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Dynamic Differentiated Correlation between Coal and Non-coal Transportation: A VAR Model Analysis of Railway Energy Transportation and Macroeconomy

Wenmi Chai[1]*, Rui Zhao[2,3], Yang Han[4], Qian Xiang[5], Wenbin Wang[1], Zedong You[1]

1.New Energy Technology Research Institute Co., Ltd., CHN ENERGY Investment Group Co., Ltd., Beijing, 102209, China

2.Chengdu Jinjiang Center for Disease Control and Prevention, Chengdu, 610000, China

3.School of Economics and Management, Sichuan Normal University, Chengdu, 610101, China

4.Shuohuang Railway Development Co., Ltd., CHN ENERGY Investment Group Co., Ltd., Beijing, 100080, China

5.Laboratory of Intelligent Control, PLA Rocket Force University of Engineering, Xi'an, 710025, China

Corresponding author: Wenmi Chai, wenmi.chai@ceic.com

Abstract: As a strategic artery for the development of the national economy, the dynamic correlation between energy transportation and the macroeconomy is particularly important against the backdrop of the restructuring of the global energy supply chain. We take the transportation data of a self-operated railway of an energy enterprise from 2020 to 2025 as a sample, select Gross Domestic Product (GDP), Producer Price Index (PPI), Coal Transportation Plan (CTP), Coal Transportation Volume (CT), Non-coal Transportation Plan (NCTP) and Non-coal Transportation Volume (NCTP) as research objects, construct a Vector Autoregression (VAR) model, and explore the dynamic correlation mechanism between coal and non-coal transportation indicators and the macroeconomy through Granger causality test, impulse response function and variance decomposition. The results show that the coal transportation volume is mainly driven by the planned volume and GDP, with their contribution rates being 35.59% and 20.88% respectively, which reflects the strong planned attribute under the integration mode of production, transportation and marketing; the non-coal transportation volume is significantly affected by GDP and PPI, with the influence degrees being 25.71% and 23.02% respectively, which reflects the market sensitivity under the agency mode. Based on the above-mentioned differentiated correlation characteristics, this study can provide theoretical support and decision-making reference for energy enterprises to formulate differentiated transportation scheduling strategies and improve the response efficiency of the supply chain.

Keywords: Energy Transportation; Macroeconomy; Vector Autoregression Model; Granger Causality Test; Variance Decomposition

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1.Introduction

1.1 Background

Energy transportation occupies an important strategic position in the development of the national economy. Against the backdrop of the world undergoing unprecedented changes in a century, the energy supply chain and trade structure are being adjusted and reshaped [1-2]. This restructuring process not only affects the efficiency of global energy resource allocation, but also directly relates to the stability of economic development in various countries. Many studies by scholars at home and abroad have shown that there is a close relationship between the macroeconomy and railway freight volume [3-9]. Specifically, during different economic development cycles in China, the correlation between railway transportation and the macroeconomy shows significant differences [5-9]. Among them, the transportation of goods closely related to the secondary industry, such as coal and smelting materials, as the main categories of railway freight volume [5,6], the changes in their transportation scale and flow direction can directly reflect the prosperity of the macroeconomy. Against the background of significant changes in the global energy supply chain and energy trade [10], the above-mentioned correlation presents more complex characteristics, which will have a profound impact on China's national economy and energy upstream and downstream enterprises. Therefore, clarifying the internal relationship between the macroeconomy and energy transportation is not only an inevitable requirement for grasping the laws of economic operation, but also an important prerequisite for energy enterprises to achieve sustainable development. Studying the correlation between energy transportation and the macroeconomy under the current economic situation helps energy enterprises accurately grasp the evolution law of freight volume, formulate transportation outline plans that meet market demand, and thus gain competitive advantages in the complex and changeable market environment.

