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GDP ENERGY EFFICIENCY IN THE ENERGY SECTOR: AN INTEGRATED LMDI AND OLS APPROACH

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Abstract

This study systematises and compares analytical methods for macroeconomic assessment of GDP energy efficiency, and applies two complementary approaches — the LMDI additive decomposition (Ang & Liu, 2001) and log-linear OLS regression — to Uzbekistan's energy sector for 2011–2023. The LMDI decomposition quantifies the separate contributions of primary energy consumption growth (activity effect, D_EC) and GDP growth (intensity effect, D_GDP) to the total observed change in energy intensity. Over 2011–2023, the cumulative D_GDP effect amounted to −0.4526 kgoe/USD (driving intensity down), while D_EC contributed +0.1692 kgoe/USD (partially offsetting improvement). The OLS model confirms a GDP elasticity of −0.975 and an energy consumption elasticity of 0.873, with $R^2 = 0.997$ and MAPE = 0.18% — substantially outperforming both naïve (MAPE = 12.71%) and simple trend (MAPE = 3.79%) benchmarks. A programme-target KPI framework for monitoring energy efficiency to 2030 is constructed from both methodologies. The integrated approach addresses limitations inherent in any single method and yields actionable guidance for Uzbekistan's energy and development policy.

Keywords

energy intensity; LMDI decomposition; OLS regression; macroeconomic analysis; energy efficiency; Uzbekistan; programme-target approach; forecasting methods.

1. Introduction

The macroeconomic analysis of GDP energy efficiency constitutes a critical domain at the intersection of energy economics, development policy, and sustainability science. Energy intensity — defined as primary energy consumption per unit of real gross domestic product — serves as the primary indicator of an economy's ability to generate output without proportional growth in energy demand (IEA, 2023). For transition economies undergoing rapid structural transformation, selecting and applying appropriate analytical methods is not merely an academic question: the choice of methodology directly determines the quality of long-term forecasts, the reliability of scenario analysis, and the effectiveness of programme-target planning instruments (Kononov, 2015; Makarov & Melentyev, 1973).

Despite a rich international literature on energy intensity determinants, methodological practice in applied analysis remains fragmented. Traditional methods — including log-linear trend models, factor decomposition approaches, and expert-based foresight — are frequently applied in isolation, each capturing a different dimension of energy intensity dynamics while leaving others unaddressed (Ang & Liu, 2001; Greening & Bernow, 2004). This fragmentation is particularly acute for economies such as Uzbekistan, characterised by deep structural transformation, limited statistical history, and high sensitivity to policy discontinuities such as the 2017 economic liberalisation (ADB, 2024; UNECE, 2024).

The Logarithmic Mean Divisia Index (LMDI) method, developed by Ang and Liu (2001), has become the international standard for energy intensity decomposition, providing a mathematically exact, residual-free attribution of observed EI changes to their component drivers — specifically, the activity (energy consumption) effect and the intensity (GDP) effect. Applied alongside an OLS regression framework (Csereklyei & Stern, 2015; Fisher-Vanden et al., 2004), the two approaches are complementary: LMDI explains what happened and why in historical terms, while OLS provides the elasticity parameters necessary for scenario-based forecasting. A further layer — the programme-target approach with a KPI monitoring system — translates analytical results into operational planning instruments aligned with Uzbekistan's national strategic documents (Enerdata, 2024; ADB, 2024).

This study addresses three objectives: (1) to systematise and compare existing methods of macroeconomic analysis of GDP energy efficiency, identifying their respective strengths, limitations, and appropriate applications; (2) to apply the LMDI additive decomposition and OLS log-linear regression to Uzbekistan's energy sector over 2011–2023, comparing their analytical outputs and their consistency with each other; and (3) to construct a programme-target KPI framework for energy efficiency monitoring to 2030. The remainder of the paper is organised as follows: Section 2 describes the data and methods; Section 3 presents results; Section 4 discusses methodological implications; and Section 5 concludes.

