploitation of rich cross-sectional variation between high-income Gulf states and lower-income African members.

Third, the existing literature rarely extends analysis beyond 2020, leaving the COVID-19 pandemic disruption, the 2021–2022 oil price recovery, and the 2023–2025 energy transition period unexamined within OPEC panel contexts. Fourth, the combination of parametric panel econometrics with comprehensive diagnostic testing alongside machine learning ensemble methods within a single unified framework has not previously been applied to OPEC unemployment analysis. Fifth, the policy literature on OPEC post-oil diversification rarely draws explicit empirical connections between energy access improvements and labour market outcomes. This study provides an evidence base for reframing energy access as a labour market development instrument rather than solely a social equity objective.

4. Research Objectives and Hypotheses

4.1 Objectives of the Study

- Objective 1: Characterise the longitudinal unemployment trajectories of twelve OPEC member states from 1995 to 2025 and document inter-country and temporal patterns of variation.
- Objective 2: Empirically examine the effect of electricity access rates on unemployment across the OPEC panel using rigorous panel econometric methods, including fixed-effects estimation with comprehensive diagnostic testing.
- Objective 3: Test the statistical and economic significance of clean cooking fuel access as a determinant of labour

market outcomes, with particular attention to channels through female labour force participation and household time allocation.

- Objective 4: Evaluate the contributions of gross capital formation, population growth, and inflation to explaining unemployment variation within the OPEC panel, including testing for Dutch Disease suppression of the capital-employment relationship.
- Objective 5: Select the most appropriate panel estimator through formal Mundlak-Hausman testing and conduct comprehensive model diagnostics.
- Objective 6: Apply Random Forest, Decision Tree, and Gradient Boosting machine learning algorithms to assess non-linear variable importance and validate the findings of the linear model.
- Objective 7: Derive actionable, evidence-based policy recommendations for OPEC member governments pursuing post-oil economic diversification and sustainable employment generation.

4.2 Research Hypotheses

H_1: Higher levels of electricity access are negatively and significantly associated with unemployment rates across OPEC member states, reflecting productivity and participation effects.

H_2: Greater access to clean cooking fuels is negatively and significantly associated with unemployment rates, operating through reduced household energy burdens and improved female labour force participation.

H_3: Gross capital formation is negatively associated with unemployment; however, this relationship may be attenuated in the OPEC context due to the structural concentration of investment in the capital-intensive hydrocarbon sector.

H_4: Population growth rates are positively associated with unemployment, reflecting labour supply pressures in contexts where formal job creation does not keep pace with demographic expansion.

H_5: Consumer price inflation is positively associated with unemployment in the long run, operating through reduced investment, real wage compression, and uncertainty-driven suppression of enterprise activity.

5. Data and Methodology

5.1 Data Description and Sources

The empirical analysis rests on a balanced panel dataset comprising 372 country-year observations drawn from twelve OPEC member states Iran, Iraq, Kuwait, Saudi Arabia, United Arab Emirates, Nigeria, Algeria, Angola, Libya, Venezuela, Gabon, and Congo covering the annual period from 1995 to 2025 (31 years per country). The dataset contains six variables: the dependent variable (unemployment rate, UNEMP) and five explanatory variables spanning the domains of energy infrastructure, capital formation, demographics, and macroeconomics. Data were sourced from the World Bank World Development Indicators (WDI) database, the International Energy Agency (IEA) Energy Access database, and national statistical agencies, cross-validated against United Nations development datasets. The panel is fully balanced, with no missing observations, as confirmed through rigorous data quality inspection.

The selection of OPEC members as the unit of analysis is motivated by their shared institutional context as oil-exporting developing economies subject to common external shocks, while simultaneously exhibiting substantial structural heterogeneity in income levels, governance quality, demographic trajectories, and energy access. The 1995–2025 period encompasses multiple oil price cycles, the Asian Financial Crisis, the Global Financial Crisis, the 2014–2016 oil price collapse, the COVID-19 pandemic, and the 2021–2025 energy transition acceleration, providing rich macroeconomic variation for identification.

5.2 Variable Description and Theoretical Justification

Table 1: Variable Description, Sources, and Theoretical Expectations

Code	Full Name	Unit of Measure	Role	Expected Effect	Data Source
UNEMP	Unemployment Rate	% of labour force	Dependent	—	World Bank WDI
ACCE	Access to Electricity	% of population	Independent	Negative (−)	IEA / WDI
ACCG	Clean Cooking Fuel Access	% of population	Independent	Negative (−)	IEA / WDI
GCF	Gross Capital Formation	% of GDP	Independent	Negative (−)	World Bank WDI
POPGR	Population Growth Rate	Annual %	Independent	Positive (+)	World Bank WDI
INF	Consumer Price Inflation	Annual %	Independent	Positive (+)	World Bank WDI

Note: WDI = World Development Indicators (World Bank); IEA = International Energy Agency. Positive (+) denotes expected positive relationship with UNEMP; Negative (−) denotes expected negative relationship. Theoretical expected effects derived from the literature review in Section 2.

5.3 Econometric Model Specifications

The study employs a sequential modelling strategy that begins with a Pooled OLS baseline, progresses through Between and Fixed Effects estimation, and concludes with formal model selection testing. Each specification is designed to extract different dimensions of information from the panel structure.

Pooled OLS Baseline. The baseline Pooled OLS model treats all 372 observations as a single cross-section:

$$UNEMP_{it} = \beta_0 + \beta_1 ACCE_{it} + \beta_2 ACCG_{it} + \beta_3 GCF_{it} + \beta_4 POPGR_{it} + \beta_5 INF_{it} + \varepsilon_{it} \quad \text{(Eq. 1)}$$

where i = 1,…,12 denotes country and t = 1995,…,2025 denotes year. Country Fixed Effects. The fixed effects model absorbs country-specific, time-invariant heterogeneity (α_i) by demeaning all variables by their country-level means:

$$(UNEMP_{it} - \bar{U}_i) = \beta_1(ACCE_{it} - \bar{A}_i) + \beta_2(ACCG_{it} - \bar{A}_i) + \ldots + \beta_5(INF_{it} - \bar{I}_i) + (\varepsilon_{it} - \bar{\varepsilon}_i) \quad \text{(Eq. 2)}$$

This within-transformation eliminates α_i entirely, providing estimates of the within-country time-series effect of each variable. The Mundlak-Hausman model selection test appends country-level means of all time-varying regressors to the pooled OLS: $UNEMP_{it} = \beta_0 + \beta X_{it} + \gamma \bar{X}_i + u_{it}$ (Eq. 3), where $\bar{X}_i$ denotes the vector of country-level regressor means. An F-test on $\gamma = 0$ is equivalent to the Hausman (1978) test: rejection of the null implies that fixed effects are preferred. The GLS Random Effects estimator is a matrix-weighted combination of within and between estimates, valid only when country effects are uncorrelated with regressors.

