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Influence mechanism of electricity price distortion on industrial green transformation: A spatial analysis of Chinese regions

Asif Razzaq [a,e], Arshian Sharif [b,e,f,g], Xiaodong Yang [c,*], Eyup Dogan [d]

[a] Research Division, CAREC Institute, Urumqi, China
[b] Department of Economics and Finance,Sunway University Business School, Sunway University, Malaysia
[c] School of Economics and Management, Xinjiang University, Urumqi, China
[d] Department of Economics, Abdullah Gul University, Turkey
[e] Adnan Kassar School of Business, Lebanese American University, Beirut, Lebanon
[f] University of Economics and Human Sciences in Warsaw, Warsaw, Poland
[g] College of International Studies, Korea University, Seoul, South Korea

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ABSTRACT

Electricity price distortion (DIS) can significantly affect industrial green transformation (IGT), influencing the pace and direction of sustainable economic growth. Understanding this link is essential for crafting effective green energy policies. Initially, this study evaluates the direct and heterogeneous effects of DIS on IGT and then investigates the indirect influence channels using a sample of 30 Chinese provincial-level administrative regions from 2006 to 2019. Spatial analysis techniques (standard deviation ellipse and geographically and temporally weighted regression methods) are applied to explore the spatial and temporal dependence and non-stationary association between DIS and IGT. The outcomes suggest that DIS significantly reduces IGT in the eastern region through R&D input intensity and energy mix, while insignificant in the central and western regions. The adverse effect of DIS is more substantial at higher quantiles of IGT. The individual spatial heterogeneity characteristics reveal that the gravity centre of IGT is located in the southeast of the geometric centre of China, displays a southwest-northeast-southeast directional migration, and distributed at the junction of Henan and Hubei. Manifestly, the ellipse and azimuth of IGT vary significantly between 0.862°-32.854°. The IGT level steadily progresses from discrete to concentrated, reflected by the ellipse's long and short semi-axes. These regions are mainly concentrated in the eastern and northwestern areas, with the most significant inhibitory effects in Fujian, Anhui, Shaanxi, Zhejiang, and Yunnan. These findings offer valuable policy implications.

1. Introduction

Industry has always been the driving force behind economic growth, dominating changes in the global economic landscape, and its steady growth has significantly contributed to stabilizing global economies . China has undergone years-long industrialization and emerged as one of the world's leading industrial countries (Zhao et al., 2022; Ren et al., 2022). However, the contradiction between high factor input, low benefit output, high pollution, and low added value in the industrial sector is striking . It brings excessive resource consumption and serious environmental problems (Li et al., 2020b; Cao et al., 2024). China's Ecological and Environmental Report 2019 highlights that industrial emissions of SO_2, NO_X, and particulate matter are 3.954 million tons (an 86.5% share of national sulphur dioxide emissions), and 9.259 million tons (85.1% share of national particulate matter emissions), respectively.[1] These statistics indicate the weak environmental performance of Chinese industry reflects the urgency of accelerating industrial green transformation (IGT) (Han et al., 2020; Zhou et al., 2022).

China has implemented several measures to assist IGT in addressing the country's deteriorating ecological and environmental status, changing its economic growth trajectory, and achieving sustainable development (Yu, 2022; Yang et al., 2023a). The Chinese government repeatedly emphasizes green transformation as a vital prerequisite of modern industry and a required means of implementing environmental governance. Meanwhile, the 14th Five-Year Plan for industrial green development advocates vigorous promotion of industrial energy saving

* Corresponding author.
E-mail addresses: arshian.aslam@gmail.com (A. Sharif), yxdlovezt@126.com (X. Yang).

[1] See: https://www.mee.gov.cn/hjzl/sthjzk/zghjzkgb/202006/P020200602509464172096.pdf.

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and carbon reduction, fully utilizing resources to improve efficiency, and building an industrial pattern of industrial green and low-carbon transformation and industrial empowerment for green development. Nevertheless, a thriving industrial green transition needs to consider a variety of factors in addition to policy-based ones. Many studies have evaluated their impact on IGT in terms of government environmental regulation, economic structure, foreign trade, and technological innovation (Xie et al., 2020; Hou et al., 2018; Yue and Zhang, 2022), while less attention has been given to electricity, a factor considered one of the vital energy sources for industry.

Electricity is the dominant energy source and power for modern industrial production (Borowski, 2022). To guarantee the normal use and stable transmission of electricity across regions, the Chinese government's price authorities have intervened in electricity prices through administrative means for a long time, causing a certain degree of distortion on both the demand and supply sides of the electricity market, i.e., end power consumption prices generally deviate from the optimal price of electricity for marginal output (electricity price distortion) (Xu and Lin, 2022). Distorted electricity prices, as a signal for electricity market clearing, inevitably lead to loss of social welfare and efficiency and thus affect IGT. Electricity price distortion (DIS) does not reveal the cost of electricity supply and resource scarcity, which can produce a resource misallocation and be detrimental to energy conservation, resulting in a waste of electricity resources. The marketization of electricity prices is seriously hampered by distorted tariffs that hardly reflect the actual cost of electricity supply and market demand (Aytaç and Güran, 2011; Kwon et al., 2016; Khobai et al., 2017). Higher electricity prices expand the burden of energy expenses for industrial sectors, restrict the production incentives of industrial sectors, cause a decline in total output, and thus affect IGT (Ai et al., 2020).

