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Dynamic Coupling Between the Ecological Evolution of Industrial Structure and the Optimization of Energy Consumption Structure: Evidence from the Beijing-Tianjin-Hebei Region

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Abstract: This study constructs a comprehensive evaluation framework encompassing the ecological transformation of industrial structure, the degree of energy consumption structure optimization, and their respective evolutionary characteristics. Employing a vector autoregression (VAR) model, the paper systematically investigates the dynamic coupling relationship between industrial ecological evolution and energy structure optimization in the Beijing-Tianjin-Hebei (BTH) region. The findings indicate that the region has experienced a sustained improvement in the ecological orientation of its industrial structure, alongside a significant degree of spatial interdependence. In the long term, industrial ecologization exerts a notable positive influence on the optimization of the local energy consumption structure. In the short term, energy structure optimization in Beijing and Tianjin generates effective feedback that further facilitates their own industrial ecological upgrading. Distinct differences are observed across the three sub-regions in terms of evolutionary pathways and adjustment mechanisms, highlighting the critical role of regional functional positioning in shaping the coupled evolution of the industrial–energy system. The study not only enriches the empirical understanding of ecological economic interactions at the regional scale, but also offers theoretical guidance and policy insights for advancing low-carbon, green, and coordinated development across the BTH region.

Keywords: Beijing-Tianjin-Hebei (BTH); Industrial structure; Ecologization; Energy consumption structure; VAR model

1 Introduction

The ecologization of industrial structure, grounded in ecological economics, refers to the restructuring and optimization of resource allocation and factor flows across industries in accordance with ecological development principles. The goal is to enhance production efficiency while ensuring the sustainable utilization of environmental and resource capacities, thereby supporting long-term, stable economic growth. The structure of energy consumption denotes the proportional composition of various energy types—such as coal, oil, natural gas, and electricity—within total energy usage. Industrial upgrading has the potential to steer energy consumption toward cleaner and more efficient configurations, while improvements in the energy consumption structure, in turn, provide critical support for further industrial transformation. The two systems are inherently interdependent and mutually reinforcing. As the Beijing-Tianjin-Hebei (BTH) regional integration strategy advances into a more substantive phase, accurately identifying the trajectory of industrial restructuring and facilitating the optimization of energy consumption has become essential. Such efforts are crucial for propelling the region toward deeper, higher-quality, and more sustainable collaborative development.

A considerable body of scholarship has explored the relationship between industrial transformation and energy consumption optimization. Domestically, Zhang [1] developed an "industry–energy" interaction model to examine the spatial distribution of carbon emissions in China, revealing that the evolution and diversification of industrial structures significantly shape the layout and growth dynamics of regional energy consumption. The studies [2, 3] provided empirical evidence that industrial structure is a key driver of changes in energy consumption patterns. Zou et al. [4] further elucidated the mechanism through which industrial structure influences energy systems, highlighting the positive impacts of both structural rationalization and sophistication at the national level. Zhou et al. [5] identified a significant degree of spatial correlation in regional energy consumption structures. Focusing on the BTH region, Han and Ma [6] constructed a novel set of indicators based on rationalization and sophistication dimensions to evaluate the progress of industrial restructuring. Their findings suggest that Beijing's structural transformation outpaces that of Tianjin and Hebei. Wang and Zhang [7] observed that changes in the shares of the primary and secondary sectors have hindered reductions in energy intensity, while expansion of the tertiary sector plays a facilitative role; they thus advocate the development of green agriculture and strategic emerging industries. Bai et al. [8], based on empirical analysis of data from 2000 to 2011, found that industrial structure is a major determinant of energy consumption in the BTH region. On the international front, scholarly perspectives have expanded beyond traditional concerns with economic efficiency to encompass ecological efficiency, integrating environmental impacts and resource constraints. There is also growing attention to the role of digital platforms in enhancing the coordination and efficiency of industry–energy systems [9, 10]. Methodologically, industrial ecology provides a foundational framework for analyzing material and energy flows within industrial systems [11, 12], while advanced econometric models are increasingly employed to investigate complex system dynamics [13, 14].

Despite these advancements, several gaps remain. First, most existing studies emphasize either "sophistication" (such as increasing the proportion of the tertiary sector) or "rationalization" (coordination and balance among sectors), while largely overlooking "ecologization" as a comprehensive core dimension. In contrast to output-focused approaches, the concept of ecologization incorporates environmental constraints and sustainability imperatives, offering a more holistic lens for examining structural transformation. Second, the majority of prior studies adopt national-level or static comparative frameworks, which limit the ability to uncover dynamic evolutionary processes and spatial heterogeneity within functionally differentiated regions like BTH. Third, from a methodological perspective, prior research tends to focus on unidirectional causality or static correlations, lacking robust investigation into the dynamic, bidirectional feedback mechanisms between industrial ecologization and energy consumption structure optimization—particularly those based on time-series modeling.

In response to these shortcomings, this study adopts an integrative ecological perspective to construct a multidimensional indicator system for measuring industrial structure ecologization, encompassing dimensions such as resource consumption, environmental pressure, and ecological performance—thus addressing the limitations of economic-centric approaches. A VAR model is employed to capture the dynamic, bidirectional interactions between industrial ecologization and energy consumption structure optimization in the BTH region. Impulse response functions (IRF) and variance decomposition techniques are used to identify the pathways and intensities of interdependence. Furthermore, the distinct evolutionary patterns observed across BTH are analyzed to reveal how differentiated functional roles under a coordinated development framework shape unique trajectories in industry–energy coupling. The findings provide both empirical insights and theoretical foundations for formulating region-specific policies aimed at advancing a green, low-carbon, and synergistically integrated development model.

2 Framework for Assessing the Ecologization of Industrial Structure

Based on ensuring data accessibility and completeness, and in line with regional output efficiency and the goal of sustainable environmental resource utilization, this study extends traditional measures of industrial structure—namely rationalization and sophistication—by incorporating a sustainability dimension that accounts for energy consumption and pollutant emissions. Based on this framework, a composite index of industrial structure ecologization is developed from three interrelated dimensions: rationalization, sophistication, and sustainability. This integrated index is designed to comprehensively capture the multifaceted characteristics of industrial structure optimization. A non-parametric geometric aggregation method is adopted to measure the ecologization level of the industrial structure across BTH.