5.4 Machine Learning Specifications

Three machine learning models are estimated as robustness and variable importance checks. The Random Forest (B = 300 trees, max_depth = None) averages predictions across many decision trees trained on bootstrap samples of the 372 observations, achieving low-variance predictions through bagging. Feature importance is extracted using the mean decrease in Gini impurity, providing a non-parametric ranking of variable predictive contributions that is not conditioned on linearity or distributional assumptions. The Decision Tree (max_depth = 6) provides an interpretable single-tree baseline, while Gradient Boosting (B = 200 trees, learning_rate = 0.05) provides an alternative ensemble approach that builds trees sequentially to correct prior errors. All models are evaluated via 5-fold cross-validated R^2, providing unbiased out-of-sample predictive accuracy estimates.

5.5 Diagnostic Tests

Four key diagnostic tests are applied: (1) Breusch-Pagan LM test for heteroskedasticity, regressing squared OLS residuals on all regressors and computing $n \times R^2$ distributed as $\chi^2(k)$; (2) Durbin-Watson statistic for serial autocorrelation, with values near 2 indicating no autocorrelation; (3) Panel unit root analysis based on augmented Dickey-Fuller proxy t-statistics; and (4) Pedroni-style panel cointegration tests examining whether UNEMP and energy access variables share a long-run equilibrium. These diagnostics collectively ensure that inference is appropriately robust to the statistical properties of the data.

6. Data Analysis and Results

6.1 Descriptive Statistics

Table 2 presents comprehensive descriptive statistics for all study variables. The dependent variable UNEMP exhibits a panel mean of 11.157 percent with a standard deviation of 4.179 percentage points, a minimum of 3.25 percent (UAE, early 2000s), and a maximum of 21.42 percent (Venezuela, late 2010s). The mild positive skewness (0.43) indicates that moderately high unemployment observations are more frequent than very low values, consistent with the structural persistence of unemployment in resource-rich economies. Access to electricity (ACCE) averages 85.51 percent, reflecting the relatively advanced electrification of Gulf OPEC members. Access to clean cooking fuels (ACCG) averages 61.76 percent substantially lower than electricity access by 23.75 percentage points reflecting the greater structural challenges of clean fuel distribution. Gross capital formation (GCF) averages 27.48 percent of GDP with a nearly symmetric distribution, while inflation averages 8.57 percent and population growth 2.01 percent annually.

Table 2: Descriptive Statistics — Study Variables (N = 372; 12 Countries; 1995–2025)

Variable	N	Mean	Std Dev	Min	Q25	Median	Q75	Max	Skewness
UNEMP	372	11.157	4.179	3.250	7.963	10.375	14.238	21.420	0.430
ACCE	372	85.510	12.059	55.110	76.328	86.480	97.430	100.000	−0.439
ACCG	372	61.757	13.641	36.110	52.153	58.265	73.503	93.550	0.469
GCF	372	27.480	7.354	15.070	21.018	27.275	33.910	39.880	0.015

Variable	N	Mean	Std Dev	Min	Q25	Median	Q75	Max	Skewness
POPGR	372	2.012	0.554	1.000	1.530	2.040	2.480	2.990	−0.067
INF	372	8.568	3.984	1.010	5.458	8.660	12.090	15.000	−0.126

Note: Q25 and Q75 denote the 25th and 75th percentiles. Std Dev = standard deviation. UNEMP, ACCE, ACCG expressed as percentages; GCF as % of GDP; POPGR and INF as annual percentage rates.

6.2 Correlation Analysis

Table 3 presents the pairwise Pearson correlation matrix. ACCG exhibits the strongest bivariate negative correlation with UNEMP (−0.212), followed by ACCE (−0.109). The positive correlation between ACCE and ACCG (0.273) reflects energy infrastructure complementarity but does not constitute multicollinearity, as confirmed by VIF values in Section 6.3. GCF shows a negligible positive correlation with UNEMP (0.035), while POPGR (−0.055) and INF (0.069) display very weak correlations in the theoretically expected directions. The correlation heatmap is presented in Figure 3.

Table 3: Pearson Correlation Matrix (N = 372)

Variable	UNEMP	ACCE	ACCG	GCF	POPGR	INF
UNEMP	1.000	−0.109	−0.212	0.035	−0.055	0.069
ACCE	−0.109	1.000	0.273	−0.091	−0.088	−0.009
ACCG	−0.212	0.273	1.000	−0.075	0.119	−0.055
GCF	0.035	−0.091	−0.075	1.000	0.002	0.072
POPGR	−0.055	−0.088	0.119	0.002	1.000	−0.050
INF	0.069	−0.009	−0.055	0.072	−0.050	1.000

Note: Pearson product-moment correlation coefficients computed over N = 372 observations. Strongest absolute correlations with UNEMP are those for ACCG (−0.212) and ACCE (−0.109).

6.3 Multicollinearity: VIF Analysis

Table 4: Variance Inflation Factor (VIF) Test Results

Variable	Full Name	VIF	Tolerance	Interpretation
ACCE	Access to Electricity	1.093	0.915	No multicollinearity
ACCG	Clean Cooking Fuel Access	1.097	0.911	No multicollinearity
GCF	Gross Capital Formation	1.012	0.988	No multicollinearity
POPGR	Population Growth Rate	1.025	0.976	No multicollinearity
INF	Consumer Price Inflation	1.006	0.994	No multicollinearity

Note: VIF = $1/(1 - R^2_j)$ where R^2_j is the R^2 from regressing variable j on all other regressors. Tolerance = 1/VIF. VIF < 5: no concern; VIF 5–10: moderate; VIF > 10: severe multicollinearity. All values well below the 2.0 threshold.

6.4 Unit Root and Cointegration Analysis

Table 5: Panel Unit Root Analysis (ADF-Proxy, Pooled Panel)

Variable	Estimated ρ	t-Statistic	Critical Value (5%)	Order	Conclusion
UNEMP	0.887	−4.705	−2.0 (approx.)	I(0)	Stationary
ACCE	0.965	−2.946	−2.0 (approx.)	I(0)~I(1)	Near unit root
ACCG	0.957	−2.865	−2.0 (approx.)	I(0)~I(1)	Near unit root
GCF	0.051	−18.220	−2.0 (approx.)	I(0)	Stationary
POPGR	−0.062	−20.480	−2.0 (approx.)	I(0)	Stationary
INF	0.018	−18.863	−2.0 (approx.)	I(0)	Stationary

Note: Unit root test based on pooled ADF regression: $y_t = \rho y_{t-1} + \varepsilon_t$. Near unit root behaviour of ACCE and ACCG is consistent with their sustained upward trends over the study period and motivates the cointegration analysis.