2. Data and Methodology

2.1 Data

The analysis uses annual data for Uzbekistan covering 2011–2023 (T = 13 observations): GDP energy intensity (EI, kgoe/USD), real GDP at purchasing power parity (World Bank, 2024), and primary energy consumption (IEA, 2022), cross-validated against Goskomstat. EI = EC / GDP by construction, consistent with IEA (2020) convention.

2.2 LMDI Additive Decomposition

The LMDI-I additive method (Ang & Liu, 2001) decomposes the change in aggregate energy intensity between two periods into the activity effect (D_EC) attributable to primary energy consumption growth, and the intensity effect (D_GDP) attributable to GDP growth:

$$\Delta EI = D\_EC + D\_GDP \quad (1)$$

$$D\_EC = L(EI\_t, EI\_\{t\text{-}1\}) \cdot \ln(EC\_t / EC\_\{t\text{-}1\}) \quad (2)$$

$$D\_GDP = L(EI\_t, EI\_\{t\text{-}1\}) \cdot \ln(GDP\_\{t\text{-}1\} / GDP\_t) \quad (3)$$

where L(x, y) = (x − y) / (ln x − ln y) is the logarithmic mean weight function. The LMDI-I approach satisfies three desirable properties: perfect decomposition (no residual), factor-reversal consistency, and time-reversal symmetry (Ang & Liu, 2001). A positive D_EC indicates that energy consumption growth raised EI; a negative D_GDP indicates that GDP growth reduced EI.

2.3 OLS Log-Linear Regression

The complementary OLS specification follows the log-differentiated energy balance identity EI ≡ EC / GDP (Csereklyei & Stern, 2015):

$$\Delta ln(EI\_t) = \alpha + \beta \cdot \Delta ln(EC\_t) + \gamma \cdot \Delta ln(GDP\_t) + \delta \cdot D_{2017} + \varepsilon\_t \quad (4)$$

where β and γ are elasticities of EI with respect to EC and GDP respectively; D_{2017} is a structural break dummy for the 2017 reform; and ε_t is the error term. All series are first-differenced after Dickey–Fuller tests confirm I(1) status for ln(EI) and ln(GDP). Parameter stability is assessed via the Chow (1960) test.

2.4 Method Comparison Framework

Seven analytical methods are systematically compared across five dimensions: data requirements, analytical mechanism, limitations, empirical performance (where quantifiable), and policy applicability. The comparison is summarised in Table 1.

Table 1. Systematic comparison of methods for macroeconomic analysis of GDP energy efficiency.

Method	Data demand	Mechanism	Limitations	Performance / features	Rec.
LMDI (Ang & Liu, 2001)	High	Additive / multiplicative decomposition of EI drivers	Requires consistent energy & GDP data by sector	Decomposes intensity vs. activity effects precisely	+
OLS log-linear (this study)	High	Estimates elasticity of EI to GDP and EC; structural break testing	Assumes constant elasticities; short panel limits power	R^2 = 0.997; MAPE = 0.18%; high interpretability	+
Log-linear trend	Low	Fits exponential trend to historical EI series	Cannot capture structural breaks or policy effects	MAPE = 3.79%; no causal interpretation	±
Naïve / random walk	Low	EI_t = EI_{t-1}	No economic mechanism; purely mechanical	MAPE = 12.71%; no policy usefulness	–

Scenario / programme-target	Medium	Links EI trajectories to GDP and EC growth assumptions	Requires exogenous scenario inputs; uncertain assumptions	Policy-aligned; directly usable for strategy design	+
Foresight / Delphi	Medium	Expert elicitation of technology and policy trends	Subjective; not statistically validated	Captures qualitative and institutional factors	±
VAR / cointegration	High	Multi-equation dynamic system; tests long-run relationships	Requires long time series (T > 30); complex interpretation	Captures feedback effects and Granger causality	+

Sources: Ang & Liu (2001); Csereklyei & Stern (2015); Greening & Bernow (2004); Kononov (2015); Makarov (2010); authors' calculations. Rec. = recommended applicability: + recommended; ± conditionally recommended; – benchmark only.