2.1 Rationalization Index

The rationalization of industrial structure reflects the degree to which factor inputs are efficiently allocated across industries, i.e., whether the distribution and utilization of resources among different sectors approach an optimal state. Drawing upon the concept of industrial structure deviation [1], this study constructs a rationalization indicator H_t that accounts for the proportion of different industries comprehensively in the regional economy:

$$H_t = \frac{1}{\sum_i^n y_i \left(\frac{y_i}{l_i} - 1\right)} \tag{1}$$

where, H_t denotes the rationalization level of the industrial structure in period t, y_i represents the output share of sector i and l_i denotes the employment share of the same sector. A smaller value of this index implies a higher degree of rationalization, indicating better alignment between resource input and output across sectors.

2.2 Upgrading Index

With the rapid advancement of information technologies, the shift toward a service-oriented economy has become a hallmark of industrial upgrading. The sophistication of industrial structure captures the extent to which an economy transitions from primary to secondary and tertiary industries. Following standard methodologies for measuring industrial advancement [15], the sophistication indicator W_t is constructed as follows:

$$W_t = \frac{v_3}{v_1} + \frac{v_3}{v_2} \tag{2}$$

where, W_t represents the sophistication level in period t; v_i denotes the GDP share of the primary ($i = 1$), secondary ($i = 2$), and tertiary ($i = 3$) industries, respectively. A higher value of this index indicates greater industrial sophistication and a more advanced structural composition.

2.3 Sustainability Index

Regional economies can enhance sustainability by phasing out high-energy, high-emission industries and fostering low-consumption, low-emission sectors through innovation, technological progress, and rational resource allocation. Drawing on the relative potential evaluation model [16], two core indicators are selected: (1) energy intensity (E_q), which measures coal, oil, and natural gas consumption per unit of GDP; and (2) pollution intensity (P_z), which reflects the volume of wastewater, gas emissions, and solid industrial waste per unit of GDP. The sustainability indicator M_t is constructed as:

$$M_t = \frac{1}{2}\left(\sum_{q=1}^{3} \frac{E^* - E_q}{E^*} + \sum_{z=1}^{3} \frac{P^* - P_z}{P^*}\right) \tag{3}$$

where, M_t denotes the level of industrial structure sustainability in region during period t; E^* and P^* are the regional average energy and pollution intensities, respectively. This indicator is inversely related to the level of industrial structure sustainability.

2.4 Composite Ecologization Index

This study conceptualizes industrial structure ecologization from the perspective of the “three transformations”—rationalization, sophistication, and sustainability. Accordingly, a geometric aggregation method is employed to integrate these three core dimensions into a composite index, denoted as S_t, for measuring the overall level of industrial structure ecologization.

$$S_t = H_t + W_t + M_t \tag{4}$$

where, the index S_t represents the degree of industrial structure ecologization in a given region during period t, serving as a comprehensive and intuitive metric for assessing both the effectiveness and differences in industrial structure optimization across BTH. Based on quarterly statistical data from 2001 to 2024, the S_t values for the three regions were calculated using Eq. (4), and the resulting trends are illustrated in Figure 1.

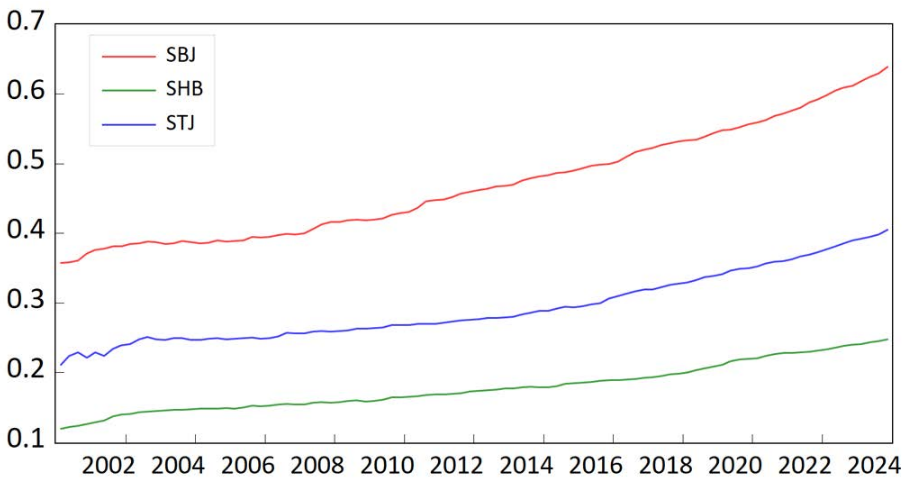

Figure 1. Industrial structure ecologization levels in the BTH region

3 Energy Structure Indicators

Given the spatial interdependence and coordinated dynamics across the BTH region, ecological adjustments in the regional industrial structure are expected to directly promote the optimization and upgrading of the energy consumption structure in neighboring areas. The BTH Coordinated Development Plan explicitly calls for a substantial increase in the share of clean energy and the establishment of a green, low-carbon energy supply system dominated by electricity and natural gas, with supplemental contributions from solar, geothermal, and biomass energy. The plan emphasizes principles of low-carbon development, energy efficiency, and technological advancement to guide the optimization of energy consumption patterns. Statistical data indicate that, alongside notable shifts in industrial structure, the share of coal consumption has decreased significantly in both Beijing and Tianjin. Meanwhile, the consumption shares of petroleum and natural gas have stabilized across all three regions, and the shares of electricity and other green energy sources have increased markedly—especially in Beijing and, to a lesser extent, Tianjin. This ongoing structural evolution has also been accompanied by continuous improvements in air quality, reflecting steady progress toward a cleaner and more efficient energy mix. Based on these trends, energy consumption in this study is categorized into three groups: coal (E_c), petroleum and natural gas (E_{og}), and electricity plus other green energy sources (E_p), and the weights are assigned based on the ecological desirability of each energy source, with higher weights given to cleaner sources. Drawing upon quarterly energy consumption data from the China Energy Statistical Yearbook spanning 2001 to 2024, the study aggregates and standardizes regional statistics. Following the methodology used to construct the industrial sophistication indicator, a composite index is developed to represent regional energy consumption structure optimization:

$$E_t = \frac{E_{ogt}}{E_{ct} + E_{ogt}} + \frac{E_{pt}}{E_{ogt} + E_{pt}} \tag{5}$$

where, E_t denotes the degree of energy consumption structure optimization in region during period t; E_{ct}, E_{ogt}, and E_{pt} respectively represent the proportions of coal, petroleum and natural gas, and electricity plus other green energy sources in total energy consumption. A higher value of E_t thus reflects a more optimized and sustainable energy consumption structure.

Quarterly data from 2001 to 2024 were used to calculate the E_t values for BTH according to Eq. (5), and the resulting time series are presented in Figure 2.

