

Article

Spatiotemporal Dynamic Evolution, Influencing Factors, and Spatial Spillover Effects of Heterogeneous Energy Consumption in Liaoning Province Under the Dual-Carbon Goal: Implications for Sustainable Regional Development

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Abstract

This study examines heterogeneous energy consumption in Liaoning Province under China's dual-carbon goals, which operationalize the energy-related Sustainable Development Goals (SDG 7 and SDG 13), extending the sample to 1985–2024. Kernel density estimation characterizes distribution dynamics; a Kaya-based LMDI decomposition quantifies contributions of energy structure, intensity, per-capita output, and population; a semi-parametric time-series model estimates factor associations with a flexible time trend; and a spatial Durbin model on a 30-province panel (2000–2024) assesses spillovers. Consumption grew from 63.25 to 259.85 Mtce (3.69% annually), decelerating markedly after 2012. The LMDI attributes 192% of the increase to per-capita output growth, offset by a −104% intensity effect, with a small net structure effect (+4.9%). In the semi-parametric model, coal share and real GDP are significantly associated with consumption (a semi-elasticity of −0.90 for the coal share and an elasticity of 0.43 for real GDP), and the fitted smooth time component captures unobserved temporal variation not explained by the included covariates. The SDM estimates a modest spatial autoregressive coefficient ($\rho = 0.055$), positive direct effects of GDP and industrial structure, and significant negative indirect effects of neighbors' GDP and industrial share, indicating competitive rather than complementary interprovincial energy relationships. Mechanisms such as resource siphoning remain hypotheses for future research. The findings inform sustainable development policy for legacy industrial regions: sustaining efficiency gains, decarbonizing the power supply, and coordinating interprovincial industrial planning.

Keywords: heterogeneous energy consumption; kernel density estimation; LMDI decomposition; semi-parametric time-series model; spatial Durbin model; dual-carbon goal; sustainable development



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1. Introduction

The persistent growth in global energy use is a major driver of rising carbon emissions, exacerbating the challenges of climate change [1]. The United Nations 2030 Agenda for Sustainable Development places clean energy (SDG 7) and climate action (SDG 13) at the center of the global sustainability transition [2]. China, the world's leading energy

consumer, has established the “dual-carbon” goal—peaking carbon emissions before 2030 and achieving carbon neutrality before 2060—which underscores the need for comprehensive investigations into energy consumption patterns and their determinants [3]. Liaoning Province, a vital component of the Bohai Rim Economic Circle and the urban agglomeration of Northeast China, holds an increasingly significant position in the national economic structure. As a traditional industrial base, the province faces complex challenges including energy scarcity, environmental pollution, and comparatively slow economic growth. Research specifically addressing the heterogeneity of energy consumption in Liaoning Province remains limited. This study therefore examines the influencing factors and spatiotemporal dynamics of energy consumption in Liaoning Province, aiming to provide practical recommendations for carbon reduction and energy conservation.

As one of China’s oldest industrial bases, Liaoning exemplifies the difficulties that legacy heavy-industry regions face in the low-carbon transition: an energy mix locked in by steel, petrochemicals, and machinery, combined with population decline and slowing growth. The findings are therefore informative beyond the province itself, because several northern and northeastern provinces face a similar combination of industrial structure and transition pressure.

China’s energy transition has been extensively studied at the national level, including energy transition and growth [4], carbon emission efficiency in the Yellow River Basin [5], spatial effects of distorted energy prices [6], and the spatiotemporal dynamics of provincial carbon emissions [7]. The literature establishes that energy outcomes are strongly heterogeneous across regions, but it focuses on national patterns or on southern and western provinces; the consumption structure of old industrial bases in the northeast remains comparatively undocumented.

Methodologically, four toolkits are routinely applied, largely in isolation. Macro-driven factor analyses address non-linearity and endogeneity in energy demand [8,9]; non- and semi-parametric methods accommodate flexible relationships between income, policy and consumption [10,11]; and spatiotemporal techniques such as GTWR and spatial kernel density estimation characterize distributional dynamics [12–14]. Studies specific to Liaoning have examined rural multifunctionality [15], residential coal combustion [16], and regional energy-economic scenarios [17], but none links distribution, decomposition and spatial dependence within a single design.

For driver quantification, the LMDI has become the standard accounting tool [18,19]: national applications attribute energy-related emissions mainly to economic output, with energy intensity as the dominant offsetting factor [20], and the same activity-versus-intensity pattern holds for China’s industrial sector [21]. Semi-parametric trending models estimate factor associations jointly with an unspecified time effect [22]. Spatial econometric work shows that provincial energy outcomes are interdependent and that spillovers must be recovered through direct, indirect and total effects computed from the spatial multiplier [23], as in recent 30-province SDM applications [24]. A recent strand further warns that declining emissions should not be read as managed decarbonization unless structural drivers are separated from policy effects [25]. Internationally, energy transitions are increasingly framed as central to sustainable development [26], and comparative evidence shows that they unfold over decades rather than years [27].

The analysis is organized around three research questions. RQ1: How do consumption distributions by energy type and by industry evolve? RQ2: Which factors drive changes in total consumption (RQ2a, accounting decomposition; RQ2b, factor associations and flexible time effects)? RQ3: Are there interprovincial spillovers of energy consumption? Table 1 maps each question to its method, data, sample period, and analytical purpose.

Table 1. Research design: questions, methods, data, and purposes.