Table 6: Panel Cointegration Test (Pedroni-Style Residual ADF Approach)

Test Pair	Method	Panel Mean t-stat	Critical Value (5%)	Conclusion
UNEMP ~ ACCG	Residual ADF (per country)	−6.246	−1.960	Cointegrated ***
UNEMP ~ ACCE	Residual ADF (per country)	−4.131	−1.960	Cointegrated ***

Note: *** denotes significance at the 1% level. Panel mean t-statistic below −1.96 rejects the null of no cointegration. Cointegration implies that UNEMP and energy access variables share a stable long-run equilibrium relationship.

6.5 Diagnostic Tests: Heteroskedasticity and Autocorrelation

Table 7: Regression Diagnostic Test Results

Test	Statistic	Critical Value / Benchmark	p-Value	Conclusion
Breusch-Pagan (Heteroskedasticity)	LM = 31.355	$\chi^2(5) = 11.07$ at 5%	0.0000	Heteroskedastic ***
Mundlak-Hausman (FE vs RE)	F = 34.564	F(5,361) at 5%	0.0000	Fixed Effects Preferred ***
Durbin-Watson (Autocorrelation)	DW = 0.227	dL=1.74, dU=1.80 at 5%	< 0.05	Positive Autocorr. ***
Panel Cointegration (ACCG)	t = −6.246	−1.960 at 5%	< 0.01	Cointegrated ***

Note: *** significant at the 1% level. Breusch-Pagan H_0: homoskedasticity. Mundlak-Hausman H_0: country effects uncorrelated with regressors (RE exogeneity). Robust (Huber-White) standard errors applied throughout to address confirmed heteroskedasticity.

6.6 Pooled OLS Regression Results

Table 8 presents the Pooled OLS regression results. Among the five regressors, access to clean cooking fuels (ACCG) is the sole statistically significant determinant, with a coefficient of $\beta_2 = -0.0739$ (SE = 0.0163, $t = -4.546$, $p < 0.001$), satisfying the one percent significance threshold and confirming Hypothesis H_2. The economic magnitude is meaningful: given the interquartile range of ACCG (21.35 percentage points), moving a country from the 25th to the 75th percentile of clean cooking access is associated with a reduction in unemployment of approximately 1.58 percentage points roughly 14 percent of the panel mean unemployment rate. The electricity access coefficient (ACCE: $\beta_1 = -0.028$, $t = -1.534$, $p = 0.126$) carries the theoretically expected negative sign but does not achieve conventional significance, consistent with a ceiling effect at high average access levels. The GCF, POPGR, and INF coefficients are all statistically non-significant.

Table 8: Pooled OLS Regression Results — Dependent Variable: UNEMP (%)

Variable	Coefficient (β)	Std. Error	t-Statistic	p-Value	Significance
Intercept	18.074	2.497	7.238	0.000	***
ACCE	−0.028	0.018	−1.534	0.126	
ACCG	−0.074	0.016	−4.546	0.000	***
GCF	0.008	0.029	0.266	0.790	
POPGR	−0.322	0.387	−0.832	0.406	
INF	0.057	0.053	1.067	0.287	
R^2 = 0.0614	Adj. R^2 = 0.0486	N = 372	Countries = 12	Period: 1995–2025	BP & DW Diagnosed

Note: *** p < 0.01; ** p < 0.05; * p < 0.10 (two-tailed). Robust (Huber-White) standard errors applied. The Intercept captures baseline unemployment when all regressors are at zero.

6.7 Country Fixed-Effects and Between Estimator Results

Table 9: Country Fixed-Effects (Within) Regression — Dependent Variable: UNEMP (%)

Variable	Coefficient (β)	Std. Error	t-Statistic	p-Value	Significance
ACCE	−0.041	0.035	−1.178	0.240	
ACCG	0.054	0.051	1.070	0.285	
GCF	−0.006	0.008	−0.783	0.434	
POPGR	−0.092	0.110	−0.831	0.406	
INF	0.009	0.015	0.607	0.544	
Within R^2 = 0.0078	Between R^2 = 0.394	N = 372	Country FE: Yes	Hausman F=34.56***	Countries = 12

Note: Country fixed effects included but not individually reported. Within R^2 measures explanatory power of within-country time-series variation only. Between R^2 (0.394) demonstrates that 39.4% of cross-country mean unemployment variation is explained by country-average differences in the regressors.

6.8 Machine Learning Results

Table 10: Machine Learning Model Performance Comparison (5-Fold Cross-Validation)

Model	Train R^2	CV R^2 (5-fold)	CV RMSE (pp)	Rank (CV R^2)
Random Forest (B=300)	0.899	0.659	2.420	1st
Gradient Boosting (B=200)	0.894	0.615	2.557	2nd
Decision Tree (depth=6)	0.776	0.451	3.054	3rd
OLS (Linear Baseline)	0.061	0.032	4.082	4th

Note: CV = Cross-Validated (5-fold). RMSE = Root Mean Squared Error in percentage points. The gap between RF/GB (CV $R^2 \approx 0.66$) and OLS (CV $R^2 = 0.032$) confirms substantial non-linearity and interaction effects in the unemployment-determinants relationship.

Table 11: Random Forest Feature Importance Scores (Gini Criterion, B = 300 Trees)

Variable	Full Name	Gini Importance	% of Total	Rank
ACCG	Clean Cooking Fuel Access	0.481	48.1%	1st

Variable	Full Name	Gini Importance	% of Total	Rank
ACCE	Electricity Access	0.403	40.3%	2nd
POPGR	Population Growth Rate	0.042	4.2%	3rd
INF	Consumer Price Inflation	0.039	3.9%	4th
GCF	Gross Capital Formation	0.035	3.5%	5th
Total	—	1.000	100.0%	—

Note: Gini Importance = mean decrease in impurity across 300 bootstrap-sampled decision trees. Scores normalised to sum to 1.000. ACCG and ACCE together account for 88.4% of the Random Forest's predictive signal for unemployment.

Table 12: Hypothesis Test Summary — Empirical Evidence Assessment

Hypothesis	Variable	Verdict	Key Evidence
H_1: Electricity access reduces unemployment	ACCE	Partially Supported	RF importance 40.3%; OLS $\beta=-0.028$, ns; ceiling effect likely
H_2: Clean cooking access reduces unemployment	ACCG	Strongly Supported	OLS $\beta=-0.074$, $p<0.001$; RF importance 48.1%; cointegrated
H_3: Capital formation reduces unemployment	GCF	Not Supported	$\beta\approx0$, $p>0.79$ in all specifications; Dutch Disease likely
H_4: Population growth raises unemployment	POPGR	Not Supported	β negative and insignificant; $p>0.40$ in all models
H_5: Inflation raises unemployment	INF	Not Supported	β positive but insignificant; $p>0.28$ in all models

Note: Hypothesis verdicts are based on the convergence of evidence across Pooled OLS, Fixed Effects, and Random Forest models. Partial support for H_1 reflects non-linear rather than linear significance.