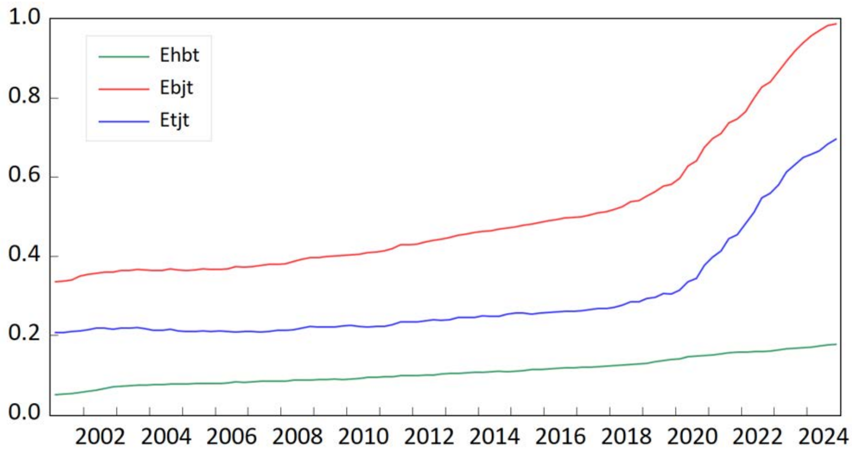

Figure 2. Energy consumption structure optimization index in the BTH region

The data reveal that all three regions have experienced a gradual decline in coal consumption shares, while the share of fossil fuels (petroleum and natural gas) has stabilized. In contrast, the proportion of electricity and other green energy has increased, though with marked regional variation: Beijing has exhibited the most significant upward trend, followed by Tianjin, with Hebei showing only a modest increase. To further capture the differential efficiency of energy consumption structure improvement—driven by variations in industrial ecologization levels across regions—this study introduces an additional indicator E_t, the Energy Consumption Structure Optimization Evolution Index, denoted as R_t:

$$R_t = E_t * E_{pt} \tag{6}$$

The R_t index serves to characterize regional disparities in energy optimization performance that are attributable to differences in industrial structure ecologization. It reflects the extent to which improvements in industrial ecological structure translate into actual gains in energy structure optimization.

4 Empirical Analysis

4.1 Model and Variables

The VAR model, a non-structural system of equations, does not require any a priori restrictions on the endogenous variables. It is primarily used to estimate the dynamic relationships among jointly endogenous variables and to analyze the responses of the system to stochastic shocks, thereby enabling the interpretation of how various economic disturbances affect key variables over time [17]. The VAR model is particularly suitable for capturing short- and long-term dynamic interactions among interrelated variables, offering robust empirical support for hypothesis testing and policy inference. The standard VAR(p) model can be expressed as:

$$y_s = \varphi_1 y_{s-1} + \varphi_2 y_{s-2} + \cdots + \varphi_p y_{s-p} + Hx_s + \mu_s \quad (s = 1, 2, \cdots n) \tag{7}$$

where, y_s is a k-dimensional vector of endogenous variables; x_s is a σ-dimensional vector of exogenous variables; p denotes the number of lags; and s is the number of samples. The matrices $\varphi_1, \ldots \varphi_p$, of dimension $k \times k$, and the matrix H of dimension $k \times d$, represent the coefficients to be estimated. The vector μ_s is a k-dimensional error term capturing the residuals of the system.

This study adopts the VAR framework to uncover the intrinsic dynamic relationships between industrial structure ecologization and energy consumption structure optimization in the BTH region. To maintain model parsimony and concentrate on the core research objective, potential exogenous variables—such as policy factors and technological innovation—are not included in the VAR system. Instead, the model focuses exclusively on key endogenous variables that directly represent the core dynamics of the system. The first variable, industrial structure ecologization, captures a region's transition toward a greener, low-carbon, and circular economy by integrating three core dimensions: resource use efficiency (rationalization), industrial upgrading (sophistication), and environmental performance (sustainability). This composite indicator goes beyond conventional measures of structural advancement by incorporating principles from ecological economics and industrial ecology to assess the sustainability of the industrial system [18, 19]. The second variable, energy consumption structure optimization, is a composite index based on the relative shares of three major energy categories. It is designed to reflect how structural changes in industry influence the composition and quality of energy demand. As an intermediate variable linking industrial transformation to environmental outcomes such as carbon emissions and pollution levels, this index provides a direct measure of energy system optimization. The third variable, energy consumption structure optimization evolution, captures the marginal rate of improvement in energy consumption structure as driven by changes in industrial ecologization. In other words, it quantifies the efficiency of optimization—i.e., how effectively shifts in industrial structure translate into progress in energy system reform. This indicator not only reflects the static level of optimization but also reveals the system's dynamic capacity to evolve, offering deeper insights into the strength of industrial transformation as a driver of energy transition [20].

Together, these three variables form a logical and empirically tractable chain:

• Industrial ecologization transformation (driver).
• Energy consumption structure optimization (static outcome).
• Optimization evolution (dynamic efficiency).
• This chain captures the internal mechanisms of their coordinated evolution.

Accordingly, to investigate the dynamic evolutionary relationships and underlying mechanisms, this study constructs a three-variable VAR model using quarterly data for BTH from 2001 to 2024. The three core variables include the industrial structure ecologization index (S_t), the energy consumption structure optimization index (E_t), and the energy consumption optimization evolution index (R_t). All data are drawn from the Beijing Statistical Yearbook, Tianjin Statistical Yearbook, Hebei Statistical Yearbook, and the China Statistical Yearbook. To eliminate potential heteroscedasticity in the time series, all variables are transformed using natural logarithms. The log-transformed variables are denoted as LnS_t, LnE_t and LnR_t, respectively. The revised VAR model incorporating these three variables is specified as:

$$Y_t = \mu + \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \cdots + \phi_k Y_{t-k} + \varepsilon_t \tag{8}$$

where, specifically, let $Y_t = (LnS_t, LnE_t, LnR_t), \mu = (\mu_1, \mu_2, \mu_3)$, and assume that ε_t is a white noise process, i.e., $E(\varepsilon_t) = 0$.

4.2 Empirical Results

4.2.1 Unit root test

To avoid spurious regression results caused by non-stationary time series, the Augmented DickeyFuller (ADF) test is employed to assess the stationarity of the time series data for the BTH region. The ADF test is first applied to the level series of the three variables (denoted as LnS_t, LnE_t and LnR_t). As shown in Table 1, the test statistics for all three variables are greater than their respective critical values at the 1% significance level, indicating the presence of unit roots-that is, the original series are non-stationary. Subsequently, the first-differenced series (denoted as $DLnS_t, DLnE_t$ and $DLnR_t$) are subjected to ADF tests. The results demonstrate that all three differenced variables pass the stationarity test at the 1% significance level. Moreover, the P -values associated with each variable are below the 0.05 threshold, confirming that the first-differenced series are stationary. These findings indicate that the original time series are integrated of order one, i.e., I(1).

