ENVIRONMENTAL EFFICIENCY AND INTER-INDUSTRY DYNAMICS OF ECONOMIC SECTORS IN CHINA'S FIRST-TIER CITIES

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Abstract. Urban economic activities have notably intensified environmental issues, especially in China's leading cities. This study evaluates the environmental efficiency of the economic sectors (ESEE) in 19 first-tier cities (comprising 4 traditional and 15 emerging first-tier cities) in China and explores the dynamic interactions between the three industries within the ESEE framework. The objective is to offer insights into achieving a balance between economic development and environmental sustainability. The research uniquely employs a combination of the Network Data Envelopment Analysis (NDEA) and Panel Vector Autoregression (PVAR) models, creating an ESEE evaluation index that reflects recent trends in sustainable development in China. The study assesses the ESEE of these cities from 2010 to 2019 and investigates the evolving relationships among the environmental efficiency of the primary, secondary, and tertiary industries within this framework. Findings indicate that the ESEE in these cities shows a variable upward trajectory, with the primary industry displaying the weakest environmental performance. Traditional first-tier cities demonstrate higher ESEE compared to emerging ones. Additionally, the primary industry's environmental efficiency lags behind, impacting the tertiary industry's efficiency and influencing the secondary industry's effects on the tertiary sector. Based on these findings, relevant policy recommendations are provided.
Keywords: *network data envelopment analysis, panel vector autoregression, industrial linkage, environmental efficiency evaluation, urban sustainability*

Introduction

Currently, nearly 75% of the world's material resources and 80% of energy consumption are utilized for human activities in urban areas (Pulido-Barrera et al., 2018). In China, the urbanization rate has risen from 17.60% in 1978 to 65.22% in 2022 (National Bureau of Statistics of China, 2023). Based on Northam's urbanization process theory (Northam, 1975), China is now in the "acceleration stage" (urbanization rate between 30% and 70%). This rapid urbanization, along with frequent economic activities in cities, has led to irreversible environmental degradation and resource depletion in Chinese urban areas (Gan et al., 2020; Tang et al., 2020), thereby impeding improvements in urban environmental performance. In recent years, the environmental pollution accompanying China's urban economic activities has put tremendous pressure on sustainable development (Wang and Feng, 2019). Studies have shown that relying on a development model heavily dependent on environmental resource inputs to drive urban economic growth not only leads to diminishing economic returns but also hinders Chinese cities from achieving their environmental protection and sustainable development goals (Chen et al., 2022). These issues are particularly prominent in China's first-tier cities, where populations exceed tens

of millions. Given the Chinese government's growing emphasis on sustainable development, investigating the environmental efficiency of the economic sectors (ESEE) in China's first-tier cities has become a crucial management issue. This research aims to provide insights into better balancing urban economic growth and environmental protection.

According to reports from the National Bureau of Statistics of the People's Republic of China and existing research (Chen et al., 2022), China's economic sector comprises three major industries. The primary industry includes agriculture, forestry, animal husbandry, and fishery. The secondary industry encompasses manufacturing and construction. The tertiary industry involves transportation, warehousing, postal services, wholesale and retail trade, and hospitality. Existing research has primarily focused on evaluating the environmental efficiency of specific sectors, such as industry (Zhou et al., 2018; Zhang et al., 2020), agriculture (Angulo-Meza et al., 2019), and transportation (Stefaniec et al., 2020; Wei et al., 2021), aiming to improve environmental efficiency within individual industries. However, sustainable development of regional economies relies on the collective efforts of all three major industries. Ignoring the interconnections between different industries in regional environmental efficiency evaluations may lead to biased results (Chen et al., 2022). It is also difficult to identify the specific industry responsible for inefficiencies within the ESEE system (Bian et al., 2016), complicating efforts to provide targeted support for improving ESEE. Although recent studies have addressed these issues and provided more accurate evaluations of ESEE by analyzing interconnections between different industries (e.g., Gan et al., 2023), they often focus on static analyses of single aspects, such as agricultural supply chains (Xie et al., 2021), industrial development structures (Sun et al., 2020), and service industry innovation (Zhou et al., 2022). These studies have not deeply explored the dynamic relationships between the environmental efficiency of the primary, secondary, and tertiary industries within the ESEE system. This oversight may lead to inconsistencies in policy implementation, hindering ESEE improvement. For example, in some regions, the development of ecological tourism to enhance the environmental efficiency of the tertiary industry (TIE) has resulted in excessive construction of transportation facilities and residential areas, even destroying arable land, significantly impacting the environmental efficiency of the primary (PIE) and secondary industries (SIE) and obstructing the improvement of regional ESEE.

Moreover, existing studies indicate a strong association between economic development and environmental efficiency (Yang et al., 2021b; Su and Jiang, 2021). Given its position as the world's second-largest economy and the leading developing country (Bi et al., 2015), China's environmental efficiency evaluation has particularly attracted scholarly interest (Zhang et al., 2023; Fang et al., 2023). To effectively evaluate China's ESEE, it is essential first to understand the operational structure of its economic sector. This sector includes three major industries: the primary industry (agriculture), the secondary industry (industry), and the tertiary industry (service industry). According to the National Economic and Social Development Statistical Bulletin of China, in 2022, the added value of China's primary industry was 8834.5 billion yuan, the secondary industry 48,316.4 billion yuan, and the tertiary industry 63,869.8 billion yuan (National Bureau of Statistics of China, 2023). The uneven development rates of these industries have led to imbalances in environmental resource consumption across the economic sector (Bian et al., 2016). Therefore, it is necessary to evaluate not only the ESEE but also the environmental efficiency of the subsystems (PIE, SIE, TIE) within the ESEE system. This approach allows for identifying which subsystem is responsible for unsatisfactory ESEE and facilitates more effective improvements.

Environmental efficiency refers to the economic value derived per unit of environmental load (Desimone and Popoff, 2000). Based on this concept, scholars have proposed various indicators to evaluate regional environmental efficiency, such as carbon intensity (Gazzheli et al., 2016) and per capita energy consumption index (Sun et al., 2020a). However, environmental problems caused by economic activities are influenced by factors such as low resource utilization and management efficiency. Consequently, a single environmental efficiency indicator may not fully capture these factors (Chen et al., 2022). In other words, the aforementioned indicators may not comprehensively reflect the complexity of regional environmental activities and potential substitution effects among different factors (Wang et al., 2013). To address this issue, methods based on the Data Envelopment Analysis (DEA) model for evaluating environmental efficiency have gained widespread attention (Sueyoshi et al., 2017; Wang et al., 2022).

Research subjects have ranged from national-level studies (such as OECD countries; Woo et al., 2015), South Asian countries (Sun et al., 2020), and BRICS countries (Baloch et al., 2020), to regional-level studies (such as port cities (Kong and Liu, 2021) and resource-based cities (Li et al., 2017)), industry-level studies (such as the power industry (Jiang and Xie, 2024), the steel industry (Zhu and He, 2022), and the manufacturing industry (Bostian et al., 2018)), and enterprise-level studies (e.g., Zhou et al., 2023). Research methods have included classical DEA models (such as the Slack-Based Measure (SBM) model; An et al., 2019) and improved DEA models that consider factors like weak disposability between desirable and undesirable outputs (Lin and Chen, 2020) and spatial dependency between production factors (Jiang and Xie, 2024).