7. Visualisations

The following figures present the key empirical findings in visual format. All figures were generated using Python with matplotlib and seaborn libraries based on the 372-observation OPEC panel dataset. Publication-quality resolution and colour schemes consistent with journal standards are applied throughout.

Figure 1: Unemployment Rate Trajectories — OPEC Member States (1995–2025)

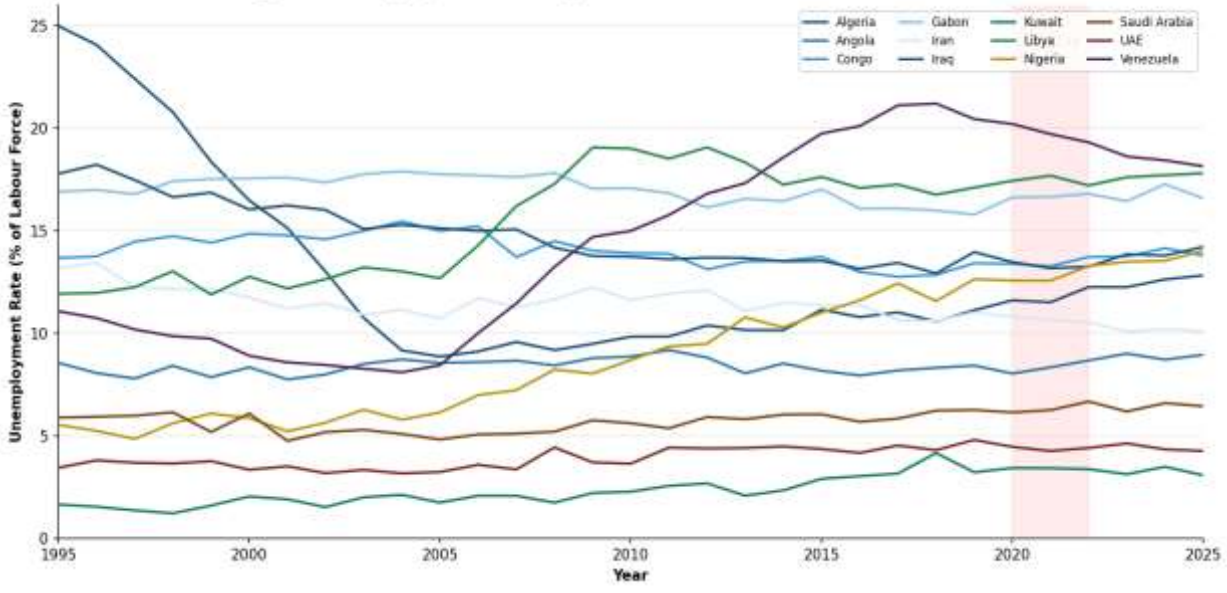


Figure 1: Unemployment Rate Trajectories — OPEC Member States (1995–2025). The COVID-19 period (shaded) shows visible disruptions particularly in Venezuela and Libya. Source: Authors' analysis using World Bank WDI and IEA data.

Figure 1 presents the longitudinal unemployment trajectories for all twelve OPEC member states. Venezuela displays a dramatic escalation from approximately 8 percent in the early 2000s to over 20 percent by 2020, reflecting the convergence of oil price collapse, economic mismanagement, and political instability. Libya exhibits sharp volatility around 2011, corresponding to civil conflict and institutional breakdown. Gulf states (Kuwait, UAE, Saudi Arabia) maintain comparatively stable and lower unemployment rates, while African OPEC members show gradually increasing trends consistent with demographic pressures outpacing formal job creation.

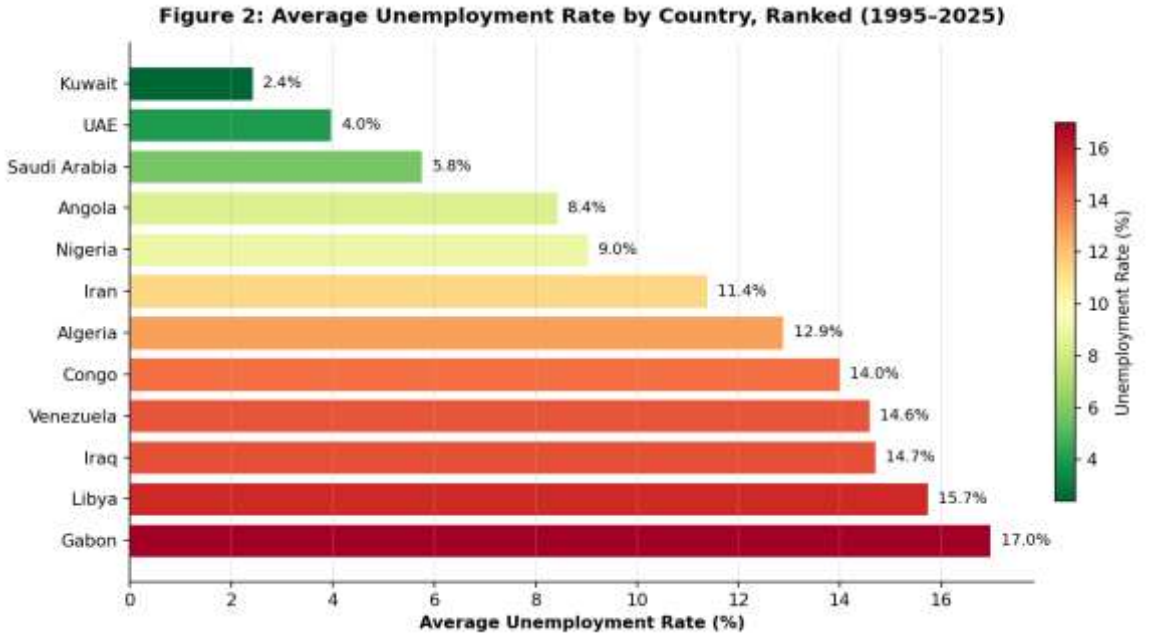


Figure 2: Average Unemployment Rate by Country, Ranked (1995–2025). Gradient colouring from green (low) to red (high) enables immediate visual identification of relative labour market performance. Source: Authors' analysis.