Based on the Akaike Information Criterion (AIC) and the Schwarz Criterion (SC), all three variables for the BTH region are identified as integrated of order one, i.e., I(1). Accordingly, the first-differenced series of these variables are used to conduct the Johansen cointegration test and to establish the subsequent VAR model.

Table 1. Results of ADF unit root tests for variables in the BTH region

Region	Variable	Log-Level Series			First-Difference Series		
		ADF Statistic	P-Value	Conclusion	ADF Statistic	P-Value	Conclusion
Beijing	S_t	-1.85114	0.6714	Non-stationary	-4.6987	0.0014	Stationary
	E_t	-1.2738	0.8881	Non-stationary	-3.1433	0.0007	Stationary
	R_t	-2.8300	0.1906	Non-stationary	-11.6712	0.0000	Stationary
Tianjin	S_t	0.7178	0.9920	Non-stationary	-9.5996	0.0000	Stationary
	E_t	-2.9055	0.1657	Non-stationary	-12.7530	0.0000	Stationary
	R_t	-12.3658	0.0000	Non-stationary	-12.3658	0.0000	Stationary
Hebei	S_t	-2.9571	0.1501	Non-stationary	-2.8588	0.0008	Stationary
	E_t	-3.1962	0.0917	Non-stationary	-9.9755	0.0000	Stationary
	R_t	-2.9063	0.1655	Non-stationary	-11.2478	0.0000	Stationary

4.2.2 Johansen cointegration and granger causality tests

Given that all variables are confirmed to be integrated of order one based on the ADF unit root tests, the optimal lag length for Model (8) is determined using the Akaike Information Criterion (AIC) [12]. At the selected lag order, the Johansen cointegration test is employed to examine whether a long-run equilibrium relationship exists among the selected variables.

(1) Cointegration Test for Industrial Structure Ecologization Indicators in BTH

Given the spatial correlation and interconnectivity across the BTH region—and in light of the ongoing coordinated development strategy and long-term policy efforts such as the relocation of non-capital functions—this section begins by testing the industrial structure ecologization indicators for the three regions as endogenous variables.

Table 2. Results of the Johansen cointegration test

Null Hypothesis	Eigenvalue	Trace Statistic	5% Critical Value	P-Value
None *	0.3420	74.3080	29.7970	0.0000
At most 1 *	0.2110	35.7893	15.4947	0.0000
At most 2 *	0.1410	13.9828	3.8414	0.0002

Note: *denotes rejection of the null hypothesis at the 5% significance level.

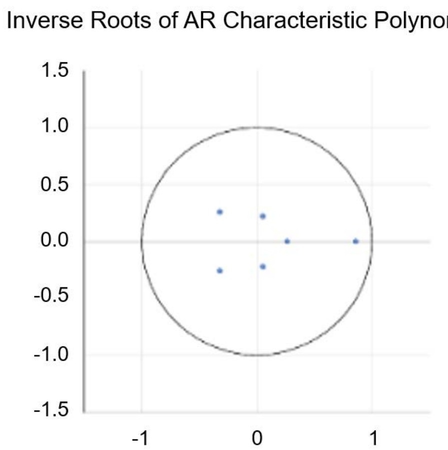

Figure 3. AR root stability test for the VAR(5) model

Based on AIC results, the optimal lag length for the cointegration test is set to 5. The Johansen test results in Table 2 show that at the 5% significance level for LnS_t of the BTH region, the trace statistics for the three variables exceed the critical values, rejecting the null hypothesis of no cointegration. Specifically, the results support the existence of three cointegrating relationships. This indicates that the ecologization of industrial structures in BTH share a stable long-term equilibrium relationship, underscoring the strong interdependence of their structural transformation processes.

The results of the AR root test for the VAR(5) model are shown in Figure 3. All characteristic roots lie within the unit circle, indicating that the model satisfies the condition of stability.

The Granger causality results in Table 3 reveal that industrial structure ecologization in Beijing Granger-causes corresponding changes in both Tianjin and Hebei, while the reverse is not true—ecologization efforts in Tianjin and Hebei do not Granger-cause changes in Beijing. Additionally, Tianjin exerts a unidirectional Granger causal effect on Hebei, but not vice versa. These findings underscore the asymmetric influence of regional structural transformation, with Beijing acting as the leading driver in the ecologization process across the BTH region.

Table 3. Granger causality test results for industrial structure ecologization in BTH

Null Hypothesis	F-Statistic	P-Value	Conclusion
S_{TJt} does not granger-cause S_{BJt}	8.2713	0.0160	Accepted
S_{HBt} does not granger-cause S_{BJt}	1.1472	0.0007	Accepted
S_{BJt} does not granger-cause S_{TJt}	0.6284	0.7304	Rejected
S_{HBt} does not granger-cause S_{TJt}	15.6457	0.0004	Accepted
S_{BJt} does not granger-cause S_{HBt}	0.1302	0.9370	Rejected
S_{TJt} does not granger-cause S_{HBt}	2.0221	0.3638	Rejected

Note: Variables are denoted as follows: S_{BJt}-Beijing, S_{TJt}-Tianjin, S_{HBt}-Hebei.

(2) Regional-Level Variable Testing

In parallel, the Johansen cointegration test is conducted separately for each of the three regions using their respective indicator variables: LnS_t, LnE_t and LnR_γ. Based on AIC values, the optimal lag lengths for the cointegration test are determined to be 4, 3, and 4 for BTH, respectively. The results, as shown in Table 4, indicate that for all three regions, the null hypothesis of no cointegration can be rejected at the 5% significance level. Specifically, each region exhibits three cointegrating vectors, thereby confirming the existence of long-run equilibrium relationships among the three variables in each region.

Table 4. Johansen cointegration test results by region

Region	Null Hypothesis	Eigenvalue	Trace Statistic	5% Critical Value	P-Value
Beijing	None	0.2742	55.7650	29.7970	0.0000
	At most 1	0.2129	22.2815	15.4947	0.0008
	At most 2	0.0451	4.2473	3.8414	0.0393
Tianjin	None	0.2710	49.3628	29.7970	0.0001
	At most 1	0.1625	20.2767	15.4947	0.0088
	At most 2	0.0421	3.9559	3.8414	0.0467
Hebei	None	0.6112	112.3088	29.7970	0.0000
	At most 1	0.1668	25.3896	15.4947	0.0012
	At most 2	0.0892	8.5998	3.8414	0.0034

Note: Critical values at the 5% significance level. "None", "At most 1", etc., denote the number of cointegrating relationships.