1.2 Research Objectives

Existing studies mostly focus on the overall correlation analysis between comprehensive freight volume and the macroeconomy, with relatively insufficient exploration into the differentiated correlation mechanism between coal and non-coal transportation, failing to fully reveal the unique laws of different types of energy transportation under the influence of the macroeconomy. As a key entity in China's energy transportation sector, a certain energy enterprise has established a sophisticated "production-transportation-marketing-storage-utilization" system relying on the "West-to-East Coal Transportation" corridor [11]. Its self-operated railway has an operation mileage exceeding 2,000 kilometers, and its transportation indicators possess the dual attributes of being the "artery" of the energy supply chain and the "barometer" of the macroeconomy, thus providing an ideal sample for studying the differentiated correlation mechanism between coal and non-coal transportation. Based on this, this paper takes the enterprise as the research object, analyzes the dynamic correlations between its coal and non-coal transportation planned volume, completed volume and macroeconomic indicators, and constructs a Vector Autoregression (VAR) model to reveal the inherent laws therein, so as to provide decision support for enterprises to optimize transportation plans and enhance market response speed.

1.3 Data Description

This study selects energy transportation data and macroeconomic data from January 2020 to April 2025, with the data sources being the self-operated railway transportation statistical reports of a certain energy enterprise in China and the database of the National Bureau of Statistics [12]. Transportation indicators include Planned Coal Transportation (PCT), Coal Transportation (CT), Planned Non-coal Transportation (PNCT), and Non-coal Transportation (NCT), where non-coal refers to other types of goods such as iron ore. Macroeconomic indicators are selected as Gross Domestic Product (GDP) and Producer Price Index (PPI). Among them, GDP reflects the growth of macroeconomic aggregate and measures the overall demand for energy transportation generated by economic activities; PPI reflects the changes in ex-factory prices of industrial products and measures the impact of market prices on the transportation of non-coal industrial raw materials.

2.Related Works

2.1 Research on Econometric and Statistical Methods

Research on the correlation mechanism between energy transportation and the macroeconomy has been gradually deepened by means of diversified econometric methods. Early studies mostly adopted simple correlation analysis and time series models. For instance, Wan [9] used the Auto-Regressive Moving Average (ARMA) model to reveal the one-way causal relationship between GDP and energy consumption during the period of rapid economic growth from 1990 to 2014, which verified the driving effect of the macroeconomy on energy demand. With the deepening of research, methods such as grey correlation analysis and cointegration analysis have been widely applied. Zhang et al. [5] studied the internal relationship between railway freight volume and the macroeconomy from 2004 to 2017 by using grey correlation analysis, and found that there is a close correlation between total coal consumption and railway freight volume. They also found that the Autoregressive Distributed Lag (ARDL) model based on industrial added value has the optimal prediction accuracy for railway freight volume. Xu [6] studied the periodic variation law of railway freight volume and GDP from 1985 to 2018 by using the correlation analysis model, elasticity coefficient model and push-pull utility relationship model, and judged railway transportation decisions through macroeconomic research. Lu et al. [13] adopted cointegration analysis to study the relationship between road freight volume and the national economy in China from 1978 to 2007, indicating that there is a long-term stable equilibrium relationship between them. Yu et al. [14] built VAR model to analyze the influencing factors of freight volume indicators in Anhui Province from 2000 to 2017, and found that there are correlation relationships among various indicators of logistics freight.

2.2 Research on the Correlation between Economic Cycles and Freight Transport

Jiang [8] explored the influencing factors of the long-term and short-term relationships between comprehensive transport freight volume and national economic development. The study found that in the long-term relationship, the freight-economy relationship tends to decouple in developed countries, while developing countries maintain a relatively close correlation between the two. In the short-term relationship, comprehensive transport freight volume generally changes synchronously with the national economy, but this coupling relationship will undergo trend changes as China's economic structure adjusts. Sun [7] found that there is a two-way Granger causality between the comprehensive freight transport index and macroeconomic indicators such as industrial added value and GDP. Empirical analysis combined with the experience of developed countries further shows that after the slowdown of industrialization, the growth rate of the comprehensive freight transport index will slow down accordingly, and freight intensity will show a significant downward trend with the improvement of economic development level; during economic downturns, the elasticity coefficient between freight transport volume and GDP will show a declining trend.