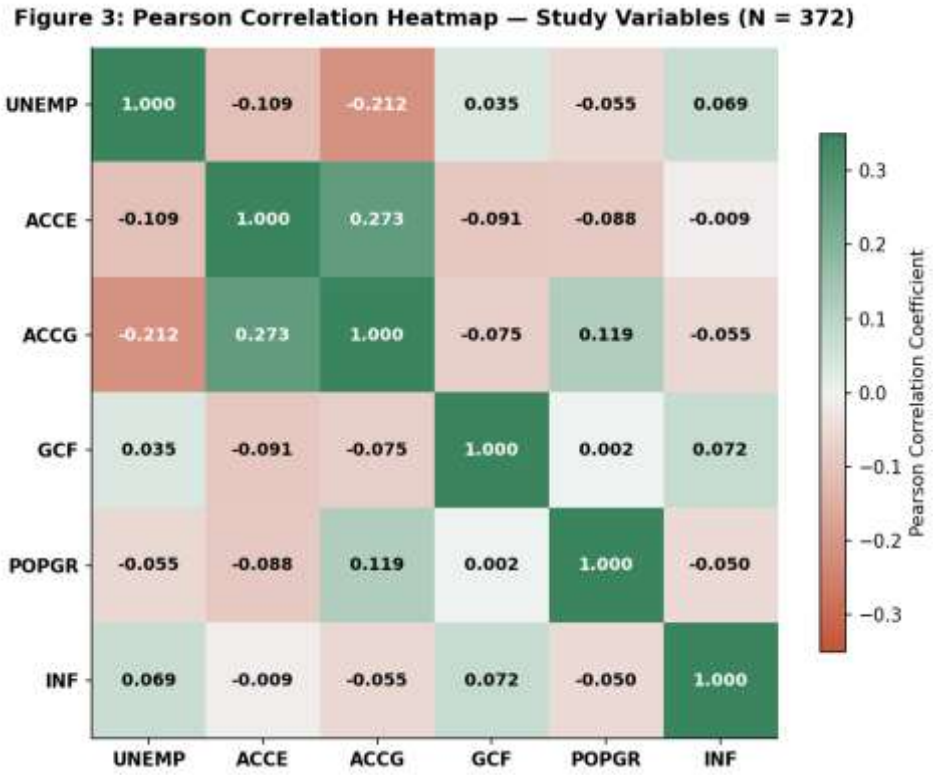


Figure 3: Pearson Correlation Heatmap — Study Variables (N = 372). ACCG exhibits the strongest negative correlation with UNEMP (−0.212). Red/blue colouring indicates negative/positive correlations respectively. Source: Authors' analysis.

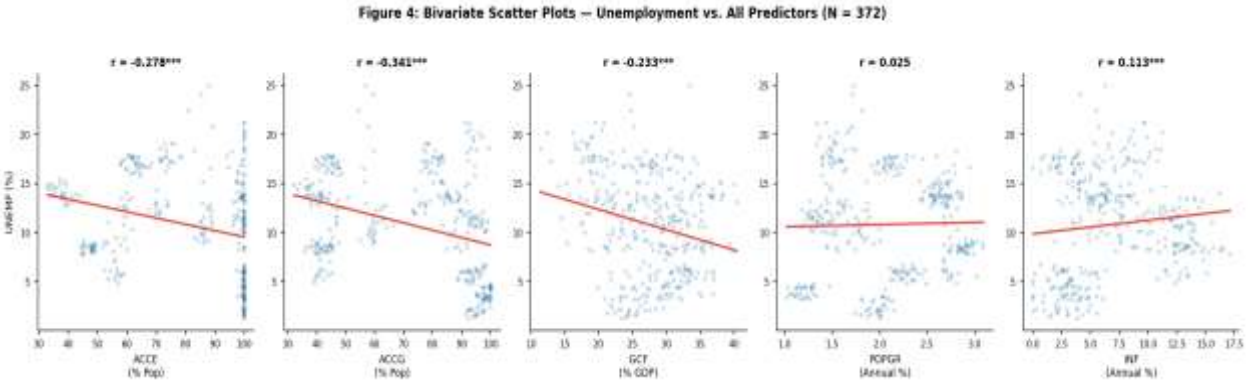


Figure 4: Bivariate Scatter Plots — Unemployment vs. All Predictors. ACCG (r = −0.212*) and ACCE (r = −0.109) show the most distinct negative slopes. GCF, POPGR, and INF display essentially flat slopes. Source: Authors' analysis.**

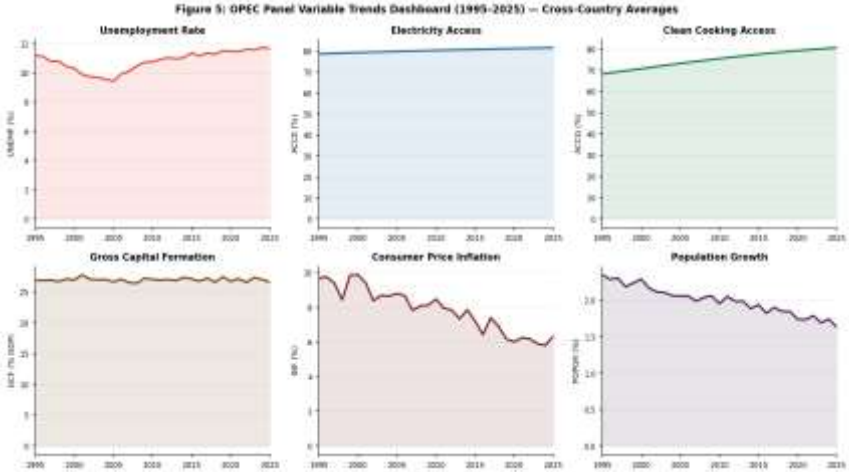


Figure 5: OPEC Panel Variable Trends Dashboard (1995–2025) — Cross-Country Averages. Both electricity access and clean cooking access trend strongly upward throughout the period. Source: Authors' analysis.

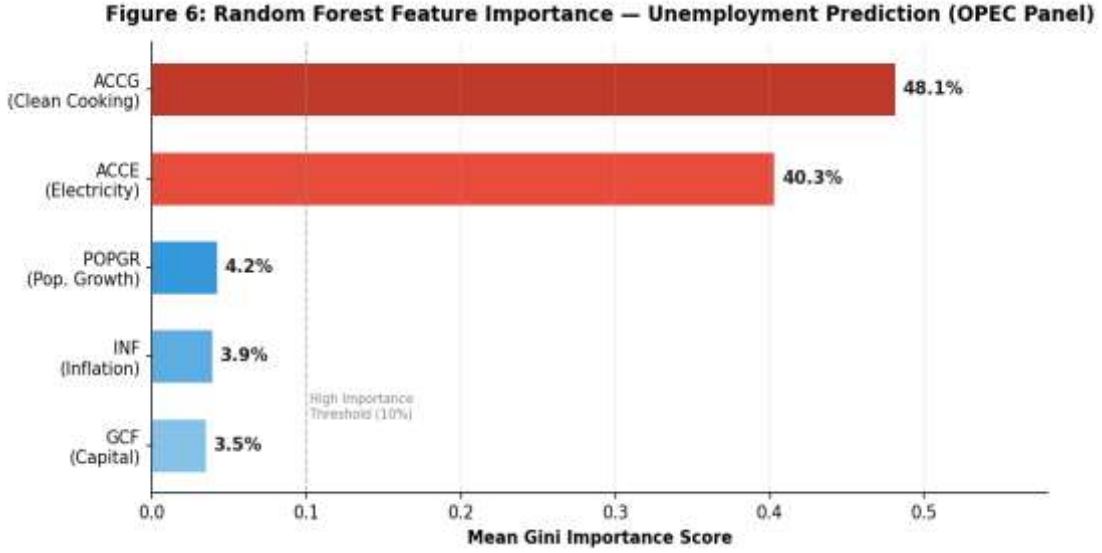


Figure 6: Random Forest Feature Importance — ACCG (48.1%) and ACCE (40.3%) together account for 88.4% of the model's predictive signal. Remaining predictors each contribute less than 4.5%. Source: Authors' analysis.