The AR root tests of the VAR models for each region (VAR(4) for Beijing, VAR(3) for Tianjin, and VAR(4) for Hebei) are shown in Figure 4. In all cases, the roots lie within the unit circle, confirming the stability of the respective models.

As shown in Table 5, the Granger causality test results for each region reveal the following:

• Beijing: Neither energy consumption structure optimization (E_t) nor its evolution (R_t) Grangercause industrial structure ecologization (S_t). However, industrial structure ecologization is found to be a Granger cause of both E_t and R_t. In addition, there is a bidirectional Granger causality between E_t and R_t, indicating mutual feedback between energy structure optimization and its evolutionary capacity.

• Tianjin: Similar to Beijing, E_t and R_t do not Granger-cause S_t, but S_t significantly Grangercauses both E_t and R_t. Again, a bidirectional Granger causal relationship is observed between E_t and R_t.

• Hebei: Unlike Beijing and Tianjin, all three variables show mutual Granger causality. That is, E_t and R_t both Granger-cause S_t, and S_t in turn Granger-causes both E_t and R_t. Additionally, E_t and R_t Granger-cause each other, reflecting a fully bidirectional relationship among the three dimensions.

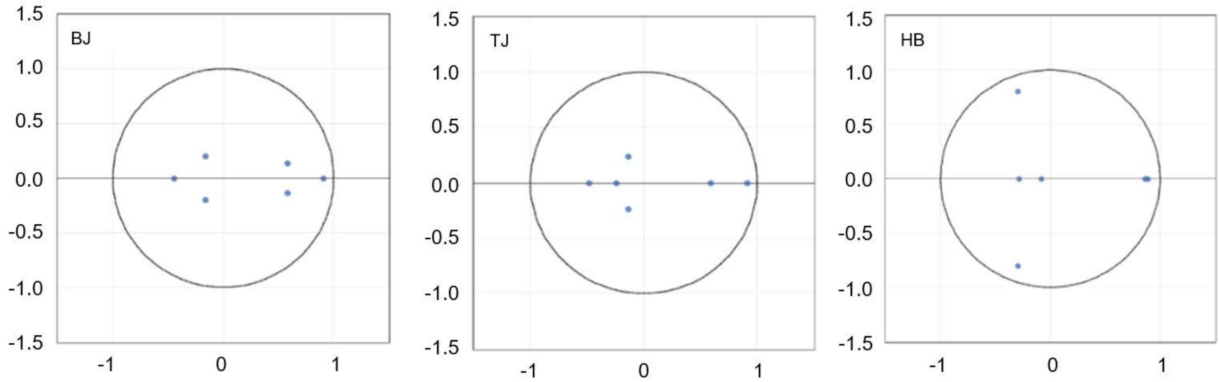

Figure 4. AR root test results for the VAR models of the three regions

Table 5. Granger causality test results for the indicator variables of BTH region

Region	Null Hypothesis	F-Statistic	P-Value	Conclusion
Beijing	E_t does not granger-cause S_t	6.1693	0.0057	Accepted
	R_t does not granger-cause S_t	7.1293	0.0283	Accepted
	S_t does not granger-cause E_t	4.4353	0.1089	Rejected
	R_t does not granger-cause E_t	0.8767	0.6451	Rejected
	S_t does not granger-cause R_t	4.5255	0.1041	Rejected
	E_t does not granger-cause R_t	0.3825	0.8259	Rejected
Tianjin	E_t does not granger-cause S_t	10.8818	0.0043	Accepted
	R_t does not granger-cause S_t	10.1093	0.0064	Accepted
	S_t does not granger-cause E_t	0.3066	0.8579	Rejected
	R_t does not granger-cause E_t	0.1309	0.9366	Rejected
	S_t does not granger-cause R_t	0.1781	0.9148	Rejected
	E_t does not granger-cause R_t	0.8300	0.6603	Rejected
Hebei	E_t does not granger-cause S_t	0.4349	0.8046	Rejected
	R_t does not granger-cause S_t	1.6106	0.4469	Rejected
	S_t does not granger-cause E_t	3.7639	0.1523	Rejected
	R_t does not granger-cause E_t	3.4390	0.1792	Accepted
	S_t does not granger-cause R_t	3.5123	0.1717	Rejected
	E_t does not granger-cause R_t	3.9905	0.1360	Rejected

4.2.3 Impulse response

The IRF of the VAR model enables the measurement of the impact of a shock to one variable on itself and on other variables, while holding the remaining variables constant. This allows for a dynamic examination of short-term relationships among variables. To accurately assess the dynamic linkages among industrial structure ecologization, energy consumption structure optimization, and the evolution of energy consumption optimization in the BTH region from 2001 to 2024, this study estimates the IRFs based on the established VAR model. The IRFs capture the dynamic characteristics inherent in the VAR system, and describe how shocks to endogenous variables affect both their current and future values, as well as those of other variables in the system.

(1) Impulse Response Analysis of Industrial Structure Ecologization in the BTH Region

As shown in Figure 5, when each of the three variables representing industrial structure ecologization in BTH experiences a one-standard-deviation shock to itself, a sharp and positive response appears in the first period. This response gradually weakens and converges toward zero around the sixth period. This indicates that the ecologization of industrial structures in all three regions exhibits a self-reinforcing mechanism that facilitates their own development.

In terms of regional spillovers:

• Beijing's industrial structure ecologization generates a significant positive spillover effect on Tianjin in the second and third periods, while exerting a slight negative impact on Hebei, which is likely associated with mismatches in industrial structures caused by Hebei absorbing part of the non-capital functions from Beijing.

• Tianjin's industrial structure ecologization produces mild positive spillovers to Beijing in the first and second periods, with the effects approaching zero after the third period. It also exerts a significant positive spillover to Hebei in the second period, which weakens thereafter.

• Hebei's industrial structure ecologization yields mild positive spillovers to Beijing during the first and second periods, with the influence dissipating after the fourth period. It has a marginally positive impact on Tianjin in the first period, and becomes negligible afterward.