One of the essential strategies for cutting industrial firm costs is minimizing energy expenditure, particularly electricity prices. Lower electricity prices drive high-energy-consuming enterprises to enlarge their profit margins by increasing factor inputs, culminating in the extension of high-energy-consuming industries' production scales (Li et al., 2022a). This perpetuates the heavy and deformed industrial structure, leaving overcapacity, making economic development fall into the low electricity price trap, and affecting IGT. It does not properly capture the real demand for electricity in the market, forcing an imbalance in IGT. As the largest industrial product producers and consumers, China's IGT level has always been lower than other developed economies. Due to its cleaner, cheaper, more stable, and more efficient advantages, electricity has become a non-negligible factor for economies coping with the fossil energy crisis, global climate change, and IGT, which is the major changing trend of future energy consumption. Therefore, investigating the influence of DIS on IGT not only contributes to the factual evidence for reducing the direct cost of IGT from the production side but also provides an evidence-based solution for formulating a reasonable and appropriate electricity price policy (Palmié et al., 2021). This serves as an objective basis for the optimal allocation of electricity prices in a significant development scenario, which is practically and theoretically crucial for leading IGT.

Against the above backdrop, this study unveils how DIS affects IGT under long-term government administrative intervention. What are the mechanisms through which the impact occurs, and what are the roles of R&D investment intensity and energy mix? How does the impact of DIS on IGT and regional heterogeneity differ across levels of IGT? Does the impact of DIS on IGT differ significantly due to variations in spatial distribution characteristics? This series of issues need to be addressed urgently. This paper identifies the multiple effects of DIS on IGT to bridge the research gap. However, measuring DIS and IGT is critical due to their complex nature. Certain estimation methods are employed for DIS, such as production function, stochastic frontier, data envelopment analysis, the shadow price method, and computable general equilibrium.

As an energy product, electricity combines the attributes of public goods and monopoly goods. In measuring its price distortion, it is necessary to consider the attributes of natural monopoly goods, such as electricity, and the attributes of the public goods industry. Hence, this study adopts the Cobb–Douglas (C-D) production function to measure DIS. IGT aims to increase output quality and technological efficiency while lowering energy use and pollutant emissions. IGT is measured using a super-efficient slacks-based (SBM) index. This study selects relevant variables to construct a panel model and uses the ordinary least squares (OLS) estimation method controlling time and individual effects to examine the direct driving effect of DIS on IGT, as well as the indirect role (mechanism) from R&D input intensity and energy mix perspectives. Considering the differences in IGT level and regional heterogeneity, it divides the data set into eastern, central, and western regions and distribution quantiles to explore the heterogeneous impact of DIS on IGT. Lastly, it introduces a spatial analysis framework (standard deviation ellipse and geographically and temporally weighted regression methods) to expose the spatial dependence between variables.

This paper seeks to broaden previous findings in the following categories. Firstly, from the perspective of resource allocation and market price signals, the influence of electricity price distortion on IGT is investigated to provide empirical support for the optimal allocation of resource products and industrial green development. Secondly, this paper tests the role mechanism of DIS on IGT from R&D input intensity and energy mix perspectives. Considering the heterogeneity within regions and the level of IGT, this paper divides the data set into eastern, central, and western regions and applies a quantile technique to verify the heterogeneous effects. Lastly, from the perspective of spatial dependence, the influence of DIS on IGT is investigated using spatial analysis techniques. The next chapter explores recent literature, theoretical framework, and material and methods. Chapter four explains the results and discussion, and the last chapter concludes the paper and presents recommendations.

2. Literature review

Electricity resources are key tools for governments to coordinate economic growth and social development; therefore, it is an essential element of IGT and policy design for electricity system reform. Literature that includes DIS and IGT in a unified investigation framework is relatively scarce. Therefore, this paper separates the relevant research on DIS and IGT for further analysis.

2.1. Electricity price distortion

Electricity is currently one of the dominant forms of end-use energy in the world, so extensive research has investigated the effects of DIS, mainly in terms of their effects on economic growth, economic structure, and innovation. Few argue that positive distortions in electricity prices can somewhat inhibit economic growth (Aytaç and Güran, 2011). Specifically, higher electricity prices have the most pronounced cost burden on the industrial sector, which is more sensitive to electricity prices than other sectors due to its higher electricity consumption, thus depressing aggregate output (He et al., 2010; Lin and Jiang, 2011). Evidence for this argument is found in South Africa, where Khobai et al. (2017) reveal a strong negative relationship between electricity prices and economic struggles from 1985 to 2014.In contrast, others argued that positive distortion of electricity prices positively influences economic growth. Xie et al. (2015) reveals that positive distortions in electricity prices significantly increase the intensity of electricity consumption, which benefits economic growth. Deng et al. (2018) explore that higher electricity prices can substantially increase electricity production, contributing to economic growth. Many support that electricity prices may impact economic growth in the short term, while the relationship is not substantial in the long term (Heidari et al., 2011; Jamil and Ahmad, 2010; Saari et al., 2013).