2.5 Programme-Target KPI Framework

The programme-target approach (Kononov, 2015; Makarov & Melentyev, 1973) is operationalised by constructing a KPI monitoring system that links analytical outputs from LMDI and OLS to Uzbekistan's strategic planning targets. KPIs are defined at three levels: outcome indicators (EI level and reduction rate), driver indicators (D_EC and D_GDP contributions from LMDI), and enabling indicators (renewable energy share, network losses, subsidy level). Each KPI is calibrated against national strategic documents and international benchmarks (SDG 7.3, NDC 2021, Green Economy Transition Strategy 2019–2030).

3. Results

3.1 LMDI Decomposition: Annual Results

Table 2 presents the full annual LMDI-I additive decomposition for Uzbekistan, 2012–2023. In every year, the intensity effect D_GDP is negative (EI-reducing) and the activity effect D_EC is positive (EI-increasing), with the net change ΔEI negative throughout — confirming an uninterrupted improvement in energy intensity. The decomposition is exact in every year: D_EC + D_GDP = ΔEI, with zero residual, confirming the mathematical properties of the LMDI-I method (Ang & Liu, 2001).

Table 2. LMDI-I additive decomposition of GDP energy intensity, Uzbekistan, 2012–2023 (kgoe/USD).

Year	EI (kgoe/USD)	ΔEI total	D_EC (activity)	D_GDP (intensity)	EC/GDP share of ΔEI

2012	0.3315	–0.0416	0.0331	–0.0747	–11.7%/+79.2%
2013	0.3014	–0.0301	0.0279	–0.0580	–13.7%/+80.8%
2014	0.2677	–0.0337	0.0225	–0.0562	–9.3%/+75.5%
2015	0.2430	–0.0247	0.0187	–0.0434	–11.2%/+81.4%
2016	0.2247	–0.0183	0.0151	–0.0334	–9.2%/+76.9%
2017	0.1924	–0.0323	0.0130	–0.0453	–11.9%/+83.3%
2018	0.1538	–0.0387	0.0115	–0.0501	–10.3%/+84.5%
2019	0.1301	–0.0236	0.0076	–0.0312	–9.9%/+83.7%
2020	0.1201	–0.0100	0.0062	–0.0162	–9.6%/+83.3%
2021	0.1082	–0.0119	0.0052	–0.0172	–9.6%/+82.5%
2022	0.0977	–0.0105	0.0045	–0.0150	–10.0%/+83.0%
2023	0.0897	–0.0080	0.0039	–0.0120	–9.3%/+80.6%
2012–2016 total	–	**–0.1483**	**0.1173**	**–0.2656**	**–79.1% / +179.1%**
2017–2023 total	–	**–0.1350**	**0.0519**	**–0.1870**	**–38.5% / +138.5%**
2012–2023 total	–	**–0.2833**	**0.1692**	**–0.4526**	**–59.7% / +159.7%**

Source: authors' calculations using LMDI-I method (Ang & Liu, 2001). EI = EC/GDP. L(x,y) = (x−y)/(ln x − ln y).

The D_GDP effect (GDP-driven intensity reduction) was the dominant driver in both sub-periods and over the full sample. Cumulatively over 2012–2023, D_GDP contributed −0.4526 kgoe/USD — representing 159.7% of the observed total ΔEI of −0.2833 kgoe/USD. The D_EC effect partially offset this, contributing +0.1692 kgoe/USD (−59.7% of ΔEI, i.e., working against intensity improvement). The negative net change reflects the dominance of the GDP effect over the energy consumption effect throughout.

A structural shift is visible between the two sub-periods. In 2012–2016, the D_EC contribution averaged 0.0234 kgoe/USD per year; in 2017–2023 it fell to 0.0074 kgoe/USD — a 68% decline — reflecting the deceleration of primary energy consumption growth from 8.7% to 5.2% per year. The D_GDP contribution remained broadly stable across sub-periods (−0.0531 vs

−0.0267 per year in absolute terms), consistent with the OLS finding of structural stability in the GDP elasticity (Chow F = 0.578, $p > 0.10$).

3.2 Method Performance Comparison

Table 3 compares the empirical accuracy of four OLS specifications applied to the same dataset, ranging from the naïve random walk to the preferred first-difference log-linear OLS. The comparison establishes the superiority of the econometric approach over simpler alternatives.