Research Question	Method	Data	Sample Period	Purpose
RQ1: How do consumption distributions evolve?	KDE; Gini concentration; distribution maps	Energy types, industries, major cities	2008–2024; city detail 2017–2024	Characterize location, polarization, peaks, tails
RQ2a: How much of the change is accounted for by each driver?	Kaya-based additive LMDI	Total consumption by four aggregated energy categories; real GDP; population	1985–2024	Exact decomposition into structure, intensity, affluence, population
RQ2b: What are the factor associations and flexible time effects?	Semi-parametric time-series model	Total consumption; coal share; real GDP	1985–2024	Estimate factor associations and smooth $g(t)$
RQ3: Are there interprovincial spillovers?	Panel spatial Durbin model; impact decomposition	30-province panel of energy consumption, GDP, secondary-industry share	2000–2024	Estimate direct, indirect, and total effects

This study contributes in three ways. First, methodologically, it integrates the four toolkits into a single design in which each method answers a distinct question: KDE characterizes distributional evolution (RQ1); the Kaya-based LMDI decomposes changes in consumption into drivers (RQ2a); the semi-parametric model estimates factor associations while flexibly absorbing omitted time effects (RQ2b); and the panel SDM quantifies interprovincial spillovers through impact decomposition (RQ3). Second, the specification restores identification where common practice does not: the decomposition is built on the Kaya identity, so that the structure effect is identified even though the shares sum to one, and the SDM follows LeSage and Pace, so that spillovers are interpreted through direct, indirect and total effects rather than raw coefficients. Third, empirically, it provides evidence for a legacy industrial region: the decomposition shows that intensity improvements, not fuel substitution, have counteracted scale-driven growth; that electricity substitution currently adds to total consumption; and that interprovincial energy relationships are competitive rather than complementary. These findings are informative for other heavy-industry regions facing similar transition pressures.

2. Materials and Methods

2.1. Research Design, Data Sources and Variables

Table 1 maps each research question (RQ) to its method, data, sample period, and analytical purpose, clarifying how the four methods form an integrated design: KDE and concentration measures characterize distributions (RQ1); LMDI provides an exact accounting decomposition of changes in total consumption into factor contributions (RQ2a); the semi-parametric model provides statistical inference on factor/consumption associations and a flexible time trend (RQ2b); and the panel SDM quantifies interprovincial spillovers (RQ3). LMDI and the semi-parametric model are complementary: the former decomposes the amount of change into drivers, the latter estimates factor associations and uncertainty.

Total energy consumption and macro-level variables cover 1985–2024; energy-type detail covers 2008–2024 and industry detail 2009–2024. Annual terminal energy consumption by industry and type and national accounts are from the Liaoning Statistical Yearbook (2023–2025 editions); provincial panel data are from the China Energy Statistical Yearbook (2025) and the China Statistical Yearbook. GDP is measured at constant 1985 prices using the official GDP indices. Eight energy sources are analyzed: coal, coke, diesel, fuel oil, crude

oil, natural gas, gasoline, and kerosene; the four aggregated categories used in the aggregate decomposition (coal, oil, gas, primary electricity) follow the balance sheet classification of the Liaoning Statistical Yearbook.

Throughout this paper, energy structure denotes the set of shares $\{s_i\}$ of each energy category in total consumption, and heterogeneous energy consumption refers to consumption disaggregated by energy type, by industry, and by city, in contrast to the aggregate total; this disaggregation is what makes the distributional analysis of RQ1 possible.

Symbols are used consistently across equations: E denotes total energy consumption, Y real GDP, $\{s_i\}$ the energy structure shares, I energy intensity, A per-capita output, and P population.

Three data revisions are documented. (i) From 2015, total energy consumption is computed by the coal consumption method of power generation; earlier years use the heat-equivalent method, creating a level break that we flag when interpreting long-run trends. (ii) Figures for 2020–2022 were revised following the Fifth National Economic Census. (iii) Figures from 2020 are compiled under GB/T 28398-2023 [28]. The replication package (processed data templates, the spatial weight matrix, and the R analysis scripts) is available in Supplementary Materials S1. All computations and figures were produced with R software (version 4.4.1, 64-bit; R Foundation for Statistical Computing, Vienna, Austria); no instruments or commercial agents were used in this study.

2.2. Kernel Density Estimation

KDE characterizes the distribution of energy consumption across energy types and industries—its location, polarization, main peak evolution, and skewness. For a sample $\{x_1, \dots, x_n\}$ with empirical distribution F , the kernel density estimator is

$$f(x) = (1/nh) \sum_i K((x - x_i)/h) \quad (1)$$

where x is the point at which the density is evaluated, $K(\cdot)$ is the Gaussian kernel, h is the bandwidth, and x_i are i.i.d. observations. For each year, one density curve is estimated from the cross-section of energy types (or industries) observed that year.

Bandwidths follow Silverman's robust rule $h = 0.9 \min(s, \text{IQR}/1.34) n^{(-1/5)}$, where s and IQR are the sample standard deviation and interquartile range. Because bandwidth choice involves a bias-variance trade-off, we verify that the number of detected peaks and the sign of skewness are unchanged at $0.5h$ and $1.5h$ in every year of both panels. Concentration is summarized by the Gini coefficient computed on the same annual cross-sections.

2.3. Kaya-Based LMDI Decomposition

To identify the drivers of changes in total energy consumption E , we adopt the additive LMDI decomposition [18,19] based on the Kaya identity,

$$E = \sum_i s_i \cdot I \cdot A \cdot P, \quad s_i = E_i/E, \quad I = E/Y, \quad A = Y/P \quad (2)$$

where E_i is consumption of energy type i (coal, oil, gas, primary electricity), Y is real GDP, and P is population. The four factors are energy structure $\{s_i\}$, energy intensity I , per-capita output A , and population P . Population, mentioned but missing from the previous Equation (2), now enters explicitly.