Some scholars have used DEA to investigate the environmental efficiency of different industries in China's economic sector, such as agriculture (Liu and Feng, 2019), industry (Wu et al., 2019), construction (Zhou et al., 2021), and services (Xiao et al., 2019). Additionally, some researchers have explored evaluating China's overall ESEE, which includes PIE, SIE, and TIE, based on the DEA model. Early studies applying DEA to evaluate ESEE frequently regarded it as a "black-box" framework, focusing solely on the aggregate inputs and outputs of ESEE while neglecting the internal linkages among PIE, SIE, and TIE, and thus relied on conventional DEA models(e.g., Picazo-Tadeo et al., 2011). However, some studies suggest that these measurement methods may be unreasonable (Bian et al., 2016). On one hand, each industry in the economic sector consumes similar resources (such as labor, energy, and capital) to promote GDP growth. Under these circumstances, it is impossible to determine which industry is responsible when ESEE is unsatisfactory. On the other hand, there are inherent relationships between PIE, SIE, and TIE within ESEE. Specifically, the primary and secondary industries draw on natural resources and combine them with labor to generate goods, which are then supplied to the tertiary industry. The development of the tertiary sector relies on the extraction and processing of raw materials originating from agriculture and industry (such as mining, manufacturing, and construction). These outputs support the continued expansion of the tertiary sector and maintain the functioning of urban production activities and daily life (Gan et al., 2023). Therefore, ESEE evaluation needs to consider the environmental resource inputs of the primary industry into the tertiary industry and the secondary industry into the tertiary industry. Ignoring these relationships during evaluation may lead to inaccuracies in ESEE assessments.

Subsequent studies have improved the accuracy of ESEE evaluations by enhancing traditional DEA models, such as applying non-radial models (Anser et al., 2020) and considering super-efficiency models (Wang et al., 2019). However, these approaches still

treat ESEE as a "black box" and fail to accurately reflect the relationships between the three subsystems within the ESEE system (Yang et al., 2022). To address these issues, some scholars have begun using NDEA to evaluate ESEE, such as Bian et al. (2016) and Gan et al. (2023). While the Network Data Envelopment Analysis (NDEA) model offers a more precise assessment of ESEE by accounting for the connections between the Primary Industry Efficiency (PIE) and Tertiary Industry Efficiency (TIE), as well as the Secondary Industry Efficiency (SIE) and TIE, it does not clarify the dynamic impact relationships among these subsystems. This limitation hampers the ability to provide policy recommendations that can effectively promote ESEE improvements. The PVAR model, rooted in dynamic equilibrium theory as its macroeconomic theoretical background (Liu, 2021), analyzes the interaction between endogenous variables in panel data (Yang et al., 2021a). The PVAR model has been widely applied to explore complex and dynamic relationships across various systems (e.g., Berdiev and Saunoris, 2016). By combining the respective advantages of the NDEA and PVAR models, this framework targets inefficiencies in environmental resource use associated with low management efficiency across the three industrial network components of the ESEE system. (Gharaei et al., 2019).

In light of the above analysis, this study seeks to systematically explore the development of ESEE in China's first-tier cities in recent years. It seeks to identify the weak subsystems (industries) that restrict ESEE development in these cities and reveal the dynamic relationships among PIE, SIE, and TIE within the ESEE system and analyze the heterogeneity between traditional and emerging first-tier cities. Based on these findings, policy implications more suitable for ESEE development in China's first-tier cities will be proposed. The remainder of this paper is organized as follows. Materials and Methods describes the data, variables, and analytical methods. Results reports the empirical findings on ESEE and its subsystems. Discussion provides interpretation of the results and policy implications. Conclusion summarizes the main findings and contributions of the study.

Materials and methods

Study area and data source

First-tier cities are mega-cities characterized by robust economic strength, abundant political resources, deep cultural heritage, convenient transportation, and populations exceeding 10 million (Gan et al., 2023). These cities are typically directly governed municipalities, key transportation centers, or core urban nodes that promote growth at the regional level. Their urban growth has a strong influence on surrounding areas and plays a crucial role in advancing China's overall sustainable development. Traditional first-tier cities are large urban centers that lead national politics, society, and economic progress. New first-tier cities are significant due to their advantages in urban hub types, demographic dynamism, concentration of business resources, diverse lifestyles, and long-term growth potential. Examining the environmental efficiency of the three industries in these first-tier cities helps identify the key challenges facing China's urban industries in sustainable development. This analysis provides valuable insights for designing targeted policies to address these challenges and is crucial for optimizing the future development path of China's urban sectors. This study focuses on 19 cities from the latest list of first-tier cities in China as of 2022, including four traditional first-tier cities and fifteen new first-tier cities, as shown in *Table 1*.

Table 1. *The list of Chinese first-tier cities*

Category	Number	Cities	Resident population (million)
Traditional first-line cities	4	Beijing	21.84
		Shanghai	24.76
		Guangzhou	18.73
		Shenzhen	17.66
New first-tier cities	15	Chengdu	21.27
		Chongqing	32.13
		Hangzhou	12.38
		Xi'an	12.99
		Suzhou	12.91
		Wuhan	13.73
		Nanjing	9.49
		Tianjin	13.63
		Zhengzhou	12.82
		Changsha	10.42
		Dongguan	10.43
		Ningbo	9.61
		Foshan	9.55
		Hefei	9.63
		Qingdao	10.34

Given the availability, completeness, and authority of the data, this study sourced its information from the Urban Statistical Yearbook, China Urban Construction Statistical Yearbook, and the Statistical Bulletins on National Economic and Social Development for 19 first-tier cities in China from 2011 to 2020. Missing observations were supplemented using the average annual growth rate together with interpolation techniques. Additionally, as the statistical yearbooks after 2020 have not yet been published, the data utilized in this paper were collected up to 2020. Since these yearbooks reflect the statistical data of the previous year, this study is based on data from 2010 to 2019.

This period covers the stages of the national environmental governance plans spanning the "11th Five-Year Plan" through the "13th Five-Year Plan". During this time, China consistently introduced measures to advance the development of Environmental-Economic Structural Efficiency (ESEE) and the environmental efficiency of its three major industries. These measures focused primarily on optimizing industrial structures and promoting the green and modern development of industries. For example, in 2011, the Ministry of Agriculture issued the "12th Five-Year Plan for the Development of National Agricultural and Rural Informatization", which explicitly called for strengthening agricultural informatization and sustainable development. In 2014, the Chinese government proposed the concept of "smart agriculture" to advance modern agriculture and improve its efficiency. In 2015, the government officially promoted the concept of green development, encouraging all three major industries to pursue a modern path of green growth. That same year, the National Development and Reform Commission issued the "Decision on Amending the Relevant Provisions of the Catalogue for Industrial Structure Adjustment", further guiding industrial structure optimization.

Investigating the development trends of ESEE, as well as the Primary, Secondary, and Tertiary Industry Efficiencies (PIE, SIE, and TIE) in China's first-tier cities over this stage, can better capture the experiences and recent features of sustainable development in China's
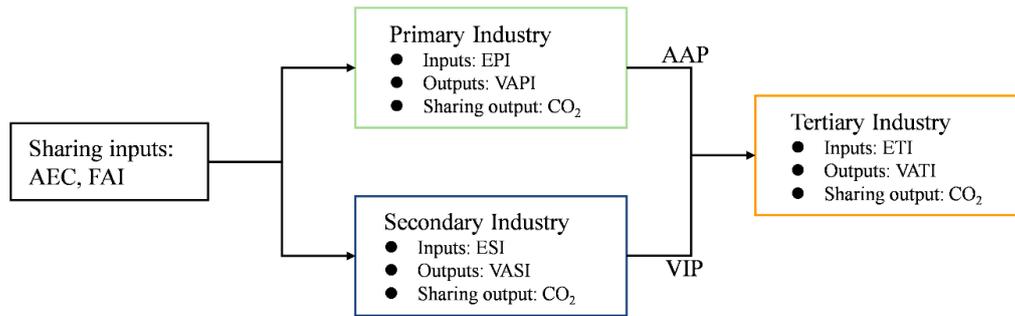
economic sectors. This analysis can help inform the design of policies better aligned with the demands of the new era, thereby enhancing ESEE.