2.3 Limitations

Existing studies have certain limitations. First, most focus on aggregate analysis of comprehensive freight volume, neglecting structural differences between coal and non-coal transportation. As a basic energy source, coal transportation is significantly regulated by national energy strategies and regional production layouts, while non-coal industrial raw material transportation depends on market supply-demand adjustment. Due to their different regulatory logics, their correlation paths with the macroeconomy diverge. However, existing literature lacks targeted analysis of such differences, failing to accurately capture heterogeneous responses. Second, existing studies insufficiently integrate energy enterprises' operational models. Enterprises adopt integrated production-transportation-marketing management for coal, making the correlation between transportation indicators and the macroeconomy planned and stable; non-coal transportation mostly adopts agency-based operation, with transportation indicators responding more flexibly and immediately. These differences in micro-operational models directly affect the correlation logic between transportation indicators and the macroeconomy. Yet, existing research mostly relies on industry-level macro data and fails to incorporate the heterogeneity of enterprise operational models into the analytical framework of correlation mechanisms, limiting the explanatory power for their interaction. To address this, this paper, based on enterprise-owned railway data, distinguishes between coal and non-coal transportation categories, combines with enterprise operational models, and explores their differentiated correlation mechanisms with the macroeconomy, so as to provide references for improving the theoretical framework and optimizing enterprise transportation management.

3.Research Methods

3.1 Establishment of the VAR Model

The Vector Autoregression (VAR) model [15] is an econometric model based on the statistical properties of data. Its core idea is to treat each endogenous variable in the system as a function of the lagged values of all endogenous variables, and capture the dynamic interaction between variables by constructing a multi-equation simultaneous system. This model does not require presupposing the theoretical causal relationship between variables, and is suitable for analyzing the linkage effects and shock transmission paths among multiple economic variables.

Its basic form is：

$$Y_t = c + \sum_{i=1}^{p} \Phi_i Y_{t-i} + \varepsilon_t \tag{1}$$

Where $Y_t = (X_{1t}, X_{2t}, \ldots, X_{kt})'$ is the vector of endogenous variables, including 6 variables in this paper: PCT, CT, PNCT, NCT, GDP, and PPI;， c is the constant term; Φ_i is the lag coefficient matrix;， p is the lag order， ε_t is the vector of random disturbance terms, whose elements may have contemporaneous correlation, but are not correlated with their own lagged terms, nor with the variables on the right side of the equation.

The VAR model can capture the dynamic correlation between energy transportation indicators and macroeconomic indicators, including short-term fluctuations and long-term equilibrium relationships. On this basis, the impulse response function can be used to reveal the differential impact of macroeconomic fluctuations on different transportation categories. In addition, variance decomposition can determine the contribution of each variable to system fluctuations and identify the dominant factors.

3.2 Empirical Analysis Steps

The VAR model is a multivariate time series framework used to capture the dynamic relationships between multiple endogenous variables. Below are the key steps involved in implementing a VAR model:

1) Data preprocessing: Perform linear interpolation on GDP and PPI to convert them into monthly data, so as to unify the time frequency with transportation indicators; test the stationarity of all variables through the Augmented Dickey-Fuller (ADF) test [16], and test the stationarity of the first-order difference variables for non-stationary variables.

2) Determination of lag order: Select the optimal value from alternative orders according to information criteria such as Akaike Information Criterion (AIC) [17], Bayesian Information Criterion (BIC) [18], Final Prediction Error (FPE) [19], and Hannan-Quinn Information Criterion (HQIC) [20], to balance the model fitting goodness and degrees of freedom.

3) Model estimation and testing: Estimate parameters based on the selected order to obtain the lag term coefficient matrix; ensure the model stability through Autoregressive (AR) root test [21], and then conduct Granger causality test [22].

4) Impulse response analysis [15]: Simulate the dynamic impact of a specific variable's external shock on other variables to observe the transmission direction, intensity, and duration of the shock.

5) Variance decomposition [23]: Calculate the contribution ratio of each variable to the prediction error of other variables in the system, quantify their relative importance in the interaction relationship, and clarify the influence weight between macroeconomic indicators and transportation indicators.

4.Empirical Analysis

4.1 Stationarity Test

The VAR model requires variables to be stationary sequences to ensure the consistency and validity of estimation [23]. Non-stationary variables are prone to spurious regression, so this paper adopts the ADF unit root test to judge stationarity [16]. The test makes a judgment by comparing the p-value [24] with the 0.05 significance level: if $p < 0.05$, the null hypothesis is rejected, and the sequence is stationary; otherwise, the sequence is non-stationary.