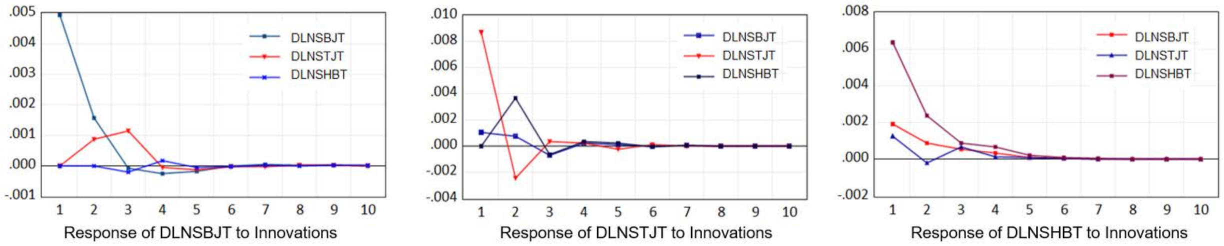

Figure 5. IRFs for industrial structure ecologization

In general, the industrial structure differences among the three regions are evident. The overall degree of industrial structure ecologization development ranks as Beijing $>$ Tianjin $>$ Hebei. Beijing has demonstrated superior performance in industrial transformation and upgrading, and its advantages in comprehensive development have become increasingly pronounced over time—consistent with its role as a national innovation hub. Tianjin has also achieved moderate progress, although it has not yet reached optimal performance. Hebei, due to its function as a receiving area for relocated industries, shows more pronounced mismatches in its industrial structure. In the short term, the ecologization of industrial structures in Beijing and Tianjin has an inhibitory effect on Hebei's industrial ecologization. However, in the long term, the positive spillover effects from Beijing and Tianjin become more prominent, demonstrating leading and demonstrative roles in driving Hebei's industrial upgrading.

The IRFs reveal the nuanced interaction patterns among the three regions, reflecting the phased characteristics of the BTH coordinated development process. For example, Beijing's ecologization exerts a short-term suppressive effect on Hebei, which transitions into a long-term positive spillover. This aligns closely with the core policy of "relocating non-capital functions." In the early stages of industrial relocation, traditional manufacturing sectors or high-energy-consuming and high-emission industries transferred to Hebei may not initially match in terms of technical standards, management capabilities, or environmental infrastructure, thus causing a temporary decline in Hebei's ecologization index—a phenomenon referred to as the "inhibitory effect." However, over the long run, these transfers are not merely spatial relocations but are accompanied by technology diffusion, managerial spillovers, and improved green standards. Beijing's long-term positive spillover effects on Tianjin and Hebei substantiate its role as an innovation and high-end service hub. This observation is in line with the spatial structure outlined in the BTH Coordinated Development Plan, specifically the "one core, two cities, three axes, four zones, and multiple nodes" strategic layout, which emphasizes using core urban areas as growth poles to drive the upgrading of the entire region.

(2) Impulse Response Analysis of the Three Core Indicators in BTH

Figure 6 illustrates the impulse response relationships among Beijing's three key variables. A shock to industrial structure ecologization (S_t) produces a slight negative impact on energy consumption structure optimization (E_t) in periods 1 and 2, followed by a sustained positive effect from period 3 onward. This indicates that ecologization exerts a long-term promoting effect on energy optimization in Beijing. Regarding $S_t \rightarrow R_t$ (evolution of energy optimization), the response is significantly positive during periods 1 to 3, and gradually fades afterward. For E_t (self-shock), the strongest positive response occurs in period 1, followed by gradual attenuation, suggesting that Beijing's energy consumption structure exhibits a self-reinforcing dynamic. E_t also has a short-term positive influence on S_t during periods 1–2, which diminishes after period 3. Additionally, $E_t \rightarrow R_t$ shows moderate positive effects in periods 2 to 4, with the influence fading over time. For R_t (self-shock), the largest response occurs in period 1, and then declines, indicating that R_t also follows a self-reinforcing pattern. R_t exerts positive effects on S_t in periods 1 to 3, with the influence disappearing after period 4. This implies that energy optimization evolution can effectively drive the ecologization process in the short term. Moreover, R_t has a significant and lasting positive impact on E_t, highlighting its central role in upgrading the region's energy structure.

These findings are consistent with Beijing's industrial development pathway as the capital's core function zone. From 2014 to 2024, the proportion of tertiary industry rose from 77.9% to 83.5%, with low-carbon sectors such as finance and information services accounting for over 40%—a structural shift that directly promoted the optimization of energy consumption. For instance, coal consumption fell from 13.2% in 2015 to 3.8% in 2023, while the share of electricity and other green energy sources increased to 58%. However, the short-term negative response can be attributed to energy consumption rigidities during structural transition—e.g., from 2016 to 2018, rapid clustering of headquarters economy led to a surge in commercial energy use, pushing annual natural gas consumption growth to over 12%, which temporarily slowed the pace of energy structure optimization.

As shown in Figure 7, a shock to Tianjin's S_t produces slight positive effects on E_t in periods 1 and 2, which gradually dissipate thereafter. This suggests that the long-term impact of ecologization on energy optimization in Tianjin is limited, consistent with its existing second- and third-sector structures and current energy use profiles. For $S_t \to R_t$, there are notable negative effects in periods 2 and 3, which also disappear over time. E_t in Tianjin shows a strong self-reinforcing response: the largest effect occurs in period 1 and weakens thereafter. $E_t \to S_t$ displays a weak long-term positive effect, while $E_t \to R_t$ has virtually no influence over the long run. R_t also shows a positive selfresponse, peaking in period 1. As for $R_t \to S_t$, a slight long-run positive effect is observed, while $R_t \to E_t$ exhibits a significant long-term positive effect, suggesting that evolutionary improvements in energy consumption structure do contribute to sustained optimization.

Overall, the weak long-run effect of S_t on E_t in Tianjin reflects path dependence on its "Heavy Industry + Port Economy" composite structure. As of 2022, petrochemical industries still accounted for 18% of Tianjin's large-scale industrial output, and diesel consumption from port logistics remained around 25%. These traditional energy demands diluted the greening effects of structural upgrades. Furthermore, Tianjin's natural gas share in energy consumption reached 32% in 2023, leaving limited room for further optimization—a pattern echoed in the rapidly fading positive effects observed in the impulse responses.