Indicators selection

The specific process of selecting ESEE evaluation indicators in this study is as follows: Firstly, in constructing the evaluation indicator system, representativeness, operability, adaptability, and systematicity are taken as the guiding criteria (Liu et al., 2011). Based on these principles, this study selects evaluation indicators for the corresponding industries' environmental efficiency in the economic sector, aiming to construct a scientific indicator system in this field. Firstly, indicators that are widely referenced in the relevant literature are selected to enhance their representativeness. Secondly, the selected indicators should be readily obtainable and comprehensible so as to satisfy the requirements of operability. Thirdly, the indicators must follow the contents of relevant policies issued by the Chinese government (e.g. industrial structure optimization), to enhance the adaptability of the indicator system. Fourthly, the important components of different industries within the economic sector need to be covered to ensure the systematicity of the indicator system. Secondly, after preliminary screening of relevant indicators based on the principles mentioned above, this study also took into account the objective conditions pertaining to the availability, completeness, and authority of the data source. The final selection of 21 indicators shown in *Table 2* was made to evaluate the ESEE, PIE, SIE, and TIE of China's first-tier cities. This selection aimed to ensure that the constructed indicator system would better serve the research objectives of this study. The selection of input indicators and output indicators will be explained in detail. To provide a clearer explanation of the relationships between industries and their corresponding indicators, *Figure 1* is specifically presented in this study.

Table 2. *The introduction of the indicators selection for each industry*

Industry	Inputs	Sharing inputs	Outputs	Sharing outputs	Intermediates
The primary industry	Employees in the primary industry (EPI, 10^3 persons)	Annual electricity consumption (AEC, 10^8 kWh)	Value added of the primary industry (VAPI, 10^8 yuan)	CO_2 emissions	The amount of agricultural products (AAP): [Cotton production (CD, 10^3 tons), dairy production (DD, 10^3 tons), poultry egg production (PED, 10^3 tons), grain production (GD, 10^3 tons), meat production (MD, 10^3 tons), vegetable production (VD, 10^3 tons), aquatic product production (APD, 10^3 tons)]
The secondary industry	Employees in the secondary industry (ESI, 10^3 persons)		Value added of the secondary industry (VASI, 10^8 yuan)		The value of industrial products (VIP, 10^8 yuan)
		Fixed assets investment (FAI, 10^8 yuan)	Industrial pollutant discharge (IPS): [Industrial SO_2 emissions (ISO_2E, tons), Industrial wastewater emissions (IWE, 10^4 tons), Industrial nitrogen oxide emissions (INOE, tons), Industrial smoke and dust emissions (ISDE, tons)]		
The tertiary industry	Employees in the tertiary industry (ETI, 10^3 persons)		Value added of the tertiary industry (VATI, 10^8 yuan)		—

Figure 1. The relationship between the three major industries and their indicators

In terms of input indicators, the development of different industries requires inputs of labor, capital, and resources. Based on data availability and existing research (Bian et al., 2016), this study uses EPI, ESI, and ETI as labor input indicators for the development processes of different industries. Due to the lack of specific city-level data for capital and resource inputs across various industries in China, this study adopts a shared input approach following the research by Wu et al. (2017). Specifically, AEC and FAI are selected as shared input indicators that drive the development of all three industries. These indicators are widely recognized by scholars (e.g., Guo et al., 2020; Yang et al., 2022) and are considered representative.

For output indicators, the development of different industries results in both expected outputs (such as increased industry value) and unexpected outputs (such as pollutants generated during development). Following Chen et al. (2022), this study selects VAPI, VASI, and VATI to measure expected outputs, while ISO2E, IWE, INOE, and ISDE are chosen to represent unexpected outputs for the secondary industry (Zhang et al., 2018). However, these industrial waste emissions do not fully capture the pollutants generated by all three industries during development. Moreover, due to data availability, specific city-level pollutant output indicators for different industries in China are not accessible. Therefore, following the approach by Khoveyni and Eslami (2022), this study adopts a shared input approach. Given that CO_2 is a primary contributor to climate change and global warming (Geng et al., 2017) and is emitted during the development of all three industries, CO_2 emissions are used as the shared unexpected output. Since official data on CO_2 emissions are not available in various statistical yearbooks, this study estimates emissions using the method proposed by Zha et al. (2016), calculating them by multiplying fossil energy consumption by its carbon emission coefficient.

As for intermediate indicators, agricultural products from the primary industry and industrial products from the secondary industry support the development of the tertiary industry (Gan et al., 2023). Agricultural products typically include those from agriculture, forestry, animal husbandry, and fishery. Therefore, CD, DD, PED, GD, MD, VD, and APD are selected to represent AAP as an intermediate indicator flowing from the primary to the tertiary industry. Considering data availability, VIP is used as the intermediate indicator flowing from the secondary industry to the tertiary industry.

Methods and modeling

NDEA model

The NDEA model overcomes the "black box" limitations of the DEA model by fully accounting for environmental resource inputs from the primary and secondary sectors to

the tertiary sector. Therefore, this paper adopts the NDEA model to achieve a more accurate assessment of ESEE.

In terms of indicators, labor, capital, and energy are generally regarded as the primary factors indicators in the economic production process, and are expressed as, X_k X_l, and X_e, respectively. In terms of outputs, production activities not only contribute to rapid economic growth (represented as Y_G), but also lead to the emission of environmental pollutants (represented as U_W) and greenhouse gases (represented as U_C). Similarly, the input indicators of the three major industries in the economic production system can be expressed as X_l^p, X_k^p, and X_e^p, p = 1,2,3; and the corresponding output indicators can be represented as Y_G^p, U_W^p and U_C^p, p = 1,2,3. In addition, there may also be connection indicators between different industries. In this paper, we represent the connection indicator between the primary industry and the tertiary industry as Z_h^{13} (h = 1,...,H), and the connection indicator between the secondary industry and the tertiary industry as Z_k^{23} (k = 1,...,K). It should be pointed out that due to the availability of data at the city level, specific data at the industry level cannot be obtained for some input and output indicators (such as capital, energy and greenhouse gas emissions). To tackle this problem, we draw on existing studies (Chen et al., 2010; Kao, 2017; Wu et al., 2016, 2017) and adopts the method of shared input and common output to model them. Specifically, letting $X_k^p = \alpha_p X_k$, $X_e^p = \beta_p X_e$ and $U_C^p = \gamma_p U_C$, where $\sum_{p=1}^{3} \alpha_p = \sum_{p=1}^{3} \beta_p = \sum_{p=1}^{3} \gamma_p = 1$. Then, the ESEE of city considering the three major industries can be obtained through the following model. Assuming there are n (j = 1,...,n) cities, the ESEE of the j city is given by *Equation 1* below:

$$ESEE_j = \max(w_{1j} * PIE_j + w_{2j} * SIE_j + w_{3j} * TIE_j)$$

$$s.t. \quad PIE_j = \frac{u_1 * Y_{Gj}^1 + q_h * Z_{hj}^{13} - s_w * U_{wj}^1 - m * \gamma_1 * U_{cj}}{v_l * X_{lj}^1 + v_k * \alpha_1 * X_{kj} + v_e * \beta_1 * X_{ej}} \le 1, \quad j = 1,...,n$$

$$SIE_j = \frac{u_1 * Y_{Gj}^2 + d_k * Z_{kj}^{23} - s_w * U_{wj}^2 - m * \gamma_2 * U_{cj}}{v_l * X_{lj}^2 + v_k * \alpha_2 * X_{kj} + v_e * \beta_2 * X_{ej}} \le 1, \quad j = 1,...,n$$

$$TIE_j = \frac{u_1 * Y_{Gj}^3 - s_w * U_{wj}^3 - m * \gamma_3 * U_{cj}}{v_l * X_{lj}^3 + v_k * \alpha_3 * X_{kj} + v_e * \beta_3 * X_{ej} + q_h * Z_{hj}^{13} + d_k * Z_{kj}^{23}} \le 1, \quad j = 1,...,n \quad \text{(Eq.1)}$$

$$\sum_{p=1}^{3} \alpha_p = \sum_{p=1}^{3} \beta_p = \sum_{p=1}^{3} \gamma_p = 1$$

$$\alpha_1 < \alpha_2, \quad \alpha_1 < \alpha_3$$

$$\beta_1 < \beta_2, \quad \beta_1 < \beta_3$$

$$\gamma_1 < \gamma_2, \quad \gamma_1 < \gamma_3$$

$$u_1, s_w, q_h, d_k, m, v_l, v_k, v_e \ge 0$$

In model, $u_1, s_w, q_h, d_k, m, v_l, v_k$ and v_e are the unknown weights of different input (output) indicators, respectively. Model (1) seeks the maximum ESEE of the j city under the constraint that PIE, SIE and TIE of all cities are not greater than 1. Considering that the development level of China's primary industry is much smaller than that of the secondary and tertiary industries, model (1) further constrains the distribution ratio of shared indicators. Through n iterations, the ESEE, PIE, SIE, and TIE for each city can be obtained.