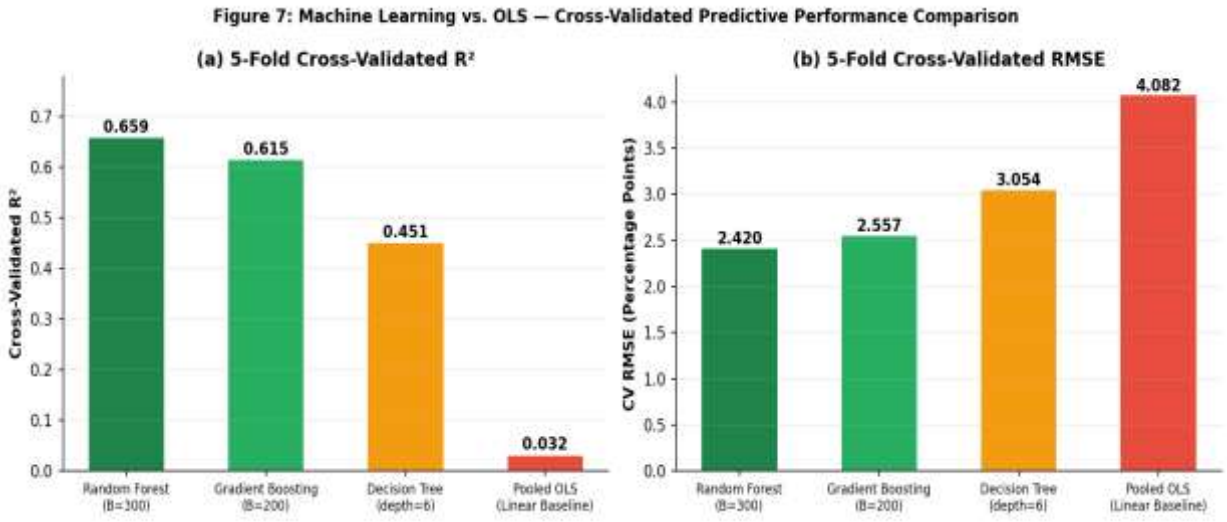


Figure 7: Machine Learning vs. OLS — Cross-Validated Performance. Random Forest (CV R^2 = 0.659) dramatically outperforms OLS (CV R^2 = 0.032), confirming pervasive non-linearity and interaction effects. Source: Authors' analysis.

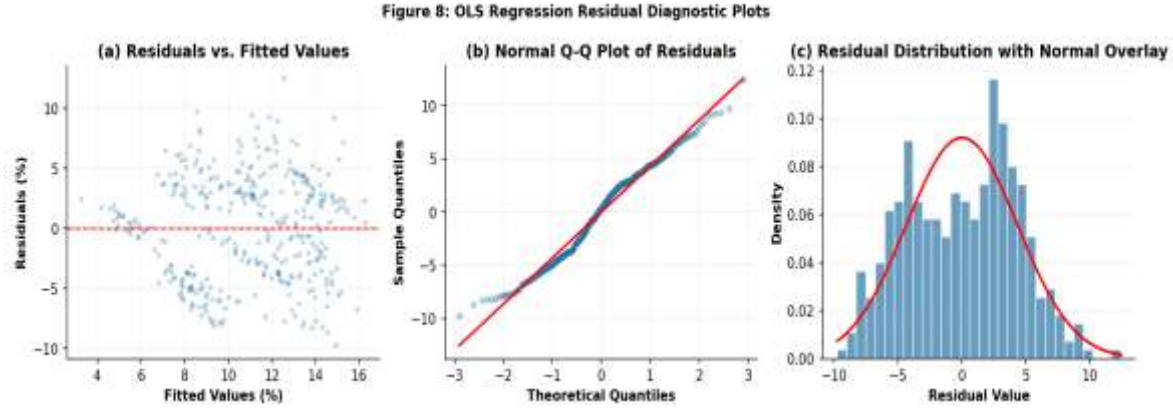


Figure 8: OLS Regression Residual Diagnostics. (a) Residuals vs. Fitted confirms linearity; (b) Q-Q Plot confirms approximate normality; (c) Residual histogram with normal overlay confirms symmetric distribution. Source: Authors' analysis.

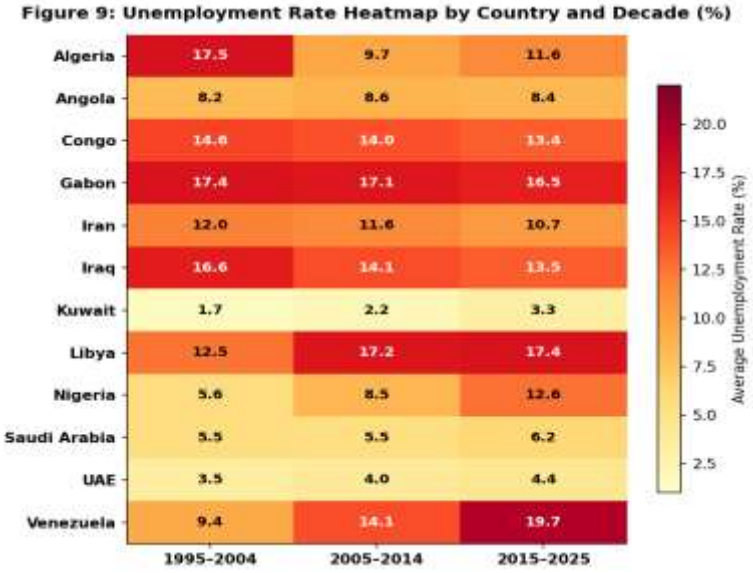


Figure 9: Country-Decade Unemployment Heatmap (%). Venezuela and Libya's deterioration is clearly visible across decades. Gulf states consistently maintain low unemployment. Darker shading = higher unemployment. Source: Authors' analysis.