Table. 1 ADF Unit Root Test Results of Variables

Variable	ADF Test Statistic	p-value	1% Critical Value	5% Critical Value	Stationarity
GDP	-1.082	0.722	-3.560	-2.918	Non-stationary
PPI	-2.257	0.186	-3.563	-2.919	Non-stationary
PCT	-5.108	1.35e-05	-3.539	-2.909	Stationary
CT	-5.604	1.25e-06	-3.539	-2.909	Stationary
PNCT	-4.365	0.00034	-3.539	-2.909	Stationary
NCT	-4.988	2.34e-05	-3.539	-2.909	Stationary

Table 1 shows that coal transportation volume, non-coal transportation volume, total freight volume, and key material transportation volume all pass the test and are stationary sequences; GDP and PPI are non-stationary ($p > 0.05$). After first-order differencing, the differenced values of both have $p < 0.05$. In summary, all variables meet the stationarity requirements of the model.

4.2 Lag Order Selection

The lag order of the VAR model determined by multiple information criteria is shown in Table 2, where the values marked with * are the minimum values obtained by each information criterion. The optimal lag order selected according to the AIC criterion is 6, the optimal lag order selected according to the BIC is 0, the optimal lag order selected according to the FPE is 3, and the optimal lag order selected according to the HQIC is 1. Considering that the transmission of macroeconomic shocks usually has a relatively long-time lag effect and that the AIC criterion performs better in prediction tasks, this paper determines the optimal lag order of the VAR model as 6.

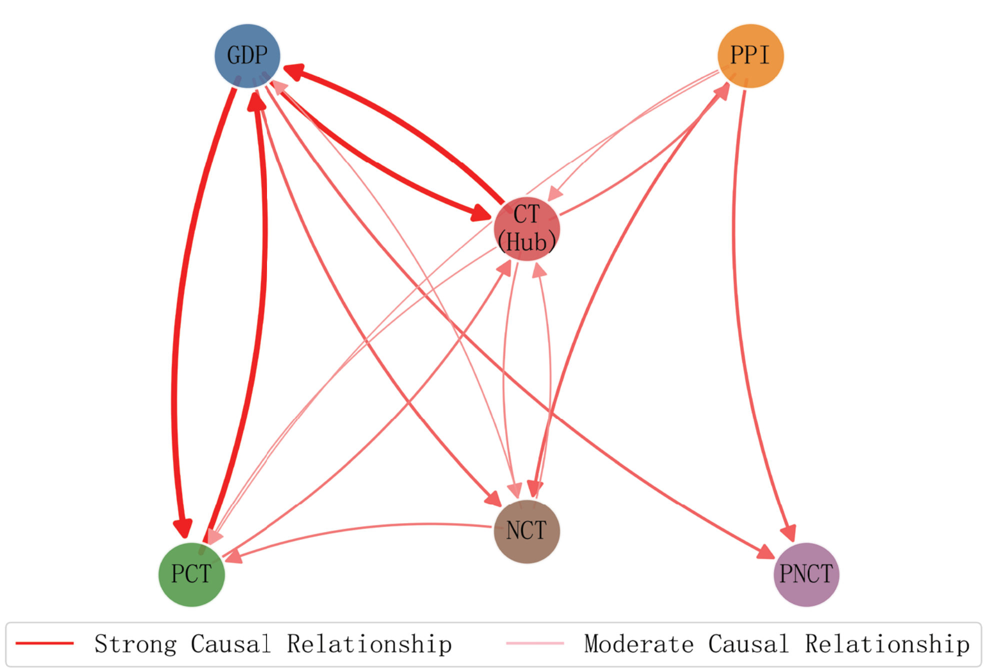
Table. 2 Optimal Lag Order of the VAR Model

Lag Order	AIC	BIC	FPE	HQIC
0	-2.688	-2.472*	0.06805	-2.604
1	-3.334	-1.829	0.03592	-2.749*
2	-3.445	-0.6488	0.03352	-2.358
3	-4.330	-0.2444	0.01543*	-2.742
4	0.9637	0.9637	0.01777	-2.323
5	-4.262	2.405	0.03104	-1.671
6	-5.393*	2.564	0.02030	-2.300

4.3 Granger Causality Test

The Granger causality test is used to determine the direction of causal relationships between variables ("whether X is a Granger cause of Y"), and the significance is judged by the p-value (if $p < 0.05$, there is a causal relationship). Figure 1 presents the Granger causality test relationship network of the 6 variables.