It is not difficult to find that in order to obtain the city's ESEE, it is necessary to determine the corresponding weights of the three major industries within the ESEE

system, namely, (w_{1j}, w_{2j}, and w_{3j}). Based on existing research (Wu et al., 2016; Khoveyni and Eslami, 2022), the weights of the three major industries in the ESEE system can be obtained by *Equation 2*:

$$w_{1j} = \frac{v_l * X_{lj}^1 + v_k * \alpha_1 * X_{kj} + v_e * \beta_1 * X_{ej}}{v_l * X_{lj} + v_k * X_{kj} + v_e * X_{ej} + q_h * Z_{hj}^{13} + d_k * Z_{kj}^{23}}$$

$$w_{2j} = \frac{v_l * X_{lj}^2 + v_k * \alpha_2 * X_{kj} + v_e * \beta_2 * X_{ej}}{v_l * X_{lj} + v_k * X_{kj} + v_e * X_{ej} + q_h * Z_{hj}^{13} + d_k * Z_{kj}^{23}} \qquad \text{(Eq.2)}$$

$$w_{3j} = \frac{v_l * X_{lj}^3 + v_k * \alpha_3 * X_{kj} + v_e * \beta_3 * X_{ej} + q_h * Z_{hj}^{13} + d_k * Z_{kj}^{23}}{v_l * X_{lj} + v_k * X_{kj} + v_e * X_{ej} + q_h * Z_{hj}^{13} + d_k * Z_{kj}^{23}}$$

By substituting Model (2) into Model (1), Model (3) can be obtained by *Equation 3*:

$$ESEE_j = \max \frac{u_1 * Y_{Gj} + q_h * Z_{hj}^{13} + d_k * Z_{kj}^{23} - s_w * U_{wj} - m * U_{cj}}{v_l * X_{lj} + v_k * X_{kj} + v_e * X_{ej} + q_h * Z_{hj}^{13} + d_k * Z_{kj}^{23}}$$

$$s.t. \quad PIE_j = \frac{u_1 * Y_{Gj}^1 + q_h * Z_{hj}^{13} - s_w * U_{wj}^1 - m * \gamma_1 * U_{cj}}{v_l * X_{lj}^1 + v_k * \alpha_1 * X_{kj} + v_e * \beta_1 * X_{ej}} \le 1, \quad j = 1,...,n$$

$$SIE_j = \frac{u_1 * Y_{Gj}^2 + d_k * Z_{kj}^{23} - s_w * U_{wj}^2 - m * \gamma_2 * U_{cj}}{v_l * X_{lj}^2 + v_k * \alpha_2 * X_{kj} + v_e * \beta_2 * X_{ej}} \le 1, \quad j = 1,...,n$$

$$TIE_j = \frac{u_1 * Y_{Gj}^3 - s_w * U_{wj}^3 - m * \gamma_3 * U_{cj}}{v_l * X_{lj}^3 + v_k * \alpha_3 * X_{kj} + v_e * \beta_3 * X_{ej} + q_h * Z_{hj}^{13} + d_k * Z_{kj}^{23}} \le 1, \quad j = 1,...,n \qquad \text{(Eq.3)}$$

$$\sum_{p=1}^3 \alpha_p = \sum_{p=1}^3 \beta_p = \sum_{p=1}^3 \gamma_p = 1$$

$$\alpha_1 < \alpha_2, \quad \alpha_1 < \alpha_3$$

$$\beta_1 < \beta_2, \quad \beta_1 < \beta_3$$

$$\gamma_1 < \gamma_2, \quad \gamma_1 < \gamma_3$$

$$u_1, s_w, q_h, d_k, m, v_l, v_k, v_e \ge 0$$

Clearly, model (3) is the fractional programming, which is difficult to solve directly. Letting $1/(v_l * X_{lj} + v_k * X_{kj} + v_e * X_{ej} + q_h * Z_{hj}^{13} + d_k * Z_{kj}^{23}) = t$ and $t * u_1 = u_1$, $t * s_w = s_w$, $t * q_h = q_h$, $t * d_k = d_k$, $t * m = \hat{m}$, $t * v_l = v_l$, $t * v_k = v_k$, $t * v_e = v_e$, as well as $v_l * \alpha_p = a_p$, $v_e * \beta_p = b_p$, and $m * \gamma_p = f_p$, model (3) can be transformed into following linear programming, as shown in *Equation 4*:

$$ESEE_j = \max u_1 * Y_{Gj} + q_h * Z_{hj}^{13} + d_k * Z_{kj}^{23} - s_w * U_{wj} - m * U_{cj}$$

$$s.t. \quad v_l * X_{lj} + v_k * X_{kj} + v_e * X_{ej} + q_h * Z_{hj}^{13} + d_k * Z_{kj}^{23} = 1$$

$$u_1 * Y_{Gj}^1 + q_h * Z_{hj}^{13} - s_w * U_{wj}^1 - f_1 * U_{cj} - (v_l * X_{lj}^1 + a_1 * X_{kj} + b_1 * X_{ej}) \le 0, \quad j = 1,...,n$$

$$u_1 * Y_{Gj}^2 + d_k * Z_{kj}^{23} - s_w * U_{wj}^2 - f_2 * U_{cj} - (v_l * X_{lj}^2 + a_2 * X_{kj} + b_2 * X_{ej}) \le 0, \quad j = 1,...,n$$

$$u_1 * Y_{Gj}^3 - s_w * U_{wj}^3 - f_3 * U_{cj} - (v_l * X_{lj}^3 + a_3 * X_{kj} + b_3 * X_{ej} + q_h * Z_{hj}^{13} + d_k * Z_{kj}^{23}) \le 0, \quad j = 1,...,n \qquad \text{(Eq.4)}$$

$$\sum_{p=1}^3 a_p = v_k$$

$$\sum_{p=1}^3 b_p = v_e$$

$$\sum_{p=1}^3 f_p = m$$

$$a_1 < a_2, \quad a_1 < a_3$$

$$b_1 < b_2, \quad b_1 < b_3$$

$$f_1 < f_2, \quad f_1 < f_3$$

$$u_1, s_w, q_h, d_k, m, U, U, v_l, v_k, v_e, a_1, a_2, a_3, b_1, b_2, b_3, f_1, f_2, f_3 \ge 0$$

After obtaining ESEE of each city through model (4), PIE, SIE and TIE of the corresponding city can be obtained through model (5), as shown in *Equation 5*:

$$PIE_j = \frac{u_1 * Y_{Gj}^1 + q_h * Z_{hj}^{13} - s_w * U_{wj}^1 - f_1 * U_{cj}}{v_l * X_{lj}^1 + a_1 * X_{kj} + b_1 * X_{ej}}$$

$$SIE_j = \frac{u_1 * Y_{Gj}^2 + d_k * Z_{kj}^{23} - s_w * U_{wj}^2 - f_2 * U_{cj}}{v_l * X_{lj}^2 + a_2 * X_{kj} + b_2 * X_{ej}} \quad \text{(Eq.5)}$$

$$TIE_j = \frac{u_1 * Y_{Gj}^3 - s_w * U_{wj}^3 - f_3 * U_{cj}}{v_l * X_{lj}^3 + a_3 * X_{kj} + b_3 * X_{ej} + q_h * Z_{hj}^{13} + d_k * Z_{kj}^{23}}$$

It should be noted that to ensure the effectiveness of DEA evaluation results, the number of DMUs (Decision-Making Units) generally needs to be more than twice the number of indicators (Staessens et al., 2019). To address this, this study adopts an approach developed by Pastor and Lovell (2005) and Oh (2010), which introduces global technology (GT) into the NDEA model. Before incorporating GT, the production frontier is constructed using only the DMUs from the current period. With GT, however, all DMUs from all periods within the study timeframe contribute to constructing the production frontier. The primary goal of global technology is to make evaluation results across different periods comparable, effectively increasing the number of DMUs. In this study, with the inclusion of GT, the number of DMUs rises from 19 to 190 (with 19 DMUs each year over a 10-year study period), thereby meeting the DEA model's requirements for both the number of DMUs and indicators.