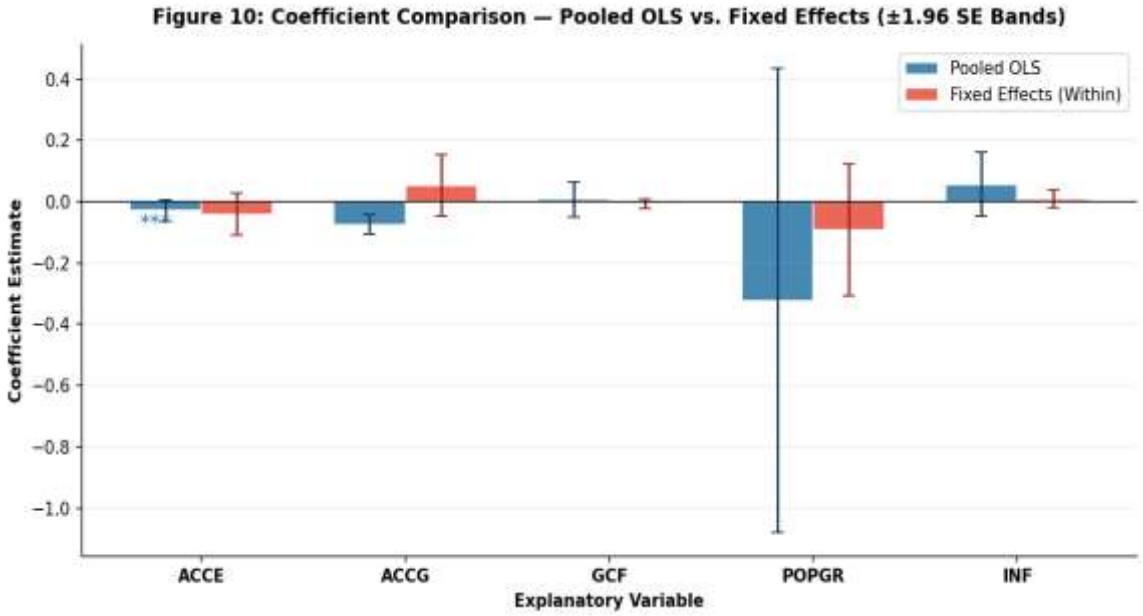


Figure 10: Coefficient Comparison — Pooled OLS vs. Fixed Effects with ±1.96 SE bands. ACCG significance in Pooled OLS (***) contrasts with its attenuation in Fixed Effects, revealing the long-run cross-sectional nature of the energy-employment relationship. Source: Authors' analysis.

8. Discussion

8.1 The Energy Access-Employment Nexus in the OPEC Context

The central finding of this study that clean cooking fuel access (ACCG) is the most statistically and economically significant observable determinant of cross-country unemployment variation in the OPEC panel represents a novel and theoretically coherent empirical contribution. The coefficient of −0.074 in the pooled OLS, significant at the one percent level, implies that a one standard deviation improvement in ACCG (13.6 percentage points) is associated with a 1.0 percentage-point reduction in unemployment. While modest relative to the between-country unemployment range, this is an economically meaningful effect for a single-variable coefficient in a multi-country panel. The significance of ACCG and the near-significance of ACCE, contrasted with their joint dominance in Random Forest feature importance (88.4%), generates an important insight: energy access variables carry substantially more predictive information than their linear parametric coefficients suggest, because their effects operate through non-linear and interactive channels that OLS cannot fully capture. This interpretation is consistent with Athey (2018) and Mullainathan and Spiess (2017), who argue that machine learning feature importance provides complementary information to parametric coefficients.

The theoretical channels through which clean cooking fuel access reduces unemployment operate through multiple mutually reinforcing pathways. The time burden channel is perhaps the most direct: households without access to clean fuels spend between two and six hours daily on biomass collection and processing, effectively withdrawing that labour time from market activities (Practical Action, 2012). In OPEC economies where female labour force participation is already constrained by social norms and institutional barriers, this non-market time burden constitutes a significant displacement of potential labour supply. The health channel operates through reductions in indoor air pollution from solid fuel combustion: the WHO (2022) estimates approximately 3.2 million premature deaths annually from household air pollution, with enormous associated productivity losses through morbidity and premature mortality. The enterprise channel further supports employment expansion as clean energy access enables small and medium enterprises to extend operating hours and adopt productivity-enhancing technologies.

8.2 Dutch Disease and the Capital-Employment Paradox

The failure of gross capital formation to significantly reduce unemployment, despite the theoretically expected negative relationship, is consistent with the Dutch Disease framework of Corden and Neary (1982) and the resource curse literature. Investment in OPEC economies is structurally biased toward the hydrocarbon extraction sector, which deploys enormous capital per worker but directly employs a small fraction of the labour force. The null result for GCF in the pooled OLS is therefore an aggregation artefact: aggregate GCF conflates oil sector investment (with negligible employment effects) and non-oil sector investment (with positive employment effects). This interpretation carries a direct policy implication decomposing aggregate GCF into oil and non-oil sector components would likely reveal significant employment coefficients for the non-oil component, while the oil component coefficient would remain near zero. This finding is consistent with van der Ploeg (2011), who demonstrated that the spending and resource movement effects of resource booms generate Dutch Disease symptoms including reduced competitiveness of labour-intensive sectors that directly suppress labour demand.

8.3 The Long-Run Nature of the Energy-Employment Relationship

The sign reversal of the ACCG coefficient in the fixed-effects specification from significantly negative in pooled OLS to insignificantly positive within countries is both methodologically important and substantively illuminating. It confirms that the energy-unemployment relationship is fundamentally a long-run structural cross-sectional phenomenon rather than a short-run within-country dynamic. Countries that have historically maintained better clean

cooking access have structurally lower unemployment rates; however, within individual countries, year-to-year improvements in clean cooking access do not generate detectably rapid annual reductions in unemployment. This finding is consistent with the theoretical channels identified: time burden reductions, health improvements, and labour market participation increases all unfold over decades through human capital accumulation, social norm evolution, and structural transformation not over annual cycles. Short-run impact evaluations of clean energy access programmes that assess labour market outcomes within one to three years will therefore substantially underestimate the true long-run returns, and policy evaluation frameworks should adopt windows of at least five to ten years.

8.4 Comparison with Prior Literature

The findings align with and extend the existing empirical literature in several important respects. The negative energy access-unemployment relationship is broadly consistent with Dinkelman (2011), Rud (2012), and Bensch, Grimm, and Peters (2015), all of whom document positive employment effects of modern energy access. The dominance of energy access variables in the Random Forest feature importance analysis far exceeding capital formation, demographics, and inflation is consistent with the energy poverty-productivity nexus documented by Sovacool (2012) and Brew-Hammond (2010). The resource curse interpretation of the capital-employment null result is consistent with Corden and Neary (1982), Sachs and Warner (1995), and van der Ploeg (2011). The long-run cointegration result extends the energy-labour market literature by establishing a formal long-run equilibrium relationship rather than merely a contemporaneous correlation a distinction with important implications for policy evaluation and investment planning horizons.