Figure. 1 Granger Causality Network (p<0.05)



In terms of economic indicators, there is a two-way causal relationship between macroeconomics and coal transportation. GDP and PCT, as well as GDP and CT, are mutual Granger causes ($p < 0.01$), indicating that there is two-way feedback of "growth-demand-transportation" between coal transportation and macroeconomics, which confirms the strategic position of coal as a basic energy source. PPI is a one-way cause of PCT and CT ($p < 0.05$), suggesting that fluctuations in industrial product prices lead to changes in coal transportation demand; PPI is a Granger cause of PNCT and NCT ($p < 0.01$), while the impact of non-coal transportation on PPI is not significant ($p > 0.05$), reflecting that the transportation of non-coal industrial raw materials is unidirectionally driven by market price fluctuations, embodying price sensitivity under the agency model.

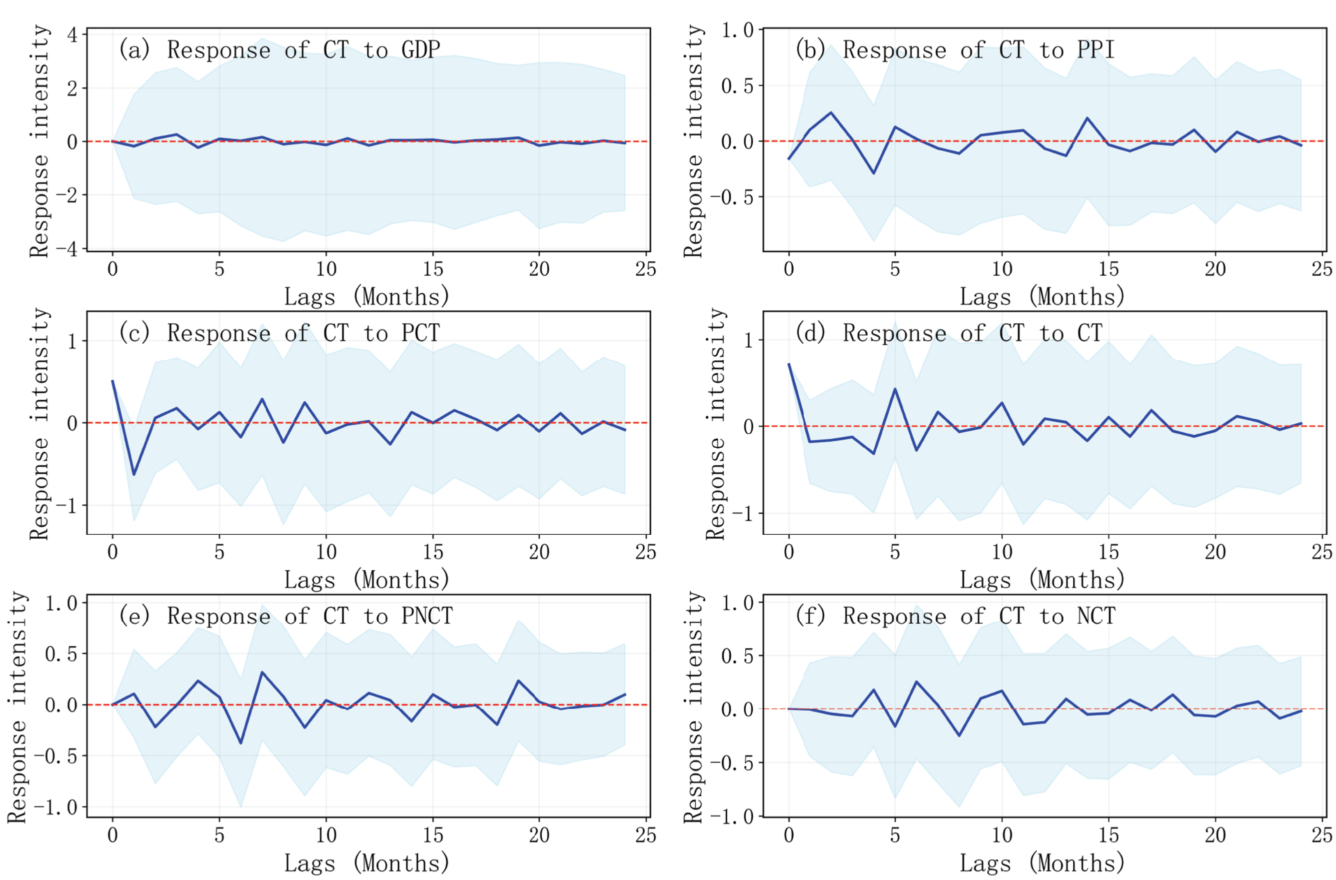
In terms of transportation indicators, CT is a Granger cause of NCT ($p < 0.05$), meaning that coal transportation affects non-coal transportation through capacity resource competition and industrial chain transmission. In addition, the planned and completed quantities of coal and non-coal show different causal relationships. Among them, PCT is a Granger cause of CT ($p < 0.05$), while the causal relationship between PNCT and NCT is not significant ($p = 0.325$), indicating the strong correlation between "Plan-Completion" in coal transportation, while the constraint of non-coal transportation plans on the actual completed quantities is weak, which is consistent with the operational differences between the planning system and the agency system.