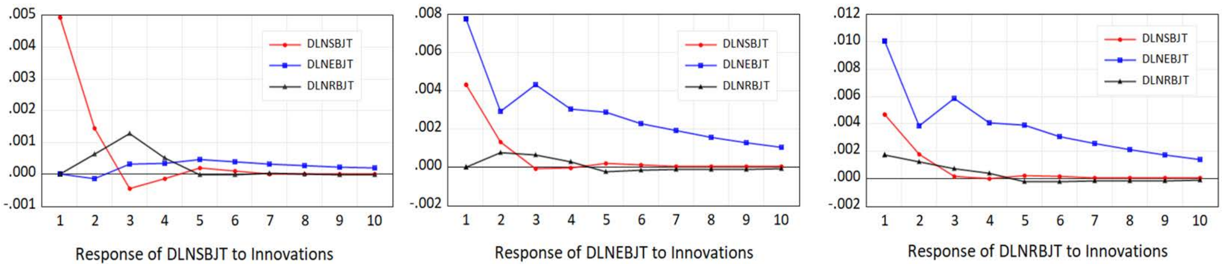

Figure 6. IRFs for Beijing

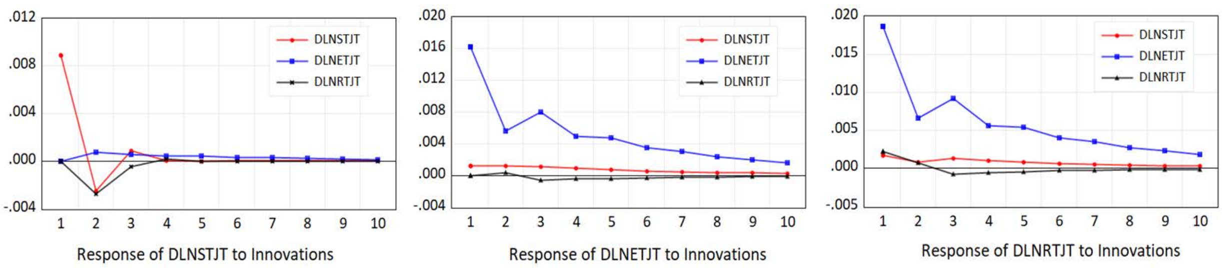

Figure 7. IRFs for Tianjin

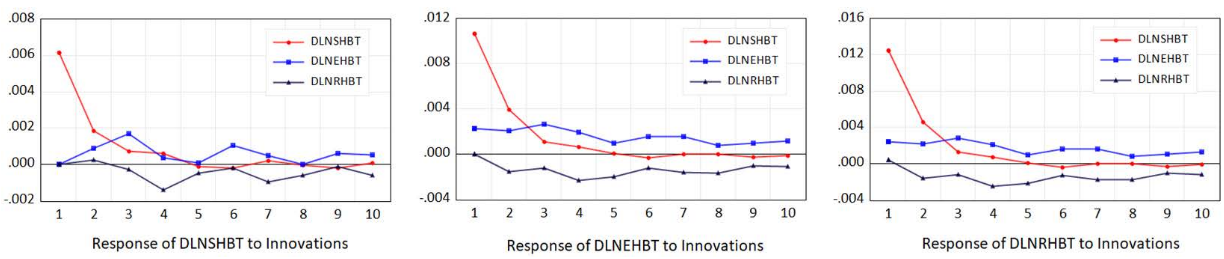

Figure 8. IRFs for Hebei

Figure 8 highlights the distinct impulse dynamics in Hebei compared to Beijing and Tianjin. Specifically:

• A shock to S_t yields positive effects on E_t in periods 3, 6, and 9, which gradually decline. Conversely, $S_t \to R_t$ shows negative effects, suggesting trade-offs between structure greening and optimization evolution in the short term.

• $E_t \to S_t$ is significantly positive in period 1, diminishing after period 5. E_t (self-shock) exhibits a modestly positive long-term self-response, while $E_t \to R_t$ shows a negative long-run effect, possibly due to inefficiencies in resource reallocation.

• $R_t \to S_t$ is significantly positive in period 1, but fades after period 5. $R_t \to E_t$ shows a positive long-run effect, while R_t (self-shock) has a negative long-term response, indicating adjustment pressure within the energy system.

These dynamics reveal the unique challenges faced by resource-based regions like Hebei. In the short term, energy-saving upgrades in traditional sectors (e.g., steel, cement) significantly enhance energy structure optimization—by 2021, 90% of Hebei's steel industry had completed ultra-low emissions upgrades. However, the long-term effects of ecologization on the energy structure are cyclical. Between 2016 and 2019, capacity reduction policies promoted optimization; between 2020 and 2022, post-pandemic rebounds in heavy industries reversed some gains; since 2023, green transition policies have regained momentum. These cycles are reflected in the multi-peak patterns observed in the IRFs.

On the whole, industrial structure ecologization in BTH exerts long-term positive effects on their respective energy consumption structure optimization. Conversely, energy structure optimization also positively influences ecologization in each region to a certain extent—particularly in Beijing and Tianjin, where short-term effects are strong and significant. Additionally, the evolutionary aspect of energy optimization (R_t) consistently shows positive long-term impacts on S_t across all three regions. Notably, short-term effects are strongest in Beijing and Hebei, suggesting that enhancing the share of electricity and other green energy sources—while reducing reliance on coal and petrochemical energy—offers an internally driven and sustainable path toward high-quality economic development in the BTH region.

4.2.4 Variance decomposition

Variance decomposition analysis enables further examination of the relative contribution of each variable to the forecast error variance of the others. Specifically, it allows quantification of the extent to which industrial structure ecologization (LnS) contributes to the optimization of energy consumption structure (LnE), and vice versa, in BTH.

Variance decomposition is employed to further evaluate the extent to which industrial structure ecologization (LnS) contributes to the variation in energy consumption structure optimization (LnE), and vice versa, in the three subregions of the BTH region. As shown in Table 6, Table 7, and Table 8, in Beijing, the influence of industrial structure ecologization on energy consumption optimization gradually increases—from 0.005% in period 2 to 2.146% in period 10. Conversely, the contribution of energy consumption optimization to the changes in industrial structure ecologization declines from 23.78% in period 1 to 14.99% in period 10. In Tianjin, a similar upward trend is observed: the influence of industrial structure ecologization on energy consumption optimization rises from 0.667% in period 2 to 1.639% in period 10. Meanwhile, the explanatory power of energy consumption optimization for industrial structure ecologization decreases from 14.891% in period 1 to 12.893% in period 10. In Hebei, the mutual dynamic is more pronounced. The contribution of industrial structure ecologization to energy consumption optimization rises sharply—from 2.768% in period 2 to 21.075% in period 10. Conversely, the contribution of energy consumption optimization to industrial structure ecologization declines from a very high 87.026% in period 1 to 67.609% in period 10. These results reveal that the degree and direction of interaction between industrial structure ecologization and energy consumption optimization vary significantly across regions, largely depending on their respective stages of development and industrial complexity.