With the logarithmic mean $L(a, b) = (a - b)/(\ln a - \ln b)$ for $a \neq b$ (and $L(a, a) = a$), the change between periods 0 and T decomposes exactly as $\Delta E = E^T - E^0 = \Delta E_{\text{str}} + \Delta E_{\text{int}} + \Delta E_{\text{aff}} + \Delta E_{\text{pop}}$, with

$$\Delta E_{\text{str}} = \sum_i w_i \ln(s_i^T/s_i^0), \quad \Delta E_j = W \cdot \ln(j^T/j^0), \quad j \in \{I, A, P\}, \quad W = \sum_i w_i = \sum_i L(E_i^T, E_i^0) \quad (3)$$

We implement the additive form (results in Mtce); zero values do not occur in our sample, so no zero-substitution rule is needed. The reference period is 1985; both cumulative (1985–2024) and sub-period decompositions are reported. The identity closes exactly: the four effects sum to ΔE up to machine precision.

2.4. Semi-Parametric Time-Series Model

The semi-parametric specification follows Chen, Gao and Li [22], adapted from their trending panel data model with cross-sectional dependence to a single aggregate time series ($T = 40$). The adaptation is appropriate because the dependent variable is provincial aggregate consumption, for which a cross-section is unavailable; the identification conditions (strict exogeneity of the regressors, smoothness of g carry over to the time-series case. The corrected model is

$$\ln E_t = \beta_0 + \beta_1 s^{\text{coal}}_t + \beta_2 \ln Y_t + g(t) + \varepsilon_t, t = 1, \dots, T \quad (4)$$

where E_t is total energy consumption, s^{coal}_t the coal share, Y_t real GDP, and $g(t)$ an unknown smooth function of time.

Estimation follows the profile least-squares procedure of Chen, Gao and Li [22]. The unknown function $g(t)$ is approximated by a cubic B-spline with an interior-knot sequence chosen so that the effective degrees of freedom equal df ; for a given β , the spline coefficients are concentrated out by projecting the data orthogonal to the spline basis (a within-type transformation), and β is then updated by ordinary least squares on the partialled-out variables. The two steps are iterated until the relative change in the residual sum of squares is below 10^{-6} , which occurs within about 20 iterations in our application. Because the spline basis and the constant are collinear, $g(t)$ is normalized to have mean zero over the sample, so that the intercept β_0 pins down the overall level. Standard errors are based on a moving-block bootstrap with block length 4—chosen to accommodate the mild second-order serial correlation documented in Section 3.4—and 300 replications; the spline dimension df is selected by generalized cross-validation (GCV) over $df \in \{3, \dots, 9\}$, which attains its minimum at $df = 5$. Because the coal share enters in levels while consumption and GDP enter in logarithms, β_1 is a semi-elasticity (a one-percentage-point higher coal share, i.e., a 0.01 increase in the coal share proportion, is associated with an approximate $\beta_1\%$ change in consumption), whereas β_2 is an elasticity.

Because the unit-root evidence reported in Section 3.4 indicates that $\ln$ GDP and the coal share are difference-stationary while $\ln$ consumption is trend-stationary, a levels regression could in principle be spurious. We therefore also estimate the specification in first differences, $\Delta \ln E_t = \beta_1 \Delta s^{\text{coal}}_t + \beta_2 \Delta \ln Y_t + \Delta g(t) + u_t$, in which all transformed series are stationary; Section 3.4 reports the results, which are qualitatively unchanged.

2.5. Spatial Durbin Model

The SDM quantifies how energy consumption in one province relates to that of other provinces. The observation unit is province i (30 provinces, Tibet excluded for data reasons) in year t (2000–2024); all variables are province-specific, which removes the previous ambiguity in which Liaoning-only values were used as regressors for all provinces. The model is

$$y_{it} = \rho \sum_j w_{ij} y_{jt} + x_{it}' \beta + \sum_j w_{ij} x_{jt}' \theta + \mu_i + \lambda_t + \varepsilon_{it} \quad (5)$$

where $y_{it} = \ln(\text{total energy consumption})$, $x_{it} = [\ln \text{GDP}, \text{secondary-industry share of GDP}]'$, μ_i and λ_t are province and year fixed effects (estimated by two-way within transformation), and ε_{it} is i.i.d. Such provincial SDM specifications, with direct and indirect effects reported separately, are standard in the energy efficiency literature [24]. The spatial weights matrix

W is a row-standardized first-order contiguity matrix; an inverse-distance matrix serves for robustness. Because W is row-standardized, the admissible range of ρ is bounded and estimates are checked against it. Spatial dependence is assessed by (i) Moran's I of the levels each year, (ii) LM lag/error tests on the non-spatial fixed-effects residuals, and (iii) an LR test of the SDM against the non-spatial model and a Wald test of $\theta = 0$ against the spatial lag model. Raw coefficients are not interpreted as effects; following LeSage and Pace [23], direct, indirect, and total effects are computed as $S_r(W) = (I - \rho W)^{-1}(I\beta_r + W\theta_r)$ with bootstrap standard errors (300 replications).

Because W is row-standardized, ρ is bounded in $(-1, 1)$; our estimate of 0.055 lies well inside this range. Hainan, which has no land neighbor, is linked to Guangdong so that no province is isolated in W .