4.4 Impulse Response Analysis

4.4.1 Impulse Response of CT

Impulse response involves applying a one-standard-deviation shock to the error term of a variable and tracking the dynamic impact of this shock on other variables as well as the variable itself. Based on this, Figure 2 presents the impulse response results of GDP, PPI, PCT, PNCT, and NCT to CT, with specific characteristics as follows:

Figure. 2 Impulse response results of GDP(a), PPI(b), PCT(c), PNCT(d), and NCT(e) to CT(f).



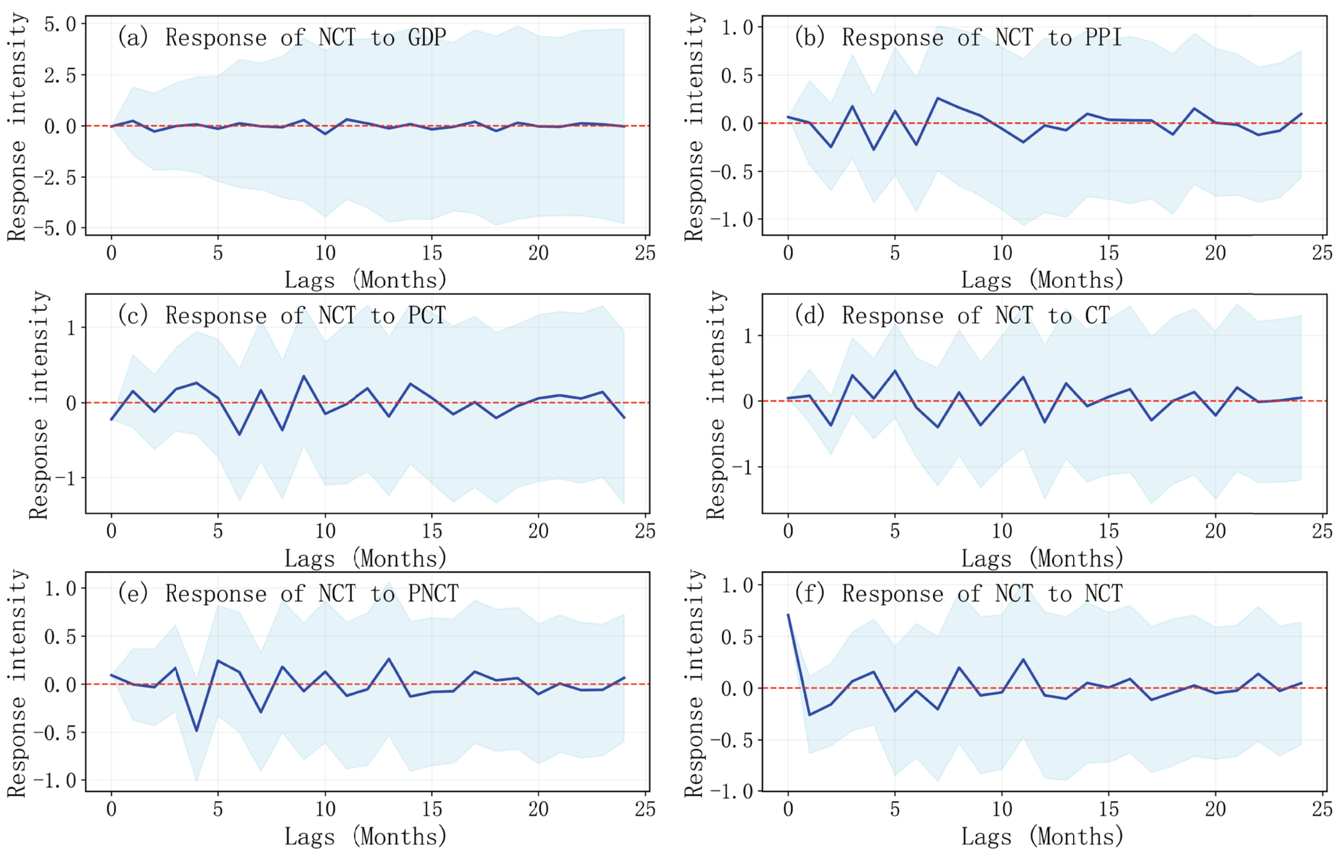
The initial response of CT to GDP is -0.002 (Period 0), dropping to -0.183 in Period 1, then fluctuating upward and reaching 0.256 and 0.153 in Period 3 and Period 6 respectively (Figure 2a). This indicates that the driving effect of economic growth on coal transportation has a lag of 6-7 periods, and the short-term impact of GDP on CT is not significant, possibly because coal transportation is buffered against short-term economic fluctuations by planned regulation. The response value of CT to