The GT-NDEA efficiency measurements were implemented using MATLAB.

PVAR model

While the Network Data Envelopment Analysis (NDEA) model offers a more precise assessment of ESEE by accounting for the connections between the Primary Industry Efficiency (PIE) and Tertiary Industry Efficiency (TIE), as well as the Secondary Industry Efficiency (SIE) and TIE, it does not clarify the dynamic impact relationships among these subsystems. This limitation hampers the ability to provide policy recommendations that can effectively promote ESEE improvements. To address this challenge, this paper adopts the Panel Vector Autoregression (PVAR) model, which excels at exploring the complexity and non-linear dynamic relationships within multiple systems (Abrigo and Love, 2016).

The PVAR model was proposed by Holtz-Eakin et al. (1988), grounded in dynamic equilibrium theory as its macroeconomic theoretical foundation (Liu, 2021), and serves to examine the dynamic relationships among endogenous variables within a panel data framework (Yang et al., 2021a). The PVAR model is an extension of the Vector Autoregression (VAR) model, first introduced by Sims in 1980 (Sims, 1980). The VAR model is widely applied to examine dynamic effects of stochastic variables on other variables (Alsadi and Tularam, 2020). However, the VAR model has limitations: it does not support panel data and overlooks individual heterogeneity (Wu et al., 2019), which can introduce biases due to spatial and temporal, as well as individual, heterogeneity. The PVAR model retains all the functionalities of the VAR model while allowing for unobserved cross-sectional heterogeneity and time-specific trend effects. Moreover, it does not impose strict requirements on data volume and format, and it effectively

controls for estimation biases arising from cross-sectional and spatial heterogeneity (Jawadi et al., 2016). The final outcomes of PVAR modeling are similar to those of multivariate regression equations (Khan et al., 2020). However, the PVAR model offers several distinct advantages over common multivariate regression equations. First, the PVAR model treats all variables as endogenous, reducing model uncertainty caused by subjective decisions (Acheampong, 2018). Moreover, common multivariate regression equations require variables to be forecasted in advance to be considered endogenous, whereas the PVAR model does not impose this requirement (Mamipour et al., 2019). Second, the PVAR model is more general in form, and parameter estimation is simpler compared to other multivariate regression equations, making the measurement process more straightforward (Yang et al., 2022).

Therefore, in order to determine the dynamic impact relationship of TIE on PIE, as well as SIE on PIE in the ESEE system, this section will measure it by setting up a PVAR (Panel Vector Autoregression) model. Let Yit be an M×1 vector of the M mutually dependent endogenous variables for individual i at time t, Xit be an N×1 vector of the N exogenous variables for individual i at time t, and εit be an M×1 vector of the unobserved individual fixed effects for individual i at time t, known as the individual intercept vector. αij(l) and βij(l) are the short-term impact coefficients of the lagged vectors Yj,t-l and Xj,t-l on the vector Yit respectively, where l is the lag length. They are M×M matrices and M×N matrices, respectively. The PVAR model has the following three characteristics: First, all lagged endogenous variables of all individuals enter into any equation of any endogenous variable, indicating that there exist dynamic inter-dependencies among the endogenous variables in the system. Second, uit only has cross-sectional correlation, indicating that there are non-zero M×M matrices for different individuals i≠j, indicating the existence of static inter-dependencies in the system. Third, the vector εit, the regression coefficients αij(l) and βij(l) are different for each individual i, indicating that there is cross-sectional heterogeneity in the system. However, the three characteristics do not appear simultaneously. For example, when Yang (2021a) study on the interaction between technological innovation and ecological environment, the analysis of dynamic cross-sectional heterogeneity is more important because the sample contains data from both developed areas in eastern China and underdeveloped areas in central and western China. Bai (2019) pointed out that static correlation may be more common when investigating the cross-national transmission of shocks to various national financial markets using quarterly data obtained from monthly data. Hence, scholars usually set up PVAR models according to their research needs. In this study, the PVAR model is set as follows (Holtz Eakin et al., 1988):

$$Y_{it} = \gamma_0 + \sum_{j=1}^{p} \gamma_j Y_{i,t-j} + \alpha_i + \beta_t + \varepsilon_{it} (i = 1,2,\cdots,n, t = 1,2,\cdots,k)$$

where Y_{it} is the endogenous variable identified by temporal and regional factors, which can reflect the conditions in PIE, SIE and TIE. γ_0 corresponds to the estimated constant term, γ_j represents the lagged endogenous variable, p stands for the lag period, j refers to the lag order, and α_i in the formula embodies the individual effects and can be used to explicate the otherness of the cross-sectional. Similarly, β_t is a time effect vector that can exhibit the temporal characteristics of variables. Lastly, ε_{it} is utilized to express the random disturbance.

All PVAR estimations, including panel unit root tests, cointegration tests, impulse response analysis, and variance decomposition, were conducted using Stata.

Results

This section mainly consists of two steps. The first is to evaluate the values of ESEE, PIE, SIE, and TIE using the GT-NDEA model. In the second step, a panel vector autoregression (PVAR) model is employed to examine the dynamic relationships between PIE and TIE, as well as between SIE and TIE, within the ESEE system.

The evaluation of ESEE, PIE, SIE and TIE

Through models (4) and (5), the development trends of ESEE, PIE, SIE, and TIE in first-tier and new first-tier cities in China from 2010 to 2019 can be obtained (see *Fig. 2*).
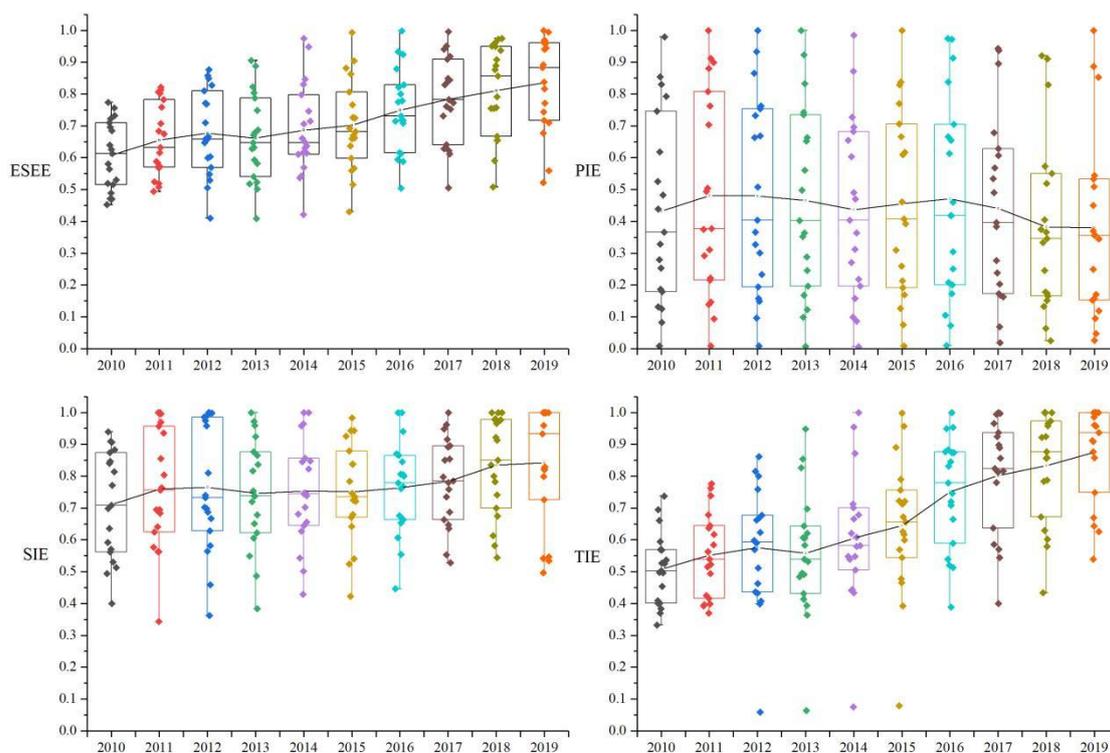