3. Results

3.1. Descriptive Analysis of Energy Consumption

Total energy consumption increased from 63.25 to 259.85 million tons of standard coal equivalent (Mtce) during 1985–2024—a 4.11-fold increase corresponding to a compound annual growth rate of 3.69% (Figure 1). Growth proceeded in four stages: 1985–1992 (~1.9% per year), 1992–1999 (~3.0%), 1999–2012 (~7.4%, the high-speed stage), and 2012–2021 (~1.5%); during 2021–2024 growth slowed further to ~0.7%. The slowdown since 2012 reflects both decelerating economic growth and a declining secondary-industry share.

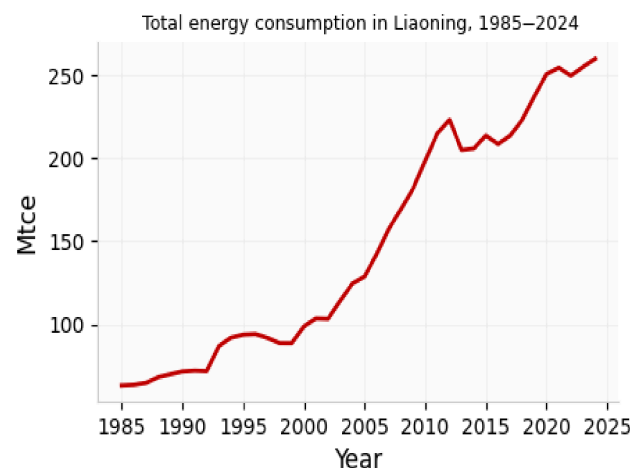


Figure 1. Total energy consumption in Liaoning Province, 1985–2024.

By energy type (2008–2024), coal remains dominant, followed by oil; the 2021 coal share was 50.8% and fell to 46.7% by 2024, while natural gas and primary electricity shares rose steadily (Figure 2). By industry (2009–2024), industry accounts for about 72% of terminal consumption, with transportation next (Figure 3). Across cities (2017–2024), Shenyang and Dalian consume the most, followed by Anshan and Fushun (Figures 4 and 5).

Liaoning's industrial energy share (about 72% of terminal consumption in 2024) ranks fifth among the 30 provinces—after Ningxia (87.8%), Qinghai (77.5%), Inner Mongolia (79.4%) and Shanxi (75.4%).

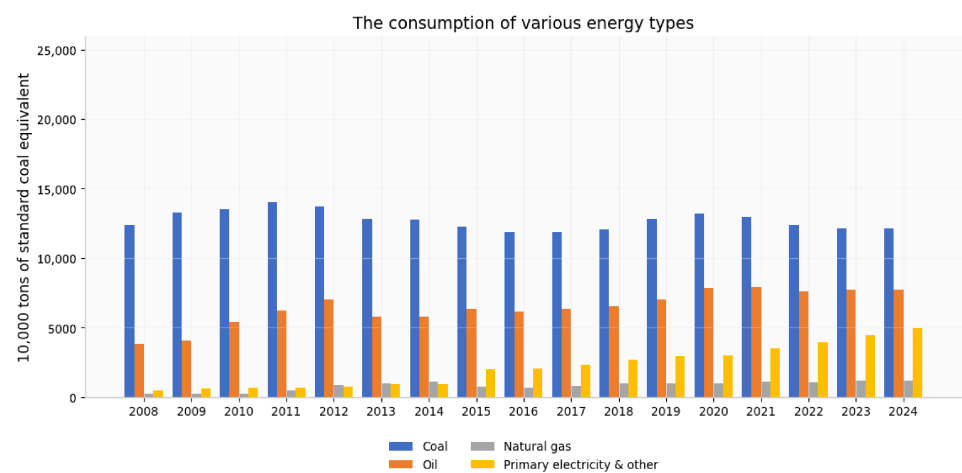


Figure 2. Consumption of various energy types in Liaoning Province, 2008–2024.

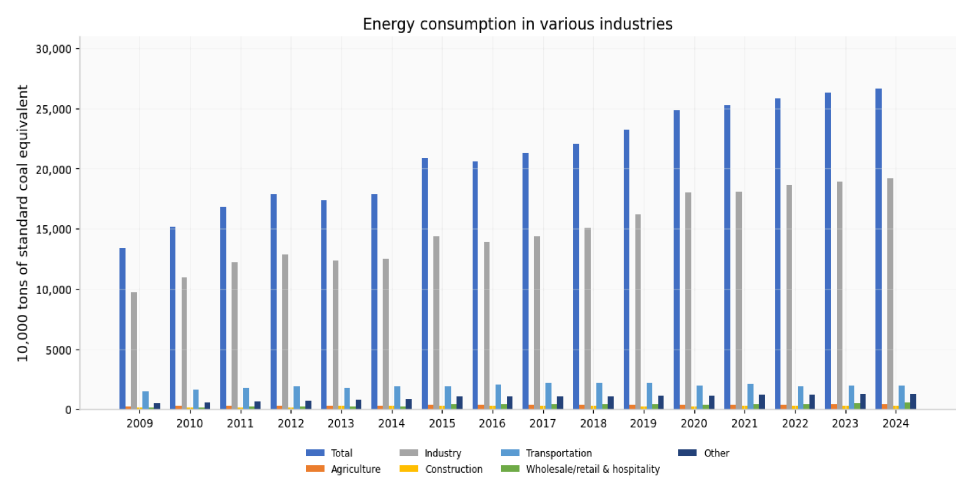


Figure 3. Distribution of total energy consumption among different industries in Liaoning Province, 2009–2024.