In terms of economic structure, DIS negatively affects GDP growth, employment levels, and the welfare status of the population in short-run, while it can improve the profitability of the electricity industry and contribute to tertiary services growth in the long term (Elliott et al., 2019). Zhao and You (2008) suggest that DIS brings the heaviest shock to motor and equipment manufacturing, petroleum processing, and chemical industries, which entails industry restructuring. Kwon et al. (2016) reach similar conclusions, finding that electricity price increases cause electricity demand to fall, manufacturing output to decline, and thus enterprises to gradually move to low-density energy industries. Li et al. (2022b) empirically show that rational tariff escalation can promote the competitiveness of renewable energy for thermal power generation, promoting renewable energy technologies and energy mix transformation. However, few hold a different view, arguing that DIS lowers the production cost of energy-intensive industries and causes the production scale of energy-intensive industries to enlarge, which in the long run deforms the industrial structure, causes overcapacity, hinders economic transformation, and makes the national economy fall into the low electricity price trap (Ai et al., 2020).

Researchers do not unanimously agree on the influence of DIS on technological innovation. Some claim that higher electricity prices put cost pressure on enterprises, stimulating technological innovation (Li et al., 2022c). Higher electricity prices boost profits, especially in the power sector, enabling them to invest in power-related technological innovations to cut power generation costs (Biresselioglu et al., 2016; Schleich et al., 2017). Although higher industrial electricity prices can induce a short-term escalation in enterprise energy costs, they can trigger competitive effects and promote technological innovation among enterprises (Ai et al., 2020). However, few studies suggest that high electricity prices can inhibit technological innovation, averring that high electricity prices drive up energy costs for industrial enterprises, which creates higher production costs, leaving them without excess profits to compensate for risky innovation behaviors with long pay-off cycles (Xin-gang and Shu-ran, 2020). Businesses switch to less power-intensive production processes when electricity costs skyrocket, diminishing machine and innovation intensity (Abeberese, 2017). There is no benefit in the near term due to the late start of innovation in renewable energy technology, higher power costs have a positive long-term influence on renewable energy technologies (Lin and Chen, 2019).

Many studies explore the influence of DIS on residential welfare, employment, demand, productivity losses, and ecology (Li et al., 2022a). Romero-Jordán et al. (2016) contend that retail electricity price increases significantly dampen residential welfare, with a particularly pronounced effect among low-income groups. Maboshe et al. (2019) that high electricity prices cause real expenditure losses to expand for the poorest households, and transferring the financial savings from the complete elimination of electricity subsidies to the poor can significantly reduce extreme poverty. Pacudan and Hamdan (2019) argue that the welfare losses and electricity bills of non-poor households are significantly higher after electricity tariff reform. Gelan (2018) agrees that DIS makes it difficult to conserve and efficiently use scarce electricity resources at the residential consumption end, inducing overconsumption of electricity and thus increasing pollutant emissions from electricity production. Khalid and Salman (2020) argue that distorted electricity prices shift the allocation of electricity resources away from optimal allocation, resulting in efficiency losses.

2.2. *Industrial green transformation*

The concept, measurement, and influencing aspects are the main topics of IGT research. Firstly, few studies developed the definition and measurement based on the industrial development mode and industrial green total factor productivity perspectives (Fu et al., 2018). Regarding the industrial development mode, Hou et al. (2018) argue that IGT is a systematic replacement of resource-intensive industrial production and consumption by sustainable industrial production and consumption. With a much more comprehensive and objective perspective, the Institute of Industrial Economics (IIE) group aims to pursue the sustainable and green transformation of the entire industrial production process, with resource-efficient utilization, environment-friendly orientation, and green innovation at the core, to achieve a win-win outcome of economic and environmental benefits (Chinese Academy of Social Sciences (CASS), 2011). The China Council for International Cooperation on Environment and Development (CCICED) discusses IGT regarding industrial greening evaluation system construction. Xie et al. (2020) claim that industrial total factor productivity can more comprehensively balance economic and environmental performance. Recent studies commonly use industrial green total factor productivity for practical research applications to assess regional IGT (Han et al., 2020; Kuai et al., 2015; Gao and Yuan, 2022). Other scholarly work on this topic elaborates on the identification and enhancement paths of industrial green development efficiency influence mechanisms. Yue et al. (2018) report that technological scale efficiency has greater potential for enhancing industrial green development by boosting industrial green total factor productivity with technological innovation. Mao et al. (2019) construct a learning-validation-generalization three-stage case-learning theoretical framework to reveal the impact of different heterogeneous drivers on the potential synergistic relationship of IGT.