Figure 2. The ESEE, PIE、SIE and TIE of the Chinese first-tier cities from 2010-2019. Each dot within the box represents the ESEE value of an individual city in the corresponding year

The black dashed line in the box plot represents the average value of ESEE, PIE, SIE and TIE of all sample cities. Firstly, it can be seen from *Figure 2* that PIE was placed at a relative lower level (<0.5 degree) throughout the study period, making it a weak subsystem of the ESEE system. Specifically, for traditional first-tier cities and new first-tier cities in China, PIE showed an increasing trend from 2010 to 2014 and a decreasing trend from 2014 to 2019, with 2014 as the turning point. This is consistent with China's recent development of agricultural green digitization (Shen et al., 2022; Wang et al., 2022). The 12th Five-Year Plan for National Agricultural and Rural Informatization Development issued by the Ministry of Agriculture in 2011 explicitly called for strengthening agricultural informatization and sustainable development, providing new opportunities for the high-quality development of the primary industry. However, in 2014, due to rapid urbanization and excessive use of pesticides, China's agricultural non-point source pollution was severe (Chen et al., 2021; Zou et al., 2021), leading to a decrease in PIE. In 2015, the Chinese

government introduced the "Implementation Opinions on Winning the Battle of Agricultural Non-point Source Pollution Control" to strengthen ecological governance in agriculture. However, as seen from the evaluation results, more efforts are needed to further enhance PIE. Secondly, traditional first-tier cities and new first-tier cities in China generally showed a fluctuating growth trend in ESEE, SIE, and TIE, with TIE growing at a faster rate. ESEE, SIE, and TIE basically showed an upward trend in environmental performance from 2010 to 2012 and 2013 to 2019, with 2013 as the turning point. In 2013, the "Belt and Road" initiative was proposed in China, which had a high-quality development nature and injected green vitality into the development of the three industries within the Chinese economic sector, greatly promoting the improvement of ESEE, SIE, and TIE. This especially drove the green development of the third industry with transportation and public facility management as its core in traditional first-tier cities and new first-tier cities along the route (Wang and Xin, 2020). In the government work report in 2004, it was emphasized to "firmly wage a war against pollution" which further promoted the change in government governance concept towards green governance (Yu et al., 2016), providing support for the enhancement of ESEE, SIE, and TIE.

Figure 3 compares the development of ESEE between first-tier and new first-tier cities in China. It shows that ESEE development in new first-tier cities is consistently lower than in traditional first-tier cities during the research period. This disparity can be attributed to several factors. First, Beijing, Shanghai, Guangzhou, and Shenzhen, as traditional first-tier cities, have prioritized environmental governance from an early stage, benefiting from rich experience and strong economic support. In recent years, these cities have also developed advanced digital infrastructure, further boosting green industrial development. In contrast, the rapid urbanization of new first-tier cities has placed significant pressure on their ecological resources, leading to lower ESEE compared to traditional first-tier cities.
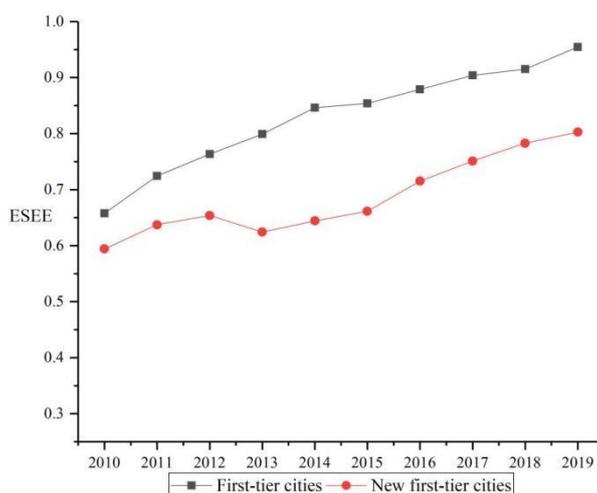
Figure 3. *Comparative analysis of ESEE between traditional first-tier cities and new first-tier cities*

Figure 4 presents a comparative analysis of the development of PIE, SIE, and TIE across traditional and newly designated first-tier cities. In terms of PIE, traditional first-tier cities show a lower level compared to new first-tier cities. Studies indicate that urbanization is a key driver of PIE (Shi et al., 2023; Deng and John, 2019). Since

traditional first-tier cities like Beijing, Shanghai, Guangzhou, and Shenzhen have already achieved a high level of urbanization, the increase in PIE driven by urbanization and other external factors in new first-tier cities is greater. On the other hand, both SIE and TIE are higher in traditional first-tier cities than in new first-tier cities. As urbanization and industrialization advance in new first-tier cities, there is a strong demand for public service facilities in sectors like industry, construction, textiles, and transportation. This results in greater pollution during their industrial and service sector development, causing SIE and TIE in new first-tier cities to lag behind those in traditional first-tier cities.
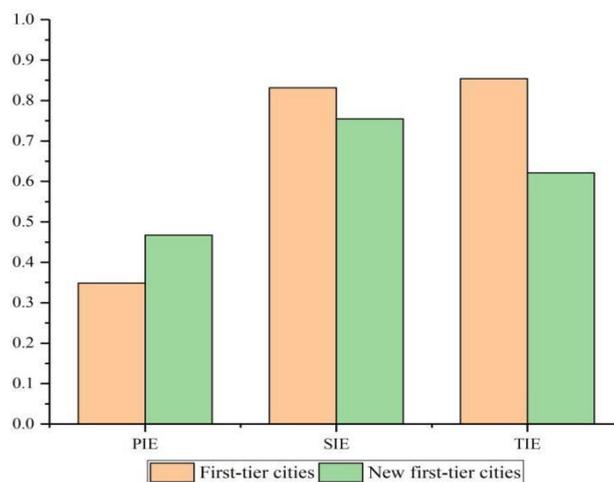
Figure 4. *Comparative analysis of PIE, SIE, and TIE between traditional first-tier cities and new first-tier cities*

The above comparative analysis between traditional and new first-tier cities indicates that urban environmental efficiency exhibits a stage-dependent pattern. Traditional first-tier cities have largely completed the early phases of rapid industrialization and urban expansion, making them more capable of transitioning toward an efficiency-oriented and governance-driven mode of environmental improvement. In contrast, new first-tier cities are still seeking to balance economic scale expansion with increasing environmental constraints, which results in relatively lower levels of ESEE. Therefore, such differences do not merely reflect performance gaps, but rather highlight the distinct development logics and transition challenges faced by cities at different stages of urban and industrial development.

Dynamic relationship analysis

Building on the preceding evaluation of environmental efficiency levels for each industry, this analysis now employs the PVAR model to explore the dynamic impact of PIE on TIE, as well as SIE on TIE, within the ESEE system of Chinese first-tier cities. The objective is to foster more balanced development among the three industries while facilitating improvements in ESEE across these cities. It is important to note that due to the limited number of traditional first-tier cities (only four), which does not meet the PVAR model's evaluation requirements, this section does not differentiate between traditional and new first-tier cities.