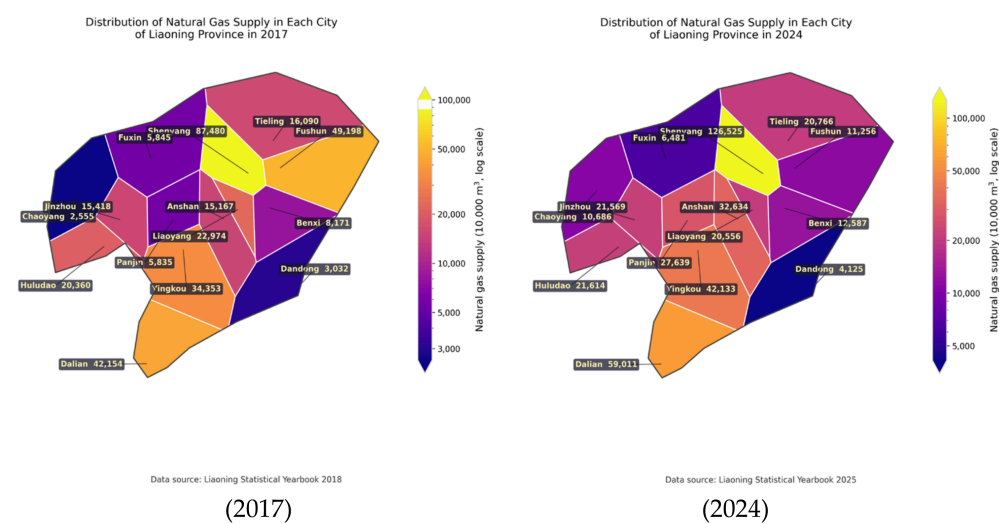


Figure 4. Total consumption of natural gas in major cities of Liaoning Province, 2017 and 2024.

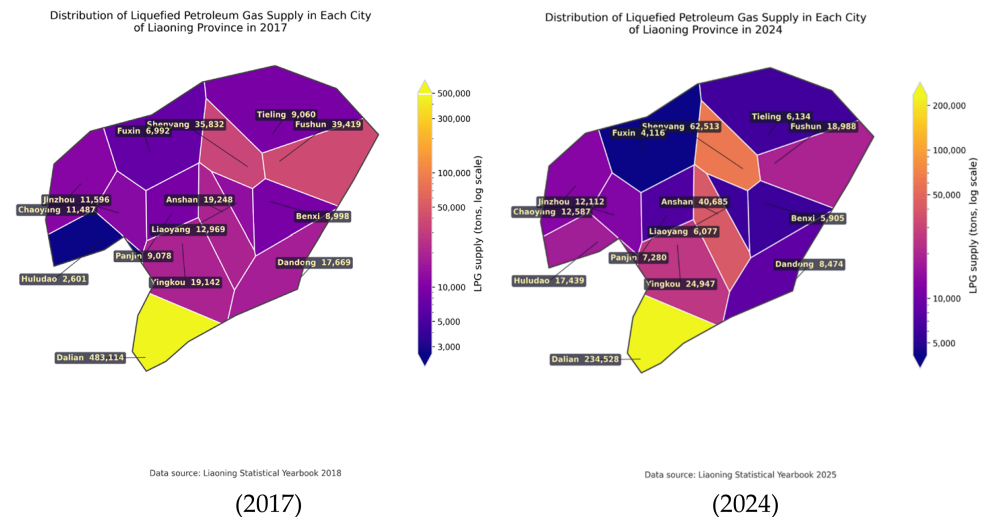


Figure 5. Total consumption of liquefied petroleum gas in major cities of Liaoning Province, 2017 and 2024.

3.2. Dynamic Evolution of Distributions

The KDE results (Figure 6) show that across energy types the main peak first declines, then rises, then declines again, with an overall lower peak and narrowing width; the right tail is lengthened while the left tail is thinned, indicating that low-consumption types converge toward the mean while high-consumption types (coal, crude oil) remain elevated; multiple peaks in most years indicate polarization. The industry distribution evolves similarly, with industry and transportation remaining at elevated levels. Table 2 summarizes these distribution pattern and dynamic evolution characteristics.

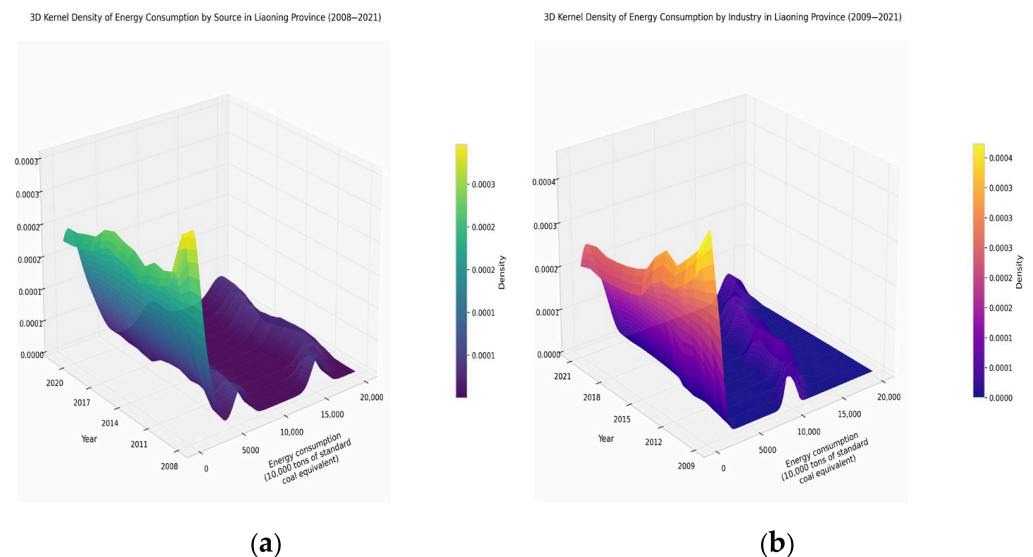


Figure 6. Kernel density estimation of energy consumption in Liaoning Province: (a) by energy type; (b) by industry.