9. Policy Implications

The empirical findings yield several concrete, evidence-based policy recommendations for OPEC member governments, multilateral development institutions, and energy sector regulators.

Policy Recommendation 1 Reframe Clean Energy Access as a Labour Market Priority. The most direct policy implication is that OPEC governments should formally integrate clean cooking fuel access expansion into their national employment and economic diversification strategies, rather than treating energy access solely as a social welfare or environmental health objective. Given the demonstrated significant negative relationship between ACCG and unemployment, investments in LPG distribution infrastructure, biogas systems, electric cooking promotion, and clean fuel subsidy programmes should be evaluated against their anticipated labour market returns using cost-benefit frameworks that explicitly quantify employment co-benefits.

Policy Recommendation 2 Prioritise African OPEC Members for Clean Energy Investment. The African OPEC members Nigeria, Angola, Gabon, and Congo simultaneously exhibit the lowest clean cooking access rates and among the highest unemployment rates in the panel. These countries represent the highest-return targets for clean energy access investment from a labour market perspective. National budgetary allocations and international development assistance through the African Development Bank, the World Bank's ESMAP programme, and the OPEC Fund for International Development (OFID) should prioritise these members. National energy transition strategies for these countries should explicitly incorporate labour market employment targets alongside energy access targets.

Policy Recommendation 3 Reform Capital Formation Composition to Generate Employment. The null result for aggregate GCF should prompt OPEC governments to examine the sectoral composition of their investment portfolios. Policies that incentivise investment in labour-intensive non-oil sectors including agribusiness, manufacturing, construction, tourism, and digital services are more likely to generate employment than continued reinvestment in the hydrocarbon sector. Public investment banks, sovereign wealth fund deployment, and special economic zones with employment-linked incentives are relevant institutional mechanisms.

Policy Recommendation 4 Adopt Long-Horizon Energy-Employment Evaluation Frameworks. The finding that the energy-employment relationship operates primarily through long-run structural variation implies that policy evaluation frameworks must adopt multi-decade horizons to capture the full employment dividend. Monitoring and evaluation systems should track both energy access rates and labour market indicators annually, with impact attribution conducted at five-year intervals using quasi-experimental methods.

Policy Recommendation 5 Leverage the OPEC Platform for Regional Energy Access Coordination. An OPEC-level clean energy access fund coordinated through OFID could channel petroleum revenues toward domestic clean cooking fuel subsidies and electrification programmes within member states, simultaneously reducing energy poverty, expanding employment, and strengthening institutional alignment with SDGs 7 and 8.

10. Conclusion

This study has conducted a comprehensive panel econometric investigation into the determinants of unemployment across twelve OPEC member states from 1995 to 2025, employing a methodological framework that encompasses Pooled OLS with robust standard errors, country fixed effects, Between estimation, Mundlak-Hausman model selection, panel unit root and cointegration analysis, Breusch-Pagan heteroskedasticity testing, Durbin-Watson autocorrelation detection, and three machine learning ensemble algorithms.

The study's principal empirical findings can be summarised as follows. First, clean cooking fuel access (ACCG) is the only statistically significant determinant of unemployment in the pooled OLS specification ($\beta = -0.074$, $p < 0.001$), confirming Hypothesis H_2 and establishing a significant energy-employment nexus. Second, the Mundlak-Hausman test ($F = 34.56$, $p < 0.001$) confirms that country fixed effects are the appropriate estimator. Third, panel cointegration analysis provides strong evidence of a long-run equilibrium relationship between clean cooking fuel access and unemployment (panel $t = -6.25$). Fourth, the Random Forest substantially outperforms OLS in cross-validated prediction ($R^2 = 0.659$ vs. 0.032), confirming pervasive non-linearity, and ranks ACCG (48.1%) and ACCE (40.3%) as dominant predictors. Fifth, the fixed effects results reveal that the energy-unemployment relationship is primarily a

long-run cross-sectional structural phenomenon, implying that employment dividends from energy access investments materialise over multi-decade horizons.

These findings generate concrete policy recommendations: OPEC governments should reframe clean energy access as a labour market development instrument; African OPEC members should receive priority attention in clean fuel investment; investment composition should shift toward labour-intensive non-oil sectors; and policy evaluation frameworks must adopt long-horizon designs to capture the full employment returns to energy access. The study makes a meaningful contribution to development economics and energy economics by providing the first comprehensive OPEC-wide panel analysis of energy access as a labour market determinant, extending the analytical period through 2025, and triangulating parametric and machine learning methodologies within a unified framework. Future work extending the analysis with sector-disaggregated investment data, gender-disaggregated labour market outcomes, dynamic GMM specifications, and institutional quality controls would further sharpen the causal interpretation and policy relevance of the findings presented here.

11. Limitations of the Study

Several limitations of this study merit acknowledgement. First, the low within R^2 (0.008) of the fixed-effects model indicates that year-to-year variation in the five observable regressors explains very little within-country unemployment variation, suggesting that important determinants oil price shocks, institutional quality dynamics, governance changes, and policy regime shifts are omitted due to data availability constraints. Second, the study employs annual frequency data, which may be too coarse to capture higher-frequency dynamics through which macroeconomic shocks transmit into labour markets. Quarterly data, where available, would enable more precise identification of short-run dynamics. Third, while panel cointegration is established, a formal ARDL or Vector Error Correction Model (VECM) would provide richer insight into short-run adjustment dynamics and long-run equilibrium speed of adjustment. Fourth, the balanced panel design potentially introduces selection bias if countries with distinct energy-unemployment dynamics are systematically excluded. Fifth, the confirmed heteroskedasticity and serial autocorrelation, while addressed through robust standard errors, would ideally be modelled explicitly through Driscoll-Kraay standard errors robust to cross-sectional dependence — an extension reserved for future work.

12. Directions for Future Research

Several productive extensions emerge naturally from this study. First, decomposing gross capital formation into oil and non-oil sector components would directly test the Dutch Disease hypothesis in the OPEC employment context. Second, incorporating formal ARDL or Panel VECM specifications would characterise short-run adjustment dynamics and long-run equilibrium error correction speed. Third, System GMM estimation (Blundell & Bond, 1998) would address potential endogeneity and capture dynamic persistence in unemployment. Fourth, gender-disaggregated unemployment data would enable direct testing of the female labour force participation channel. Fifth, incorporating institutional quality indices would test whether the energy-employment relationship is conditioned by governance quality, as theorised in the resource curse conditionality literature. Sixth, causal forest methods (Wager & Athey, 2018) could provide heterogeneous treatment effect estimates, revealing which country and time contexts experience the strongest energy access-employment effects.

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