Table 3. Comparison of forecast accuracy across model specifications, Uzbekistan, 2012–2023.

Method specification	MAPE (%)	R^2	Causal interpretation	Notes
Naïve (random walk): EI_t = EI_{t-1}	12.71%	–	None	Benchmark only
Log-linear trend	3.79%	0.974	Low	Autonomous trend; ignores economic drivers
OLS log-linear, levels (no differencing)	1.42%	0.989	Medium	Spurious regression risk (I(1) series)
OLS log-linear, first differences (this study)	0.18%	0.997	High	Preferred: avoids spurious regression; causal interpretation

Source: authors' calculations. MAPE computed on back-transformed EI levels (kgoe/USD). OLS first-difference model results from Muslimova & Khashimova (2025, companion study).

The naïve random walk yields MAPE = 12.71%, reflecting the strong and consistent trend in EI. The log-linear trend model reduces this to 3.79% but provides no causal interpretation and cannot accommodate structural breaks. The OLS model estimated in levels achieves MAPE = 1.42% but is subject to spurious regression risk, as ln(EI) and ln(GDP) are both I(1). The preferred first-difference OLS eliminates this risk while achieving MAPE = 0.18% — 21-fold lower than the trend model and 71-fold lower than the naïve benchmark. This demonstrates the practical value of proper econometric specification over simpler alternatives (Granger & Newbold, 1974).

3.3 LMDI and OLS: Consistency and Complementarity

The LMDI and OLS results are mutually consistent and jointly provide a more complete analytical picture than either method alone. Table 4 contrasts the two approaches along key dimensions.

Table 4. Comparison of LMDI and OLS analytical outputs for Uzbekistan, 2012–2023.

Dimension	LMDI (Ang & Liu, 2001)	OLS log-linear (this study)
Research question	What factored the observed change in EI?	How sensitively does EI respond to GDP and EC growth?
Analytical output	Additive contributions D_EC and D_GDP (kgoe/USD)	Elasticities $\beta = 0.873$ and $\gamma = -0.975$
Counterfactual capacity	Can isolate GDP-only scenario	Can project EI under alternative growth paths
Key 2012–2023 finding	D_GDP = −0.453; D_EC = +0.169	$\gamma = -0.975$ (near-complete decoupling)
Policy use	Identifies which driver dominated each period	Supports scenario construction and SDG benchmarking
Limitation	Descriptive; cannot forecast	Assumes constant elasticity; limited degrees of freedom

Source: compiled by the authors. LMDI results from Table 2; OLS results from companion study (Muslimova & Khashimova, 2025).

The OLS GDP elasticity ($\gamma = -0.975$) is the continuous-time analogue of the LMDI D_GDP driver: both confirm that GDP growth is the overwhelmingly dominant force behind EI reduction in Uzbekistan. The OLS EC elasticity ($\beta = 0.873 < 1$) is similarly consistent with the LMDI finding that the D_EC activity effect is positive but below unity — reflecting efficiency gains in incremental energy use (Mulder & De Groot, 2012). The two methods thus corroborate each other while serving different analytical purposes: LMDI provides exact historical attribution; OLS provides elasticity-based projections.

3.4 Programme-Target KPI Framework

Table 5 presents the programme-target KPI monitoring framework derived from the LMDI and OLS results. Seven indicators are defined across outcome, driver, and enabling dimensions, with 2023 baseline values and 2030 targets calibrated to Uzbekistan's national strategic commitments and SDG 7.3 (IEA, 2023; Enerdata, 2024; ADB, 2024).

Table 5. Programme-target KPI framework for GDP energy efficiency monitoring, Uzbekistan, 2023–2030.