Concentration remains high throughout the sample: the annual Gini coefficient ranges from 0.59 to 0.65 across the eight energy types and from 0.68 to 0.71 across the seven industries, indicating persistent imbalance across both energy types and industries.

Table 2. Distribution pattern and dynamic evolution characteristics.

Categories	Distribution Location	Main Peak Distribution Pattern	Distribution Extensibility	Polarization Phenomenon
Consumption of various energy sources	Right-shift (median 2166→6340; main peak 4233→6494, 10,000 tce)	Broadly stable at first, rising slightly in 2016–2019, dipping in 2020–2021, and rising again after 2022	Right trailing; skewness declines from 0.89 to 0.10 but remains positive	Polarization persists as two clusters (coal and oil vs. gas and electricity); the gap narrows slightly after 2021
Energy consumption in various industries	Right-shift (median 369→903; main peak 2037→3950, 10,000 tce)	The peak value decreases persistently and the distribution widens	Right trailing, extension widens (industry 9708→19,216 dominates the tail)	Single industry-dominated peak with a pronounced right tail; polarization persists without a stable multi-peak pattern

3.3. Factors Driving Total Consumption: LMDI Decomposition

Table 3 reports the additive LMDI decomposition (Section 2.3). Between 1985 and 2024 total consumption increased by $19,660 \times 10^4$ tce (196.60 Mtce). Per-capita output growth contributes +37,763 (192% of the total change)—the dominant driver. Energy-intensity decline contributes $-20,417$ (−104%), almost fully offsetting the scale effect: intensity fell from 12.20 to 2.61 (10^4 tce per 10^8 yuan, 1985 prices), a 78.6% reduction. Population contributes +1337 (7%). The net structure effect is small (+957, 5%) but masks large offsetting shifts: the 32-percentage-point decline of coal (−4196) is largely cancelled by rising oil (+2173), gas (+120) and primary-electricity (+2860) shares. The persistence of oil- and electricity-intensive consumption alongside coal substitution explains why structure alone has not reduced total consumption. Comparable decompositions for China’s industrial sector likewise attribute consumption growth mainly to activity and reductions mainly to intensity [21].

Table 3. LMDI decomposition of changes in Liaoning’s total energy consumption (10^4 tce). Note: figures are rounded to the nearest 10^4 tce, so the four components may not sum exactly to ΔE ; unrounded estimates close the identity $\Delta E = \Delta E_{\text{str}} + \Delta E_{\text{int}} + \Delta E_{\text{aff}} + \Delta E_{\text{pop}}$ exactly (Section 2.3).

Period	ΔE	Structure	Intensity	Per-Capita Output	Population
1985–2024	+19,660	+957 (coal −4196; oil +2173; gas +120; elec. +2860)	−20,417	+37,763	+1337
2012–2024	+3671	+101 (coal −3525; oil −467; gas +180; elec. +3913)	−8464	+12,973	−942

Since 2012 the intensity effect (−8464) has far outweighed all other factors except per-capita output, and population has turned negative (−942), consistent with population decline in the province; the electricity share rose sharply (+3913) as coal substitution accelerated in the approach to the dual-carbon era.

3.4. Factor Associations: Semi-Parametric Estimates

Estimates of the corrected specification (4) appear in Table 4; both regressors are statistically significant: the coal share ($\beta_1 = -0.898$, bootstrap se = 0.223, $z = -4.02$) is negatively associated with consumption, and real GDP ($\beta_2 = 0.427$, se = 0.027, $z = 15.83$) positively; the model attains $R^2 = 0.991$; because the series share common trends, this high

R^2 reflects trending behavior and is not a causal variance decomposition. The negative coal share coefficient indicates that years of higher total consumption coincide with lower coal shares—consistent with consumption growing fastest in periods when diversification away from coal was also proceeding; it does not imply that reducing coal raises consumption. Because the coal share enters in levels, β_1 is a semi-elasticity: a one-percentage-point higher coal share is associated with about a 0.9% lower level of consumption, holding GDP and $g(t)$ fixed. The fitted smooth term $g(t)$ declines over 1985–2000, rises over 2000–2010, declines over 2010–2016, and rises thereafter (Figure 7); because $g(t)$ absorbs all smooth omitted influences, these movements are descriptive and cannot be attributed to specific policies.

Table 4. Semi-parametric model estimates, 1985–2024 (dependent variable: ln total energy consumption).

Variable	Coefficient	Bootstrap se	z
Constant	6.748	0.358	18.85 ***
Coal share	−0.898	0.223	−4.02 ***
ln real GDP	0.427	0.027	15.83 ***

$R^2 = 0.991$. *** $p < 0.01$. $g(t)$: cubic B-spline, $df = 5$.