The testing of the PVAR model typically involves the following five steps (Kuang et al., 2020):

Unit root test

Data stationarity is a necessary condition for assessing the applicability of the PVAR model. Unit roots should be avoided to prevent "spurious regression" (Liao et al., 2018). Therefore, unit root tests must be conducted on each variable. There are two types of unit root tests (Kuang et al., 2020): one for cross-sectional sequences with common unit roots, such as the Levine, Lin, and Chu (LLC) test, and another for cross-sectional sequences with single unit roots, such as the Im, Pesaran, and Shin (IPS) test, Fisher-Augmented Dickey-Fuller (Fisher-ADF) test, and Fisher-Phillips-Perron (Fisher-PP) test. To avoid the limitations of a single method (Zhang et al., 2019), this study combines all four testing methods. The first-order difference sequences of PIE, SIE, and TIE are found to be stable, indicating that these variables are suitable for further analysis (Jouida, 2018).

Co-integration test

Co-integration tests determine whether a long-term equilibrium relationship exists between the variables. Referring to previous studies (e.g., Liao et al., 2018), this study uses the Augmented Dickey-Fuller (ADF) test proposed by Kao (1999). This test involves using panel regression equations to calculate residuals and construct statistical data for testing (Kao, 1999). The results show that the ADF values for the dynamic impact of PIE on TIE and SIE on TIE within the ESEE system of Chinese first-tier cities are significant at the 1% level, with t-values of 1.8081 and -0.2816, respectively. This indicates that the dynamic relationship between PIE and TIE, as well as SIE and TIE, is balanced in the long run.

Optimal lag order selection

Before applying the PVAR model, the optimal lag order needs to be determined. Following the research of Kuang (2020), this study adopts a comprehensive approach using Akaike's Information Criteria (AIC), Bayesian Information Criteria (BIC), and Hannan & Quinn Information Criteria (HQIC) to select the optimal lag order. The evaluation results, shown in *Table 3*, indicate that the time period with the smallest values according to these criteria is considered the optimal lag order.

Table 3. The results of optimal lag order test of PIE, SIE, TIE

| Lag	Optimal lag order in the PIE to TIE			Optimal lag order in the SIE with TIE		
	AIC	BIC	HQIC	AIC	BIC	HQIC
1	-1.58604	-0.750492	-1.24661	-4.89073	-4.05518*	-4.5513*
2	-2.86057	-1.86090	-2.45434	-4.87998	-3.88031	-4.47375
3	-3.00157	-1.80148	-2.51452	-4.79551	-3.59542	-4.30846
4	-4.33444	-2.88276*	-3.74785	-5.07596*	-3.62428	-4.48937
5	-4.6384*	-2.85969	-3.92754*	-4.82086	-3.04214	-4.10999
6	-3.87766	-1.65539	-3.01401	-4.20429	-1.98202	-3.34064
7	-2.22653	-0.617697	-1.21458	-3.09005	-.245822	-2.0781

For the dynamic relationship between PIE and TIE, the optimal lag order recommended by AIC and HQIC is the 5th order, while BIC recommends the 4th order as the optimal lag order. According to the research of Liao et al. (2018), the determination

of the optimal lag order is based on the detection values that pass through the most times. Therefore, the optimal lag order for the dynamic impact of PIE on TIE is set to the 5th order. Similarly, based on the results of AIC, BIC, and HQIC tests, the optimal lag order of SIE on TIE is set to the 1st order.
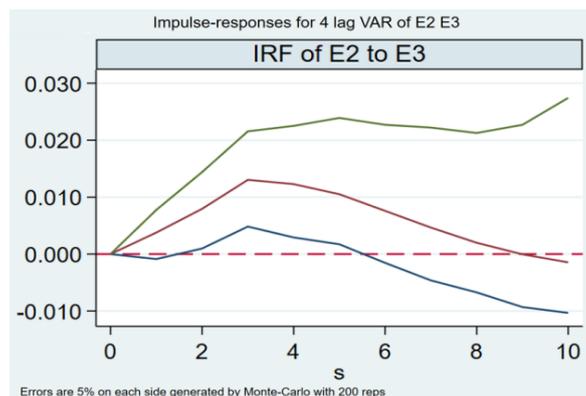
Impulse response analysis

Impulse response analysis examines the reaction of one variable to a standard deviation shock from another variable, holding all other variables constant. This analysis aims to assess how a shock to one variable affects another and whether this impact occurs with a short-term lag (Lin and Wang, 2019). In this study, the impulse response analysis visualizes the dynamic effects of PIE on TIE and SIE on TIE, helping policymakers understand interrelationships between industries and develop policies to enhance ESEE. The study conducted 200 Monte Carlo simulations to assess these effects, with results shown in *Figures 5* and *6*. The x-axis corresponds to the lag length, set at 10 following existing research (Wang et al., 2022), indicating a 10-period forecast. The y-axis corresponds to the magnitude of the impulse response, with the dashed line indicating zero response, the solid red line showing the impulse response estimate, and the solid blue and green lines showing the 5th and 95th percentile estimates, respectively. The results are interpreted as follows:

Figure 5 illustrates the impulse response of TIE to a one-unit shock in PIE, where PIE and TIE are efficiency scores derived from the GT-NDEA model and thus dimensionless. As shown in *Figure 5,* the impact of PIE on TIE remains unchanged in the current period, indicating a lagged effect. Over time, the impulse effect weakens, tending toward zero by the 10th period, demonstrating that the impact of PIE on TIE is both lagged and long-term. This aligns with China's urbanization and industrial transformation process. Recent policies and regulations emphasize green, sustainable, and high-quality development, and the deepening of digital infrastructure and establishment of a service-oriented government have promoted high-quality, green production in the primary industry of first-tier cities, triggering a series of chain reactions. The primary industry serves as a foundation for the tertiary industry, with products like cotton, dairy, and vegetables ensuring the survival and growth of sectors such as catering and education. Additionally, PIE drives the optimization and enhancement of TIE, as the digitization and ecological transformation of the primary industry can lead to industrial upgrades, like transforming forestry into tourism. However, such transformations require time, resulting in the lagged and long-term impact of PIE on TIE.
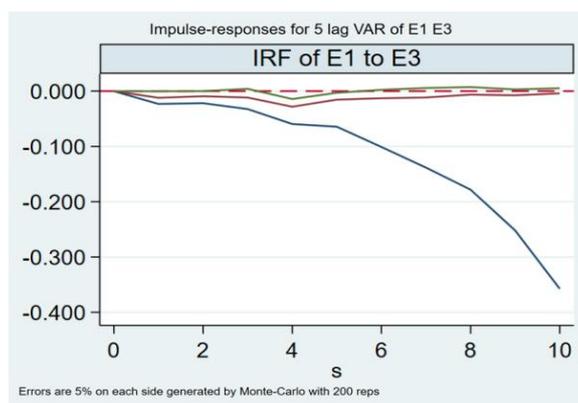
Figure 5. *Impulse response diagram of PIE (E1) to TIE (E3); SIE (E2) to TIE (E3)*

As shown in *Figure 6,* the impulse responses are expressed in terms of efficiency scores (dimensionless), reflecting the dynamic effect of SIE on TIE. the impulse effect of SIE on TIE first increases and then decreases. There is no change in the current period, indicating a lagged impact. The impact peaks in the third period before weakening and approaching zero, indicating that the dynamic impact of SIE on TIE is positive and long-term. This is because the secondary industry provides a long-term material foundation for the tertiary industry. SIE acts as a catalyst for TIE; first-tier cities, with their advanced urbanization and industrial technology, generate employment opportunities that attract talent, driving long-term growth in the tertiary sector. Furthermore, the tertiary industry—focused on transportation, real estate, public infrastructure, and social security—relies on the secondary industry for raw materials and manufacturing, making the ecological development of the secondary industry essential for TIE improvement.