PPI is close to 0 and the confidence interval includes 0 (Figure 2b), which means that fluctuations in industrial prices have minimal impact on coal transportation completion, reflecting the characteristic of low-price sensitivity under the planned system. The response of CT to PCT reaches 0.5 (positively significant) in Period 0, turns negative (-0.628) in Period 1, and then gradually converges in positive and negative fluctuations (Figure 2c). This indicates that the short-term impact of planned coal transportation volume on completion volume is significant, verifying the operational characteristic of prioritizing optimization.

4.4.2 Impulse Response of NCT

To observe the impact of shocks from other variables on NCT, Figure 3 presents the impulse response results of NCT to various variables. The results demonstrate that the response of NCT to GDP (Figure 3a) stands at 0.234 (positive) in Period 1, shifts to -0.146 in Period 5, and overall fluctuates intensely within the range of -0.401 to 0.305. The confidence interval is relatively wide and includes 0, which reflects that NCT is subjected to nonlinear influences of the economic cycle and has higher sensitivity to the economic cycle. The response of NCT to PPI in Period 1 is 0.005, turns negative (-0.247) in Period 2, and then shows a long-term negative trend in fluctuations (Figure 3b), with some intervals not including 0. This indicates that the rise of PPI will inhibit the demand for non-coal transportation, embodying the regulatory role of market prices.

Figure. 3 Impulse response results of GDP(a), PPI(b), PCT(c), PNCT(d), and NCT(e) to NCT(f).



The response of NCT to CT (Figure 3d) is 0.392 (positive) in Period 3 and -0.398 (negative) in Period 7, which indicates that there is a resource competition effect between coal transportation and non-coal transportation, with significant conflicts in short-term capacity allocation.The response value of NCT to PNCT (Figure 3e) is close to 0 and the confidence interval includes 0, indicating that non-coal transportation plans have weak constraints on the completion volume, which is consistent with the flexibility of “transportation determined by demand” under the agency system.