Secondly, the existing literature on IGT measurement is categorized into parametric and non-parametric methods, depending on whether parameters are set. The parametric method is to set the production function when performing the measurement, and the specific methods involved are the Solow residual method (SRA) and the stochastic frontier method (SFA) (Xue, 2022; Feng and Wang, 2019). Recent studies rarely use the parametric method because of the different results measured with different production function settings (Chen and Lin, 2021). In contrast, the non-parametric method does not necessitate setting specific production functions or parameters but generally forms a data envelope by a linear programming method, then measures efficiency along the frontier surface; hence it is called the data envelope approach (DEA) (Pathomsiri et al., 2008). As IGT considers desired and undesired outputs, traditional DEA models are ineffective in dealing with problems involving undesired outputs (Hou et al., 2018). Studies have improved DEA models to be more realistic (Xie et al., 2020). Following the studies of Luenberger (1992) and Färe and Grosskopf (2002), the directional distance function is incorporated into the DEA model to create a directional distance function model for undesired output, the Malmquist Luenberger (ML) index. Xie et al. (2020) and Yue and Zhang (2022) measure the IGT level using this method. Tone (2001) considers slack variables between inputs and outputs, which affect the measurement results. It builds a non-radial DEA calculation method, i.e., the SBM model, which improves the measurement accuracy due to the complete consideration of slack variables (Meng et al., 2022).

Li and Li (2021) use this technique to calculate manufacturing green total factor productivity. However, the SBM model cannot consider both radial and non-radial aspects, so Tone and Tsutsui (2010) improved it in the epsilon-based measure (EBM) model, which combines both aspects and has become favoured by scholars (Ma et al., 2022; Song et al., 2022; Wang et al., 2023a). Ma et al. (2022) employ four environmental pollutants as undesired outputs to measure industrial green total factor energy efficiency using EBM. However, when the efficiency value is above 1, the traditional DEA model loses its usefulness, and scholars, therefore, introduce super-efficiency theory to develop the super-efficient SBM (Super-SBM) model, which is widely accepted (Li et al., 2021). Thus, the DEA model, without specific functions and specific parameters, is becoming the mainstream method for scholars to measure IGT.

Existing research mainly uses multiple regression models to dissect IGT influencing factors from technological innovation, environmental regulation, governance model, government policy, trade development, resource endowment, and industrial structure perspectives. Xie et al. (2020) confirm that the source of innovation makes inhibitory differences in IGT, i.e., technology introduction significantly inhibits IGT, while technological innovation does the opposite. According to Li et al. (2019), various environmental legislation has implications for the steel industry's transition to a greener economy. Zhao et al. (2021) confirm that industrial development and urbanization enhance green transformation in manufacturing, while foreign dependence has a significant negative effect. Gong et al. (2020) show that manufacturing's comparative trade advantage is not conducive to enterprises' green transformation. Unlike other studies, Han et al. (2020) found that the nexus between renewable energy consumption and IGT is influenced by energy misallocation, and the higher the energy misallocation, the less significant this effect is. Song et al. (2022) demonstrate that high-tech industry agglomeration benefits green transformation in the manufacturing sector, particularly in less developed regions, mid-industrialized regions, or highly polluting industries. However, technological innovation can temper the impact of high-tech industry agglomeration on green transformation in the manufacturing sector.

To sum up, the extant literature investigates DIS and IGT from multiple dimensions based on diverse research methods, research data, and research objects, yet there are still certain research gaps. Most concern the impact of DIS on economic growth, economic structure, technological innovation, and social welfare, or IGT's definition, measurement, and influence factors. Many prior studies failed to elaborate on the impact of DIS on IGT and its underlying mechanism (Hong et al., 2022; Li et al., 2022b). The only research similar to this comes from Ai et al. (2020), who explore electricity prices and industrial productivity. As an essential power source for modern industry, electricity is fundamentally different from other primary energy sources. It is convenient to transmit, stable, and efficient to convert, and many industrial enterprises favour it.