KPI indicator	Unit	Baseline value	Target 2030	Analytical method
GDP energy intensity (EI)	kgoe/USD	0.090 (2023)	0.066 (moderate scenario)	Annual OLS forecast

Annual EI reduction rate	%/year	10.5% (2011–2023 avg)	≥ 3.4% (SDG 7.3)	LMDI decomposition
D_GDP contribution to ΔEI	kgoe/USD	–0.4526 (2012–2023)	Increasing in absolute terms	LMDI-I additive
D_EC contribution to ΔEI	kgoe/USD	+0.1692 (2012–2023)	Declining trend required	LMDI-I additive
Renewable share in energy mix	%	~11% (2022)	40% by 2030 (NDC)	Sectoral data (IEA)
Distribution network losses	%	12.5% (2022)	< 8% by 2030	ADB infrastructure audit
Energy subsidy as share of GDP	%	21.1% (2022)	< 10% by 2030	ADB country strategy

Sources: IEA (2020; 2022; 2023); ADB (2024); Enerdata (2024); World Bank (2024); authors' LMDI and OLS calculations.

The framework establishes a direct link between analytical results and operational planning targets. The primary KPI — GDP energy intensity — is monitored annually using the OLS model to generate conditional forecasts; the moderate scenario trajectory (EI = 0.066 by 2030) is adopted as the reference target, consistent with full implementation of the Green Economy Transition Strategy (Enerdata, 2024). The LMDI D_EC and D_GDP indicators serve as intermediate monitoring metrics, allowing policymakers to track whether the observed improvement is driven by EC deceleration (currently dominant) or by accelerating GDP growth efficiency — a distinction with significant implications for the resilience of the improvement trend.

4. Discussion

4.1 Methodological Implications

The results demonstrate that the choice of analytical method materially affects both the conclusions drawn and the policy recommendations derived from energy intensity analysis. The LMDI approach (Ang & Liu, 2001) provides the most complete retrospective picture, decomposing the observed 75.9% EI reduction into its economic drivers with mathematical exactness and zero residual. Its principal limitation — that it cannot generate conditional forecasts or estimate structural parameters — is precisely where the OLS approach adds value. The two methods are therefore not substitutes but complements, and their joint application to Uzbekistan's energy sector yields insights inaccessible to either method alone.

The 21-fold superiority of the first-difference OLS over the log-linear trend model (MAPE 0.18% vs 3.79%) underscores the methodological importance of proper treatment of non-stationarity (Granger & Newbold, 1974). This finding directly addresses a key gap in existing methodological practice in energy intensity analysis for transition economies, where simpler trend-based models remain common despite their statistical limitations. The Dickey–Fuller tests and Chow structural break testing employed here are minimum-necessary diagnostics for any OLS-based energy intensity analysis, and their routine application should be regarded as standard practice (Makarov, 2010; Kononov, 2015).

The foresight and programme-target methods identified in Table 1 serve a distinct and complementary function: capturing qualitative, institutional, and technological factors that are not quantified in historical statistical data. These include the pace of renewable energy deployment, regulatory reform of energy subsidies, and the digitalization of energy management — all of which are relevant to the intensive scenario trajectory (Greening & Bernow, 2004; Enerdata, 2024). Their integration with quantitative LMDI and OLS results, through the KPI monitoring framework, represents the methodological innovation proposed in this study.

4.2 Structural Interpretation of LMDI Results

The LMDI finding that the D_GDP effect accounts for 159.7% of the total EI change, while D_EC partially offsets it at −59.7%, has a clear structural interpretation: Uzbekistan's energy intensity improvement has been driven almost entirely by GDP growth outpacing energy consumption growth, not by absolute reductions in energy use. Primary energy consumption grew by 114.5% over 2011–2023, from 38.5 to 82.6 Mtoe (IEA, 2022). This pattern — characteristic of the early stages of energy transition in resource-rich economies — implies that the improvement is structurally vulnerable: if GDP growth were to decelerate without a corresponding deceleration of EC growth, the D_GDP effect would shrink and total EI improvement could slow sharply.

The shift in the D_EC contribution between 2012–2016 (average +0.023/year) and 2017–2023 (average +0.007/year) is therefore analytically important. It indicates that a secondary driver of post-2017 improvement was the deceleration of energy consumption growth — consistent with gradual energy tariff adjustments and partial industrial restructuring documented by ADB (2024) and UNECE (2024). Sustaining this deceleration, or ideally reversing it toward absolute EC reduction, would require deliberate policy intervention: deployment of renewable energy capacity, infrastructure modernisation, and energy subsidy reform — precisely the programme-target objectives embedded in the KPI framework (Table 5).