Table 6. Forecast error variance decomposition of LnS and LnE in Beijing

Period	**Variance Decomposition of LnS (%)**			**Variance Decomposition of LnE (%)**		
	$S.E$	LnS	LnE	$S.E$	LnS	LnE
1	0.0051	100.0000	0.0000	0.0088	23.7826	76.2174
2	0.0053	99.9943	0.0055	0.0094	23.0404	76.9596
3	0.0053	99.0736	0.9263	0.0104	18.9113	81.0887
4	0.0054	98.6105	1.3894	0.0108	17.5488	82.4512
5	0.0054	98.2967	1.7032	0.0112	16.4926	83.5074
6	0.0054 0.0054	98.1441	1.8558	0.0113	15.9281	84.0719
7	0.0054 0.0054	98.0289	1.9710	0.0115	15.5341	84.4659
8	0.0054	97.9495	2.0504	0.0116	15.2815	84.7185
9	0.0054 0.0054	97.8925	2.1074	0.0116	15.1084	84.8916
10	0.0054 0.0054	97.8539	2.1461	0.0117	14.9928	85.0072

The variance decomposition further quantifies the intrinsic drivers of the "industry–energy" system in the BTH region:

• In Hebei, the contribution of energy consumption optimization to industrial structure ecologization is substantially higher than in Beijing or Tianjin. This validates the earlier findings that Hebei's developmental stage renders its industrial transformation more sensitive to changes in energy structure. Policy shifts in the energy domain are rapidly transmitted to the industrial system, yielding visible structural responses.

• In contrast, industrial structure ecologization in Beijing and Tianjin is predominantly driven by internal inertia. This indicates that their industrial systems are more complex and mature, with transformation relying more on endogenous forces such as technological innovation, knowledge accumulation, and the input of high-end production factors. In these two regions, energy structure optimization serves more as a coordinated result, rather than the primary driving force.

This divergence provides a quantitative foundation for region-specific policy design:

• For Hebei, emphasis should be placed on energy infrastructure development and clean energy substitution to trigger structural transformation.

• For Beijing and Tianjin, policies should prioritize technological innovation and institutional reforms to activate endogenous dynamics within their advanced industrial ecosystems.

Table 7. Forecast error variance decomposition of LnS and LnE in Tianjin

Period	Variance Decomposition of LnS (%)			Variance Decomposition of LnE (%)		
	$S.E$	LnS	LnE	$S.E$	LnS	LnE
1	0.0093	100.0000	0.0000	0.0161	14.8916	85.1084
2	0.0097	99.3334	0.6665	0.0171	14.8738	85.1362
3	0.0097	98.8889	1.1110	0.0189	14.8617	85.1383
4	0.0097	98.7498	1.2501	0.0195	13.7981	86.2019
5	0.0097	98.5859	1.4141	0.0201	13.4729	86.5271
6	0.0098 0.0054	98.5045	1.4955	0.0204	13.9288	86.0712
7	0.0098 0.0054	98.4423	1.5558	0.0206	13.5747	86.4253
8	0.0098	98.4042	1.5958	0.0207	12.4895	87.5105
9	0.0098 0.0054	98.3778	1.6221	0.0208	12.3285	87.6715
10	0.0099 0.0054	98.3609	1.6391	0.0209	12.8936	87.1064

Table 8. Forecast error variance decomposition of LnS and LnE in Hebei

Period	Variance Decomposition of LnS (%)			Variance Decomposition of LnE (%)		
	$S.E$	LnS	LnE	$S.E$	LnS	LnE
1	0.0061	100.0000	0.0000	0.0109	87.0260	12.9740
2	0.0064	97.2314	2.7686	0.0122	83.1779	16.8221
3	0.0069	82.7217	17.2783	0.0132	71.7188	28.2812
4	0.0072	80.0300	19.9699	0.0136	68.7520	31.2480
5	0.0072	79.6778	20.3222	0.0137	68.3056	31.6944
6	0.0072 0.0054	79.2441	20.7559	0.0138	67.9185	32.0815
7	0.0073 0.0054	79.0235	20.9765	0.0138	67.7110	32.2890
8	0.0073	78.9663	21.0337	0.0139	67.6498	32.3502
9	0.0073 0.0054	78.9392	21.0608	0.0139	67.6233	32.3767
10	0.0074 0.0054	78.9243	21.0757	0.0139	67.6093	32.3907

5 Conclusions and Recommendations

5.1 Key Findings

The empirical analysis confirms that industrial structure ecologization and energy consumption structure optimization in the BTH region are characterized by significant spatial interdependence and dynamic feedback mechanisms. In the short term, Hebei experiences structural adjustment pressures as it absorbs relocated industries from

Beijing and Tianjin, resulting in temporary inhibitory effects. However, in the long run, spillovers in knowledge, technology, and institutional experience become dominant, positioning Beijing and Tianjin as leading forces in Hebei's industrial upgrading. This validates the strategic value of regional coordination in advancing long-term ecological transformation.

The causal relationships between variables are bidirectional: industrial ecologization drives both energy optimization and its evolutionary progression, and these, in turn, contribute back to structural transformation. Particularly in Beijing and Tianjin, short-term effects from energy optimization on industrial ecologization are strong, while Hebei exhibits greater long-term sensitivity. These differences stem from the regions' distinct industrial maturity levels. In Hebei, transformation is more responsive to energy policy adjustments, whereas in Beijing and Tianjin, upgrading is primarily driven by endogenous forces such as innovation, advanced services, and institutional quality.

Variance decomposition results quantify these dynamics, highlighting that the influence of energy optimization on industrial structure is strongest in Hebei, while Beijing and Tianjin rely more on internal mechanisms. These findings underscore the need for differentiated regional approaches to achieve integrated "industry–energy" transitions.

5.2 Policy Advice

To facilitate green and coordinated development across the BTH region, a region-specific strategy must be adopted. Beijing should leverage its advantages in innovation and high-end services to pilot urban-rural integrated smart energy systems, including distributed solar and geothermal applications. These models should be designed for replication in Tianjin and Hebei. Tianjin should focus on low-carbon transformation of port logistics and advanced manufacturing, implementing technologies such as shore power and digital process upgrading to reduce industrial carbon intensity. Hebei should enhance its role as a green industrial receiver by attracting low-carbon projects aligned with its supply chains and supporting them with clean infrastructure.

A spatially coordinated governance mechanism should be established to amplify positive spillovers. Regional platforms are needed to convert Beijing's demonstration effect into endogenous growth across the region. A unified monitoring and early warning system for "industry–energy–environment" interaction should be developed, integrating real-time data from all three regions to track system imbalances and guide timely policy adjustment.

Finally, energy structure optimization should be used as a key lever for driving industrial upgrading. In Hebei, policy should emphasize clean energy infrastructure as a forcing mechanism for transformation. In Beijing and Tianjin, efforts should focus on stimulating internal innovation through enhanced R&D capacity and institutional reform. These measures will reinforce regional spillover effects and promote sustainable and high-quality economic growth across the BTH region.

Data Availability

The data used to support the research findings are available from the corresponding author upon request.

Conflicts of Interest

The author declares no conflict of interest.

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