2.3. Influence mechanisms and research hypotheses

As China undergoes exponential economic development, it has entered a new phase characterized by an overlapping period of economic structural transformation. This situation has led to the absence of a market-based mechanism for electricity prices and a market-based reform of end-consumption electricity prices that significantly lag behind the progress in the product market (Xin-gang and Shu-ran, 2020). Many state-owned electricity corporations currently dominate the electricity market, while prices are regulated by China's National Development and Reform Commission (NDRC), which not only results in the allocation of electricity resources not being freely determined by market mechanisms but also creates distortions in electricity prices. Moreover, the NDRC prefers to lower electricity prices to increase electricity penetration, but low electricity prices will keep electricity use high for households and corporations all year round (Jia et al., 2022), resulting in negative price distortions. For energy-intensive industrial enterprises, the negative DIS lowers its production costs, which limits the scope for the development and use of new energy sources and induces them to expand their profit margins and production scale and capacity by increasing factor inputs, leading to adverse impact on IGT (Xie et al., 2015). It will limit the industrial sector's motivation to produce by increasing the incentives to consume energy and production costs, ultimately reducing total output and impacting IGT (Ai et al., 2020). As DIS escalate, corporations seek primary energy sources such as coal and oil as direct raw materials for production for economic efficiency, which directly forces the IGT in the opposite direction (Maboshe et al., 2019). Finally, DIS directly elevates the production costs of enterprises. The rise in production costs inevitably squeezes the profits of enterprises. It is detrimental to the IGT if they need to cancel green investments and research and development of green technologies to maintain their overall profit levels (Qiao et al., 2022). As a result, electricity prices are distorted so that they do not properly reflect the real market demand for electricity, inhibiting IGT and developing hypothesis 1(H1).

H1. Electricity price distortion will inhibit industrial green transformation.

DIS can affect IGT primarily through two mechanisms. First, DIS can significantly facilitate the proportion of fossil energy mix represented by coal and oil and inhibit IGT (Amin et al., 2022). In terms of factor substitution, China still uses thermal power (coal) as the primary source of electricity (Eguchi et al., 2021), and negative DIS will induce massive use of coal and new energy sources, which will consequently influence environmental quality. Negative price distortion will directly constrain the price of coal and other raw materials used in power generation, leading to a pathway of dependence on it, reducing the development and application of green, advanced power generation technologies and the large-scale use of highly polluting raw materials such as coal in power applications, thereby inhibiting power companies' transformation (Xie et al., 2015). Moreover, the negative DIS will mislead residents and corporations to reduce energy conservation awareness and energy-saving behaviour, increasing the use of fossil energy represented by coal and oil, making it difficult for scarce electricity resources to be used effectively at the consumption end (Zhao and You, 2008; Maboshe et al., 2019). The excessive use of thermal power generation, which accounts for a relatively high proportion of electricity resources, will cause an increase in pollutant emissions and inhibit the IGT (Chai et al., 2023). Regarding structural adjustment, when DIS is negatively distorted, some high-energy-consuming industrial enterprises will face lower costs and increased profits, indirectly inducing them to increase production capacity and crowd out low-energy-consuming industrial enterprises (Wang et al., 2023b).

Secondly, DIS can inhibit IGT by dampening R&D input intensity. Given that other factor prices are constant, DIS can produce significant fluctuations in corporate production costs (Lin and Chen, 2019). Following cost-effectiveness theory, DIS can crowd out productive resources, increase production and emissions costs, and reduce corporate technological innovation capacity when costs rise due to external conditions (Tang and Tan, 2013), thus undermining IGT. Meanwhile, green R&D activities in industrial corporations require significant capital investments, long lead times, and high risks (Zhao and Zhang, 2023). However, industrial corporations will curtail innovation in green technologies when the positive benefits of green innovation are not quickly available, i.e. if the increase in electricity prices is lower than the cost of promoting green R&D investments. Meanwhile, the decrease in electricity expenditure due to long-term technological innovation does not necessarily compensate for the R&D investment in innovation activities. This is insufficient to threaten corporate technology innovation costs, and corporations maintain a high energy consumption status quo, which does not provide incentives to increase the intensity of R&D capital investment (Cambini et al., 2016) and has a negative impact on the green transformation of industry. In addition, DIS enables enterprises to obtain production factors at a lower cost and earn excessive profits by expanding production scale and capacity to create a scale effect (Pelz et al., 2022). Profits drive enterprises to reduce R&D inputs, which in turn hinders IGT. Thus, we develop hypothesis 2(H2).

H2. Electricity price distortion can inhibit IGT by reducing R&D input intensity.

We present a diagram showing the relationship between variables to characterize how DIS influence to IGT (Fig. 1).

3. Material and methods

3.1. Theoretical model construction

This study expands the IPAT model following Yin et al. (2022), Nosheen et al. (2021), and Khan (2021) to identify potential determinants of IGT.