Figure 6. Impulse response diagram of SIE to TIE

Variance decomposition

Variance decomposition is a technique that separates the forecast error variance of endogenous variables into portions attributable to shocks originating from different variables within the system. Essentially, it quantifies the extent to which variations in one variable can be explained by another (Mamipour et al., 2019). This method helps assess the relative influence of individual variables in generating variations in others, thereby further validating the findings of the impulse response analysis. (Lin and Zhu, 2017). 200 Monte Carlo simulations were conducted to predict 15 periods, with results presented in *Table 4.* The table shows that the dynamic impacts of PIE on TIE and SIE on TIE stabilize in the later periods. Specifically, as the forecast period progresses, the dynamic impact of PIE on TIE becomes increasingly significant. By the 12th period, PIE's effect on TIE peaks and stabilizes at 51.1%, indicating that TIE's development heavily depends on PIE. This finding further corroborates the results from the impulse response analysis. Similarly, the dynamic impact of SIE on TIE stabilizes at 4.6% by the 8th period, suggesting that TIE is also somewhat constrained by SIE's development.

Overall, the dynamic impacts of PIE on TIE and SIE on TIE fluctuate before reaching stability, implying that it takes considerable time for these effects to materialize. This conclusion further validates the findings of the impulse response analysis. Achieving dynamic coordination and sustainable development of the three major industries based on the relationships among PIE, SIE, and TIE remains a significant challenge for policymakers.

Table 4. *The results of variance decomposition of PIE, SIE to TIE*

Response variable	s	PIE	SIE
TIE	1	0.001	0.002
TIE	2	0.077	0.014
TIE	3	0.196	0.020
TIE	4	0.276	0.030
TIE	5	0.392	0.037
TIE	6	0.431	0.042
TIE	7	0.457	0.044
TIE	8	0.478	0.046
TIE	9	0.487	0.046
TIE	10	0.499	0.046
TIE	11	0.507	0.046
TIE	12	0.510	0.046
TIE	13	0.511	0.046
TIE	14	0.511	0.046
TIE	15f	0.511	0.046

Discussion

First, since PIE is the main limitation in improving ESEE, it requires further enhancement. Improvements should target both the input and output indicators of PIE. As shown in *Figure 1,* the input indicator of PIE primarily focuses on EPI, while the output indicator is VAPI. On one hand, as urbanization continues in China, the labor force in the primary industry is decreasing, negatively impacting PIE improvement. On the other hand, as noted in the initial analysis regarding the uneven industrial structure, China's VAPI in 2022 was the lowest among the three industries, at only 8834.5 billion yuan, far below the value added in the other two industries. This low agricultural output makes it difficult to attract labor to the primary industry, leading to a vicious cycle that hinders PIE improvement. The Chinese government has recognized this issue and continues to implement policies to increase agricultural income and attract labor to this sector. This study suggests cultivating agricultural talent, nurturing new professional farmers, and using technological innovation to increase agricultural income, thereby attracting more labor and increasing the value added in the primary industry, ultimately improving PIE. Additionally, extending the value chain of agriculture, forestry, animal husbandry, and fisheries through agricultural technological innovation is an important way to create more employment opportunities and enhance PIE.

Second, compared with traditional first-tier cities, new first-tier cities exhibit relatively lower levels of ESEE, SIE, and TIE, indicating that policies aimed at enhancing ESEE should adopt differentiated rather than uniform strategies. The relatively higher ESEE observed in traditional first-tier cities suggests that improvements in environmental efficiency increasingly rely on refined governance, technological upgrading, and service-sector optimization. In contrast, the lower ESEE levels in new first-tier cities reflect the dual challenges of addressing industrial expansion pressures while simultaneously coping with environmental constraints. This implies that the sequencing and focus of policy implementation should vary across city types, allowing environmental strategies to better align with their respective stages of development. Based on these findings, this research

suggests developing a green circular industrial economic model, such as reusing old equipment through reassembly, to alleviate environmental pressures. Additionally, support for technological innovation in urban industrial development can be provided through "industry-academia-research" cooperation, effectively addressing the issue of high input but low output in new first-tier cities. Finally, new first-tier cities can introduce policies that favor the service industry, such as subsidies for tourism development and promotion of ecological tourism projects, to create a conducive environment for the high-quality development of the tertiary industry.

Lastly, considering the lagged and long-term dynamic impacts of PIE on TIE and SIE on TIE, it is recommended that the governments of China's first-tier cities deeply embed the concept of green development and further promote the new industrialization and modernization of agriculture. This will better support TIE development and promote long-term ESEE improvement. As agriculture and industrial production shift towards green practices, resource utilization efficiency can improve, providing more support for TIE with less resource consumption, ultimately achieving high-quality ESEE development. Governments can standardize the use of green financial tools and strengthen "industry-academia-research" integration to support new industrialization and agricultural modernization. Moreover, first-tier city governments can leverage opportunities presented by the Belt and Road Initiative to deepen and expand international cooperation, establishing long-term partnerships with other countries. This will help optimize the use of capital, technology, and talent across the three major industries, maximizing long-term returns on investment in PIE and SIE, and ultimately promoting ESEE improvement.

Conclusion

The environmental issues arising from the unsustainable development of industries in the economic sector have garnered global attention, particularly in China's economically active first-tier cities. Given the increasing emphasis on sustainable economic development by the Chinese government, it is crucial to scientifically evaluate the environmental efficiency of the economic sector and its three industries (i.e., ESEE, PIE, SIE, TIE) within China's first-tier cities. This evaluation aims to uncover the dynamic relationships of environmental efficiency among industries within the ESEE system and provide better insights for balancing urban economic growth and environmental protection in China. To achieve this, the study employs an integration of the GT-NDEA model and the PVAR model, constructing an evaluation indicator system for ESEE. Based on this framework, the study assesses the ESEE, PIE, SIE, and TIE of first-tier cities in China from 2010 to 2019, revealing the dynamic relationships among the environmental efficiencies of the three industries within the ESEE system. The objectives of this research are to explore the development process of ESEE and the environmental efficiency of the three major industries in China in recent years, identify existing issues, and provide targeted policy recommendations based on the findings.

The research yields three key findings. First, the ESEE of first-tier cities in China exhibited a fluctuating upward trend during the study period, with PIE being the lagging subsystem that hinders ESEE enhancement. This indicates the need for increased focus on improving environmental efficiency in agriculture to promote sustainable ESEE development. Second, compared to traditional first-tier cities, the ESEE, SIE, and TIE of new first-tier cities are lower, highlighting the importance of enhancing environmental

efficiency across various industries in these cities. Finally, the dynamic impact of PIE on TIE, as well as SIE on TIE, in first-tier cities in China is both lagging and long-term. This finding provides a basis for designing more suitable policies to promote the comprehensive development of the three industries within the ESEE system, helping to avoid the fragmented governance issue of neglecting one aspect while focusing on another.

This research holds both theoretical and practical significance. Theoretically, the evaluation index system of ESEE has been optimized. This research considers the relationships between PIE and TIE, and SIE and TIE within the ESEE system, addressing gaps where previous research treated ESEE as a "black box" or considered PIE, SIE, and TIE as parallel structures within ESEE. This improves the accuracy of ESEE evaluations. Additionally, by incorporating the latest characteristics of sustainable development in China, the evaluation indicators related to ESEE have been updated, aligning the results with China's recent ESEE developments. The application of the PVAR model clarifies the dynamic relationships between PIE and TIE, and SIE and TIE in first-tier cities, providing a methodological reference for studying dynamic impacts in other fields.

Practically, the combined use of NDEA and PVAR models enhances the understanding of ESEE development in first-tier cities and the dynamic relationships among the three major industries. This enables the formulation of more practical ESEE improvement policies, reducing difficulties and uncertainties in strategy implementation and addressing the issue of neglecting one aspect while focusing on another. This supports the sustainable development of China's economic sector.

The limitations of this research include: To begin with, the study adopts an exploratory approach and relies on data from 19 first-tier cities in China. Future research should verify and refine these conclusions by expanding the sample (e.g., to 113 major cities in China) and applying the Bootstrap regression model. Second, this research did not explicitly account for the lag effects of certain economic indicators. Future studies could optimize this by employing statistical methods based on variance and covariance equivalence.

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