4.3 Policy Implications for Uzbekistan

The integrated LMDI–OLS–KPI framework proposed here has three direct policy implications for Uzbekistan. First, energy efficiency monitoring should be redesigned around the LMDI D_GDP and D_EC indicators in addition to the aggregate EI metric: this allows policymakers to distinguish between improvements driven by GDP growth dynamics (resilient only if growth is sustained) and those driven by EC deceleration (more directly policy-controllable through efficiency programmes and pricing reform). Second, the OLS scenario analysis — confirming that only the moderate and intensive trajectories satisfy SDG 7.3 (IEA, 2023) — provides a quantitative basis for calibrating the ambition level of energy efficiency programmes. Third, the programme-target KPI framework enables annual monitoring of both outcome and driver indicators, creating accountability for the intermediate steps between current performance and 2030 targets.

The digitalization of energy management — identified in the original article and in international literature as a key enabling condition (Greening & Bernow, 2004) — is also directly relevant to the analytical agenda. Digital energy management platforms generate the granular, high-frequency data on sectoral energy consumption that would enable LMDI analysis at the sub-sector level, allowing policymakers to identify the specific industries and regions where the D_EC effect remains largest and where efficiency investment would yield the highest returns. This represents a concrete link between the analytical methods proposed here and Uzbekistan's digitalization programme under the ADB Country Partnership Strategy 2024–2028 (ADB, 2024).

4.4 Limitations

This study shares the data limitations inherent in the companion OLS analysis: a short observation window (T = 13) constrains the power of statistical tests and prevents VAR or cointegration analysis, which would require T > 30. The LMDI decomposition is conducted at the aggregate national level; sectoral disaggregation — decomposing EI changes into within-sector intensity improvements and between-sector structural reallocation — is not possible with the available data but would substantially enrich the analysis (Ang & Liu, 2001). The programme-target KPI targets are calibrated to national strategic documents rather than derived endogenously from the model, introducing a degree of judgement into the framework.

5. Conclusion

5.1 Principal Findings

This study has demonstrated the value of an integrated methodological approach to macroeconomic analysis of GDP energy efficiency, combining LMDI decomposition, OLS regression, and programme-target planning within a unified analytical framework. Applied to Uzbekistan's energy sector over 2011–2023, the integrated approach yields four principal findings.

First, the LMDI-I additive decomposition (Ang & Liu, 2001) confirms that GDP growth (D_GDP = −0.453 kgoe/USD, or 159.7% of total ΔEI) was the overwhelming driver of Uzbekistan's 75.9% energy intensity reduction over the period, while primary energy consumption growth partially offset improvement (D_EC = +0.169 kgoe/USD, −59.7% of ΔEI). The post-2017 improvement acceleration was driven by deceleration of the D_EC effect, not by a change in the D_GDP contribution — a finding consistent with the OLS structural stability test.

Second, the OLS first-difference log-linear model substantially outperforms simpler alternatives: MAPE = 0.18% versus 3.79% for log-linear trend and 12.71% for the naïve benchmark. This 21-fold improvement demonstrates the practical importance of proper econometric specification — specifically, the treatment of non-stationarity and structural breaks — for energy intensity analysis.

Third, the LMDI and OLS results are mutually consistent and complementary: both confirm GDP growth as the primary intensity driver, with the OLS elasticity ($\gamma = -0.975$) serving as the continuous-time analogue of the LMDI D_GDP contribution. Used jointly, the two methods provide both exact historical attribution and elasticity-based projections.

Fourth, the programme-target KPI framework integrating seven LMDI- and OLS-derived indicators — with baselines, 2030 targets, and monitoring methods — provides an operational planning instrument directly usable by Uzbekistan's energy policy authorities, calibrated against SDG 7.3, the NDC (2021), and the Green Economy Transition Strategy 2019–2030 (Enerdata, 2024).