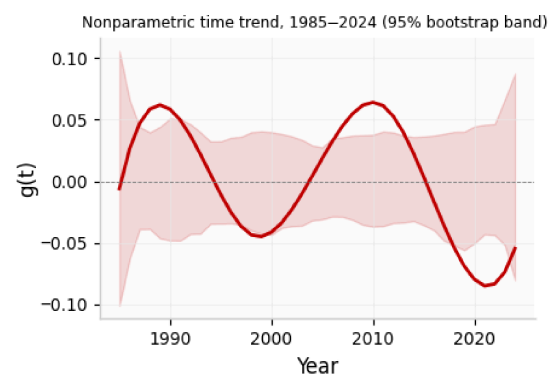


Figure 7. Fitted smooth time trend $g(t)$ from the semi-parametric model, 1985–2024. The solid line shows the fitted trend $g(t)$; the dashed lines and the shaded area indicate the 95% bootstrap confidence band.

Diagnostic checks support this associational interpretation. For the full 1985–2024 estimation sample ($T = 40$), Augmented Dickey–Fuller tests with constant and trend cannot reject a unit root in ln GDP and in the coal share, whereas ln consumption is trend-stationary; the Engle–Granger residual test does not reject the absence of cointegration ($p = 0.38$). The coefficient estimates in Table 4 therefore describe long-run comovement rather than a structural relationship. Residuals of the $df = 5$ specification show no heteroskedasticity (White test, $p = 0.39$) but mild second-order serial correlation (Breusch–Godfrey, $p = 0.01$), which motivates the block-bootstrap standard errors reported in Table 4. The spline dimension is selected by generalized cross-validation over $df \in \{3, \dots, 9\}$, which attains its minimum at $df = 5$; the estimated coefficients are nearly unchanged at $df = 7$. As a safeguard against spurious regression given the unit-root evidence above, we also estimate the specification in first differences (Section 2.4); Δ coal share and Δ ln GDP carry the same signs and remain statistically significant ($\beta_1 = -0.012$, bootstrap se = 0.005; $\beta_2 = 0.356$, se = 0.043; $R^2 = 0.61$), so the associational conclusions do not rest on the levels specification alone. Although energy intensity was removed from the specification, the coal share retains total consumption in its denominator; the coefficients in Table 4 are therefore read as partial associations rather than structural elasticities.

3.5. Interprovincial Spillovers: Panel SDM Estimates

Moran's I statistics for provincial consumption levels are insignificant in every year from 2000 to 2024 (range -0.03 to $+0.06$), so no global spatial clustering of levels exists. Nevertheless, the LR test strongly favors the SDM over the non-spatial fixed-effects model (LR = 15.49, $p = 0.0014$), and the Wald test rejects $\theta = 0$ (12.79, $p = 0.0017$). The LM diagnostics on the non-spatial fixed-effects residuals reject the null hypotheses of no spatial lag dependence and no spatial error dependence in favor of the corresponding spatial-lag alternative (LM-lag = 8.42, $p = 0.004$; robust LM-lag = 7.95, $p = 0.005$) and spatial-error alternative (LM-error = 6.17, $p = 0.013$; robust LM-error = 5.71, $p = 0.017$), respectively, and Moran's I on the SDM residuals is small but significant ($I = 0.041$, $p = 0.03$), which indicates that a modest degree of residual spatial dependence remains even after the SDM controls. Spatial dependence therefore operates through both the covariates and the lagged dependent variable, and the SDM, which nests both channels, is the appropriate specification. Table 5 reports maximum-likelihood estimates with two-way fixed effects ($N = 750$).

Table 5. Panel SDM estimates (dependent variable: ln provincial energy consumption).

Variable	Coefficient	se	z
ρ	0.0548	0.0235	2.33 *
ln GDP	0.3834	0.0485	7.90 ***
Secondary-industry share	0.0096	0.0015	6.46 ***
$W \times \ln \text{GDP}$	-0.0471	0.0143	-3.30 ***
$W \times \text{Secondary share}$	-0.0034	0.0013	-2.66 **

Note: row-standardized contiguity W ; two-way fixed effects. ***/**/* denote 0.1%/1%/5% significance.

Table 6 decomposes impacts following LeSage and Pace [23]. The direct GDP elasticity is 0.383 (se = 0.027); the indirect effect of neighboring provinces' GDP is significantly negative (-0.027 , se = 0.004). Industrial structure has a positive direct effect (0.010) and a small negative indirect effect (-0.003). The results are robust to an inverse-distance weight matrix ($\rho = 0.146$, se = 0.041; $W \times \ln \text{GDP} = -0.105$, se = 0.028) and to the 2000–2021 subsample ($\rho = 0.038$, se = 0.019; $W \times \ln \text{GDP} = -0.034$, se = 0.011); the negative indirect GDP effect is preserved in both cases.

Table 6. Direct, indirect, and total effects (bootstrap se, 300 replications).

Variable	Direct	Indirect	Total
ln GDP	0.383 (0.027) ***	-0.027 (0.004) ***	0.356 (0.029) ***
Secondary share	0.010 (0.001) ***	-0.003 (0.001) ***	0.007 (0.001) ***

Note: *** denotes 0.1% significance. (bootstrap standard errors, 300 replications).

Two findings follow. First, a province's own economic growth raises its energy use, corroborating the LMDI result that economic scale is the dominant driver. Second, the negative indirect effects indicate competitive rather than complementary interprovincial relationships: expansion of neighboring provinces' economies and industrial sectors is associated with relatively lower energy consumption at home, consistent with interprovincial relocation of energy-intensive activity under regional competition. We do not interpret these associations as causal; mechanisms such as resource siphoning, industrial homogenization, and geographical attenuation remain untested hypotheses for future research with richer data. Figure 8 summarizes the direct, indirect, and total effects implied by these spillover estimates.