4.5 Variance Decomposition

Variance decomposition identifies core influencing factors by quantifying the contribution of each variable to the fluctuation of the explained variable. Table 3 lists the variance contribution rates of each variable to CT and NCT. The results show that for the sources of CT fluctuations, PCT has the highest contribution rate (28.49%), followed by its own inertia (31.14%)

and PNCT (14.73%). The contribution rates of GDP and PPI are less than 10%, indicating that the fluctuations of coal transportation completion are mainly driven by planned regulation and internal inertia, with a weak impact from the macroeconomy.

Table. 3 Variance Contribution Rates of Each Variable to CT and NCT (%)

Variables	GDP	PPI	PCT	CT	PNCT	NCT
Variance Contribution Rate to CT	8.41	8.63	28.49	31.14	14.73	8.60
Variance Contribution Rate to NCT	14.47	9.06	18.18	27.51	12.81	17.97

For the sources of NCT fluctuations, CT has the highest contribution rate (27.51%), while PCT (18.18%) and GDP (14.47%) contribute significantly, and the contribution rate of PPI is 9.06%. This reflects that the regulatory effect of non-coal transportation plans is limited, the market freedom is strong, and the impact of macroeconomic aggregates on NCT is more prominent. Meanwhile, NCT and CT have coordinated fluctuations due to sharing transportation channels.

5.Conclusions & Suggestions

5.1 Conclusions

This study employs a VAR model to examine determinants of energy transportation through Granger causality tests, impulse response functions, and variance decomposition analysis. Key findings are:

CT has a strong planned attribute. Its completion volume is mainly driven by the planned volume, and there is a significant Granger causal relationship between CT and PCT. This confirms the core role of planned regulation under the integration mode of production, transportation and marketing, reflects the stability characteristics of coal transportation in energy security dominated by plans, and forms a sharp contrast with the market-driven non-coal transportation.

NCT shows obvious market sensitivity. Its completion volume is significantly affected by PPI and GDP, and PPI is the one-way Granger cause of NCT. This indicates that under the agency system, price fluctuations and economic cycles have a significant driving effect on non-coal transportation, reflecting that non-coal transportation is more vulnerable to changes in market dynamics, forming a differentiated characteristic from the planned attribute of coal transportation.

There exists a differentiated correlation structure between macroeconomic and energy transportation indicators, accompanied by synergistic fluctuations within the energy transportation system. CT and GDP form a two-way causality, reflecting the synergy of "economic growth→energy demand→transportation guarantee"; NCT is unilaterally affected by GDP, embodying the dependence of the manufacturing industry on the economic cycle. Meanwhile, the variance contribution rate of CT to NCT reaches 27.51%, indicating that coal and non-coal transportation may have linkage due to shared channels, equipment and other resources, which provides an important perspective for understanding the overall operation mechanism of the energy transportation system.

5.2 Suggestions

Based on the above research conclusions, the following suggestions are put forward for energy transportation-related enterprises:

For coal transportation, in view of its strong planned attribute and the significant driving effect of PCT on CT, enterprises should optimize the foresight of coal transportation plans, strengthen the dynamic adjustment in the process of plan formulation and implementation, so as to cope with possible emergencies, ensure the stability of coal transportation completion volume, and guarantee the sustainability of energy supply.

In view of the market sensitivity of non-coal transportation, since it is significantly affected by PPI and GDP, enterprises need to establish a sound market price early warning mechanism, pay close attention to changes in macroeconomic indicators, and dynamically adjust transportation strategies in a timely manner. By strengthening the monitoring and analysis of market price fluctuations and economic cycles, enterprises can make transportation resources allocation in advance, so as to improve the flexibility and adaptability of non-coal transportation in response to market changes.

Considering the synergistic fluctuation of the energy transportation system and the differentiated correlation structure between macroeconomy and energy transportation indicators, enterprises should coordinate the scheduling resources of coal and non-coal transportation, strengthen the coordination of the two transportation modes in the use of channels, equipment and other resources, avoid capacity conflicts, and improve the overall transportation efficiency. At the same time, enterprises should make full use of the buffering characteristics of the energy transportation system to short-term economic fluctuations, and formulate stable transportation strategies in complex economic environments to ensure the stable operation of the energy transportation system.

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Conflict of Interests

The authors declare that there is no conflict of interest regarding the publication of this paper.

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