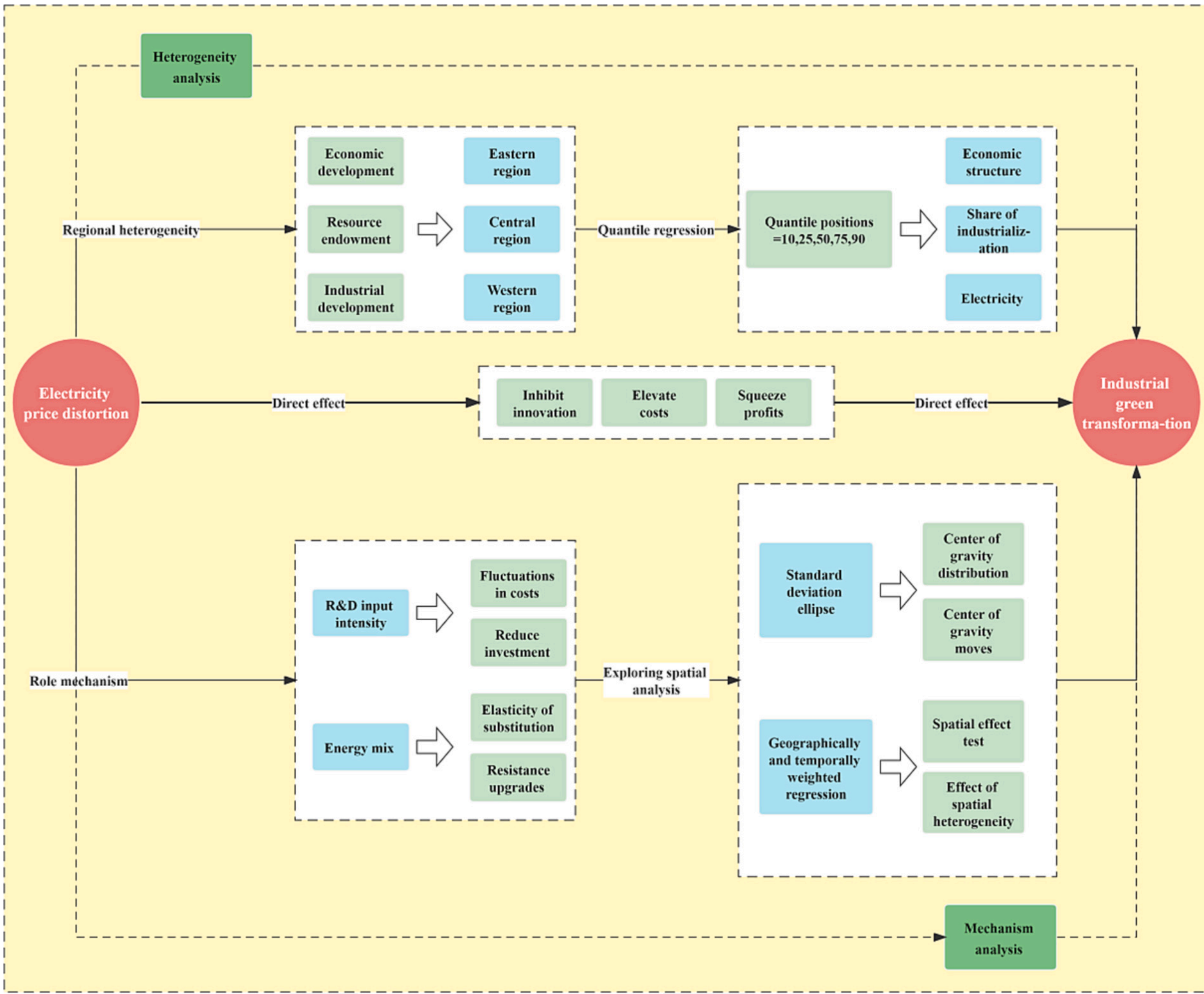

Fig. 1. Relationship between DIS and IGT.

$$I = P \times A \times T \tag{1}$$

IPAT model was proposed in the 1970s by American economists Holdren and Ehrlich (1974). They state that the factors affecting the ecological environment are population, affluence, and technology, i.e., I=PAT. The IPAT model is widely applied to the qualitative or quantitative relationship between environment, population, economy, and technology. Here, we represent the environmental load, energy consumption, environmental impact status, etc. P, A, and T represent population, affluence, and technology levels. The primary purpose of the IPAT model is to identify determinants and analyse the problem by changing one factor while keeping the others fixed. This is one of the critical limitations of the model because it can only obtain an equally proportional effect on the dependent variable. To eliminate the deficiencies of this method, Dietz and Rosa (1997) express the IPAT model in a stochastic form and propose the STIRPAT model. Many studies demonstrate that other factors also have important ecological and environmental effects (Fischer-Kowalski and Amann, 2001; Song et al., 2011). To thoroughly test the impact of DIS on IGT, the STIRPAT model is modified and extended using DIS as the core explanatory variable following Noorpoor and Kudahi (2015) and Li et al. (2020a),. Other influencing factors are incorporated into the model, and the following equation is obtained:

$$IGT = F(DIS, TEO, FIN, URB, HUM, POP) \tag{2}$$

Since industry dominates the national economy, IGT is key to harmonizing environmental protection and economic development. Therefore, this study uses IGT to reflect environmental pressure while population density (POP) and technological output (TEO) and the urbanization ratio (URB) are control variable. Notably, regions with a higher urbanization ratio (URB) are more economically developed and have a higher concentration of wealth. Apart from the indicators included in the basic STIRPAT model, DIS is the core explanatory variable, and the fiscal structure (FIN) and human capital (HUM) are introduced as additional controls. Overall, this paper constructs the following empirical relationship.