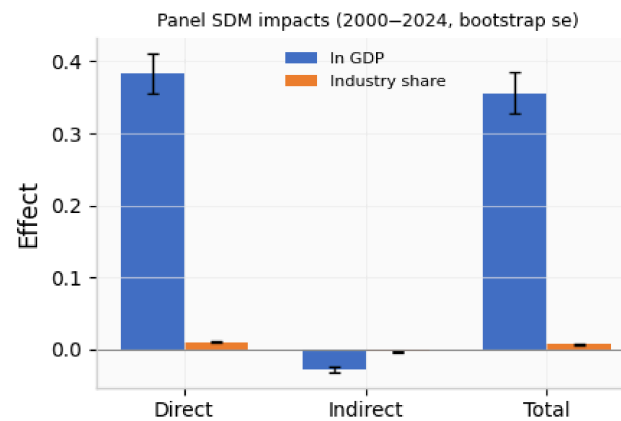


Figure 8. Estimated direct, indirect, and total effects of ln GDP and of the secondary-industry share on provincial energy consumption (SDM impact decomposition; bootstrap standard errors, 300 replications).

4. Discussion and Conclusions

4.1. Conclusions

Before summarizing, we discuss how our results relate to the broader decarbonization literature. The dominant role of per-capita output and the offsetting intensity effect mirror patterns reported for industrialized and transition economies, while the small net structure effect is consistent with evidence that fuel substitution alone does not guarantee demand reduction when electrification adds to rather than replaces fossil use [18,19,25]. The competitive interprovincial spillovers echo findings of regional relocation of energy-intensive activity, but our associational design cannot establish that mechanism; managed-decarbonization diagnostics of the kind proposed by Matukhno [25] would be a natural next step. These qualifications frame the conclusions that follow. National-level Kaya-LMDI studies similarly identify output growth as the dominant positive driver and energy intensity as the dominant negative driver [20].

This study examines the spatiotemporal dynamics, drivers, and spatial spillovers of heterogeneous energy consumption in Liaoning Province. First, Liaoning's total energy consumption grew from 63.25 to 259.85 Mtce during 1985–2024 (3.69% per year), with marked deceleration after 2012 (1.5% per year in 2012–2021 and 0.7% in 2021–2024). KDE and concentration measures confirm persistent polarization across energy types and industries, with coal and crude oil, and the industrial and transportation sectors, remaining dominant; Liaoning's industrial share of terminal consumption (~72%) ranks fifth nationally, confirming the weight of its heavy-industry structure.

Second, the Kaya-based LMDI decomposition shows that per-capita economic growth is the dominant driver of consumption growth (+192% of the total change), almost fully offset by energy intensity improvements (−104%). The net structure effect is small (+5%): the substantial decline of coal is offset by rising oil and primary-electricity shares, indicating that structural decarbonization in Liaoning hinges on cleaning the power supply rather than on fuel substitution alone. Since 2012, intensity gains have accelerated and population has become a negative contributor.

Third, the semi-parametric model indicates statistically significant associations of consumption with the coal share (negative) and real GDP (positive, elasticity ≈ 0.43); the smooth time trend is descriptive and cannot be uniquely attributed to policy.

Fourth, the panel SDM estimates a modest but significant spatial autoregressive coefficient ($\rho \approx 0.055$) and—after decomposing impacts—significant negative indirect effects of neighboring provinces' GDP and industrial structure. Interprovincial energy relationships appear competitive (substitutive) rather than complementary. We emphasize that

these are associational findings; mechanisms such as resource siphoning and geographical attenuation are proposed as hypotheses, not established results.

These policy directions directly support SDG 7 (affordable and clean energy), SDG 9 (industry, innovation and infrastructure) and SDG 13 (climate action) in a legacy industrial region. Policy implications supported by our findings are: (i) sustaining efficiency improvements, which the decomposition shows have been the main counterweight to scale-driven growth; (ii) prioritizing power sector decarbonization and electrification, given that electricity substitution currently adds to rather than reduces total consumption; and (iii) coordinating industrial planning across provinces to manage the competitive dynamics revealed by the negative spillovers. Recommendations concerning regional industrial coordination, emerging industries, and technological spillovers remain conditional on the hypothesized mechanisms and should be read as directions for policy design and future research.

4.2. Limitations

Five limitations are acknowledged. (i) Post-2020 figures follow new census and standard revisions and the 2015 method switch (coal consumption vs. heat-equivalent), so long-run comparisons embed level breaks that no adjustment fully removes. (ii) With the dual-carbon goals announced in 2020, only four post-announcement years are observable; we characterize baseline evolution rather than policy effects. (iii) The SDM identifies associations conditional on fixed effects; causal channels remain untested. (iv) City-level energy data cover 2017–2024 only, limiting the spatial analysis of within-province heterogeneity. (v) The KDE is estimated on small annual cross-sections (eight energy types; seven industries), so the distributional results are descriptive and their statistical power is limited; sensitivity to bandwidth choice is documented in Section 2.2.

Supplementary Materials: The following supporting information can be downloaded at <https://www.mdpi.com/article/10.3390/su182010580/s1>: Supplementary Materials S1 (replication package, replication_package.zip): R analysis scripts (01_kde_gini.R, 02_lmdi_kaya.R, 03_semiparametric.R, 04_sdm_spillovers.R, 05_make_figures.R, 00_make_synthetic_data.R), the processed data templates, the 30-province list, and the README documentation.

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