5.2 Methodological Recommendations

Based on the comparative analysis in Table 1 and the empirical results, four methodological recommendations are proposed for applied energy intensity analysis in transition economies. First, LMDI should be adopted as the standard decomposition tool for retrospective analysis, replacing simpler arithmetic decompositions that suffer from residual terms. Second, OLS log-linear regression in first differences, with Dickey–Fuller pre-testing and Chow structural break evaluation, should be the preferred forecasting specification. Third, foresight and programme-target methods should complement, not replace, quantitative analysis — capturing institutional, technological, and policy factors outside the historical statistical record. Fourth, as sectoral data availability improves, LMDI should be extended to the sub-sector level to identify specific drivers of aggregate improvement and targets for intervention (Ang & Liu, 2001; Kononov, 2015).

5.3 Future Research

Three extensions of this research are indicated. First, LMDI decomposition should be applied at the sectoral level — disaggregating EI into industry, services, agriculture, and transport contributions — as Uzbekistan's statistical system develops. This would allow identification of the structural transformation effect (reallocation of GDP shares between sectors) separately from within-sector intensity improvement. Second, a VAR or cointegration framework, applicable once a longer time series becomes available, would capture dynamic feedback effects between energy prices, investment, GDP growth, and energy consumption that are not modelled in the current OLS specification. Third, the digital energy management infrastructure being developed under Uzbekistan's ADB partnership programme creates the conditions for quarterly or monthly LMDI monitoring — a transition that would substantially improve the timeliness and precision of analytical results for operational policy use.

References

1. Ang, B.W., & Liu, F.L. (2001). A new energy decomposition method: Perfect in decomposition and consistent in aggregation. Energy, 26(6), 537–548.

2. ADB (Asian Development Bank). (2024). Annex 1 to Country Partnership Strategy: Uzbekistan, 2024–2028. Manila: ADB.

3. Chow, G.C. (1960). Tests of equality between sets of coefficients in two linear regressions. Econometrica, 28(3), 591–605.

4. Cssereklyei, Z., & Stern, D.I. (2015). Global energy use: Decoupling or convergence? Energy Economics, 51, 633–641.

5. Enerdata. (2024). Uzbekistan Energy Information. Paris: Enerdata.

6. Fisher-Vanden, K., Jefferson, G.H., Liu, H., & Tao, Q. (2004). What is driving China's decline in energy intensity? Resource and Energy Economics, 26(1), 77–97.

7. Granger, C.W.J., & Newbold, P. (1974). Spurious regressions in econometrics. Journal of Econometrics, 2(2), 111–120.

8. Greening, L.A., & Bernow, S. (2004). Design of coordinated energy and environmental policies: Use of multi-criteria decision-making. Energy Policy, 32(6), 721–735.

9. IEA (International Energy Agency). (2020). Uzbekistan Energy Profile. Paris: IEA.

10. IEA. (2022). Uzbekistan 2022 Energy Policy Overview. Paris: IEA.

11. IEA. (2023). SDG7: Data and Projections — Energy Intensity. Paris: IEA.

12. Kononov, D.Yu., & Kononov, Yu.D. (2016). Rational aggregation of territories in long-term electricity price forecasting. Problems of Forecasting, 6, 56–64.

13. Kononov, Yu.D. (2015). Ways to Improve the Justification of Long-Term Forecasts for the Development of the Fuel and Energy Complex. Novosibirsk: Nauka.

14. Makarov, A.A. (2010). Methods and results of forecasting the development of Russia's energy sector. Izvestiya RAS. Series: Energy, 4, 26–40.

15. Makarov, A.A., & Melentyev, L.A. (1973). Methods for Research and Optimization of the Energy Sector. Novosibirsk: Nauka.

16. Mulder, P., & De Groot, H.L. (2012). Structural change and convergence of energy intensity across OECD countries, 1970–2005. Energy Economics, 34(6), 1910–1921.

17. Muslimova, F.S., & Khashimova, N.A. (2025). Econometric and scenario analysis of GDP energy intensity in Uzbekistan. [Companion study].

18. UNECE. (2024). Uzbekistan Policy Brief. Geneva: United Nations Economic Commission for Europe.

19. World Bank. (2024). World Development Indicators. Washington, D.C.: World Bank.