$$IGT_{it} = \alpha_0 + \alpha_1 DIS_{it} + \beta_i X_{it} + \mu_i + \sigma_t + \varepsilon_{it} \tag{3}$$

where i denotes region; t denotes time; ε_{it} denotes the random disturbance term; IGT is the dependent variable, denoting industrial green transformation; DIS denotes electricity price distortion; X signifies the control variables explained above and μ_i and σ_t denote individual and time effects, respectively. This paper uses an Ordinary Least Square (OLS) model for primary estimations, however, the endogeneity caused by one or more explanatory variables in the equation may be correlated with a random disturbance term may influence the OLS estimation results. The OLS model with two-way fixed effects eliminates factors that do not vary over time or individually in the panel data model, thereby reducing endogeneity problems (De Chaisemartin and d'Haultfoeuille, 2020).

Eq. (3) determines the direct effect of DIS on IGT. What are the mechanisms through which DIS inhibit IGT? Grossman and Krueger (1995) formulated the theory of environmental quality and economic growth. They argued that industrialization exerts pressure on regional ecosystems through structural and technological effects of industrial activities (Cheng et al., 2018). Therefore, it is essential to understand that the industrial green transition is subject to shocks arising from technology spillover and energy mix effects (Xie et al., 2020; Mao et al., 2019; Zhang et al., 2020). Based on this theory, we quantify the influence mechanism of DIS on IGT through R&D input intensity and energy mix. Following Lin and Tan (2019), this paper constructs the following model:

$$M_{it} = \alpha_0 + \alpha_1 DIS_{it} + \beta_i X_{it} + \mu_i + \sigma_t + \varepsilon_{it} \tag{4}$$

where M is the potential role mechanism of DIS affecting IGT, and the rest of the parameters are as in Eq. (3). Eqs. (3) and (4) jointly verify the mechanism between DIS and IGT.

3.2. Spatial analysis techniques

The standard deviation ellipse (SDE) can accurately identify the spatial clustering and variation of objective things by capturing the spatial characteristics of distribution centres, dispersion trends, and diffusion directions of the elements, and hence is widely applied in spatial distribution statistics (Lefever, 1926; Yuan et al., 2022). The geographically and temporally weighted regression (GTWR) method can characterize the Spatio-temporal heterogeneity of variables by mining the Spatio-temporal dependence of local correlations and non-stationary relationships among variables (Fotheringham et al., 2015; Lotfata, 2022; Naikoo et al., 2022). Thus, considering the possible Spatio-temporal dependence between DIS and IGT, this study uses SDE and GTWR methods to test the spatial heterogeneity between both variables.

3.2.1. Standard deviation ellipse

The SDE method calculates gravity centre, azimuth, major axis, minor axis, area, and other characteristic parameters based on the spatial location and structure of the research object from the global perspective. It quantitatively determines spatial characteristics such as centrality, direction, and element distribution's spatial and temporal evolution processes (Yuan et al., 2022). Among these, the ellipse area reflects the range and change of spatial distribution, the major axis represents the main trend of spatial distribution, the minor axis represents the secondary trend, the ratio of the major axis to the minor axis reflects the spatial shape, and the azimuth reflects the change of main trend direction of spatial distribution (Yang et al., 2022). Since the characteristic covariates calculated by the standard deviation ellipse analysis method quantitatively characterize the directional distribution of IGT, this paper employs SDE to calculate the spatial evolution direction of IGT. The formulas for calculating the centre of gravity, azimuth, principal axis, and auxiliary axis of the ellipse are as follows.

Average centre is given by:

$$\overline{X}_w = \frac{\sum_1^n w_i x_i}{\sum_1^n w_i}, \ \overline{Y}_w = \frac{\sum_1^n w_i y_i}{\sum_1^n w_i} \tag{5}$$

where w_i is weight; $\{\overline{X}_w, \overline{Y}_w\}$ is the average centre (x_i, y_i), and n is the total number of elements.

The rotation angle is calculated by:

$$tan\theta = \frac{A = \left(\sum_{i=1}^n w_i^2 \widetilde{x}_i^2 - \sum_{i=1}^n w_i^2 \widetilde{y}_i^2\right) + B = \sqrt{\left(\sum_{i=1}^n w_i^2 \widetilde{x}_i^2 - \sum_{i=1}^n w_i^2 \widetilde{y}_i^2\right)^2 + 4\left(\sum_{i=1}^n w_i^2 \widetilde{x}_i \widetilde{y}_i\right)^2}}{C = 2\sum_{i=1}^n w_i^2 \widetilde{x}_i \widetilde{y}_i} \tag{6}$$

where $\widetilde{x}_i$ and $\widetilde{y}_i$ are the deviations of the x and y coordinates from the average centre. The standard deviations of the x and y axes, respectively, are:

$$\begin{cases} \sigma_x = \sqrt{\dfrac{\sum_{i=1}^n \left(w_i \widetilde{x}_i cos\theta - w_i \widetilde{y}_i sin\theta\right)^2}{\sum_{i=1}^n w_i^2}} \\ \sigma_y = \sqrt{\dfrac{\sum_{i=1}^n \left(w_i \widetilde{x}_i sin\theta - w_i \widetilde{y}_i cos\theta\right)^2}{\sum_{i=1}^n w_i^2}} \end{cases} \tag{7}$$

The equation of the ellipse is:

$$\left(\frac{x}{\sigma_x}\right)^2 + \left(\frac{y}{\sigma_y}\right)^2 = s \tag{8}$$

where w_i is the target variable, (x_i, y_i) are the relative coordinates of each point from the center of gravity of the study area; the azimuth angle is obtained according to tanθ; σ_x and σ_y are the standard deviations of the X-axis (short axis) and Y-axis (long axis), respectively, and S is the confidence level.

3.2.2. Geographically and temporally weighted regression

Geographically weighted regression (GWR) extends the general regression model. The major difference between the two is that GWR considers the influence of geospatial factors (Du et al., 2018). The regression coefficients of the variables vary with geographic location, and thus each sample point has a series of regression coefficients of local variables (Brunsdon et al., 1998). The basic equation of the geographically weighted regression model is:

$$y_i = \beta_0(u_i, v_i) + \sum_{k=1}^p \beta_k(u_i, v_i)X_{ik} + \varepsilon_i \ i = 1, 2, \cdots, n \tag{9}$$

where (u_i, v_i) is the coordinate of the i_{th} sample point; X_{ik} is the k_{th} explanatory variable for the i_{th} sample point; and the regression coefficient $\beta_k(u_i, v_i)$ is a function of the geographical coordinates (u, v). For convenience of presentation, the equation is simplified to:

$$y_i = \beta_{i0} + \sum_{k=1}^p \beta_{ik} X_{ik} + \varepsilon_i \ i = 1, 2, \cdots, n \tag{10}$$

The GWR method solves the spatial non-smoothness problem, but ignores the temporal effects of the model (Naikoo et al., 2022; Ma et al., 2018). According to Huang et al. (2010), the temporal dimension is introduced into the GWR model, and the original geospatial coordinates are combined with the temporal to construct the spatio-temporal three-dimensional coordinates (u_i, v_i, t_i). The model is set as follows:

$$y_i = \beta_{i0}(u_i, v_i, t_i) + \sum_{k=1}^p \beta_k(u_i, v_i, t_i)X_{ik} + \varepsilon_i \ i = 1, 2, \cdots, n \tag{11}$$

The core of GTWR is the spatio-temporal weight matrix, which necessitates the selection of different spatio-temporal weight functions to denote the spatio-temporal association of the data. The spatio-temporal distance $\left(d_{ij}^{st}\right)$ is:

$$d_{ij}^{ST}=\sqrt{a\left[\left(u_i-u_j\right)^2+\left(v_i-v_j\right)^2\right]+\beta\left(t_i-t_j\right)^2} \tag{12}$$

The spatio-temporal weight function takes the form:

$$w_{ij}^{ST}=exp\left\{-\left(\frac{a\left[\left(u_i-u_j\right)^2+\left(v_i-v_j\right)^2\right]+\beta\left(t_i-t_j\right)^2}{b_{ST}^2}\right)\right\} \tag{13}$$

where (u_i, v_i, t_i) are the latitude, longitude, and time of each region, b_{st} is the bandwidth of the spatio-temporal weight function, and the optimal bandwidth is verified by crossover.

3.3. Variable definition

3.3.1. Dependent variable

The Super-SBM model, including desired and undesired outputs, is used to calculate IGT (Yang et al., 2023b). The Super-SBM model is a non-parametric method, reflecting the IGT level in each region more comprehensively and reasonably than the traditional Solow residual or stochastic frontier method of estimating total factor productivity. The specific measurement process is as follows:

$$IGT=min\frac{1+(1/m)\sum_{i=1}^{m}\left(S_i^-/X_{i0}\right)}{1-(1/S)\sum_{r-1}^{s}\left(S_r^+/Y_{r0}\right)} \tag{14}$$

$$\begin{cases} X_{i0}\geq\sum_{j=1,j\neq0}^{n}X_{ij}\lambda_j-S^-;\, Y_0\leq\sum_{j=1,j\neq0}^{n}Y_{ij}\lambda_j+S^+ \\ \sum_{j=1}^{n}\lambda_j=1;\lambda_j\geq0 \\ i=1,2,\cdots m;j=1,2,\cdots n; \\ r=1,2,\cdots s;X_{ij}\geq0;Y_{ij}\geq0 \end{cases} \tag{15}$$

where, X_{ij} denotes the i_{th} factor input quantity of j regions; Y_{ij} denotes the i_{th} factor output quantity of j regions; m denotes the prior input; s is the desired and undesired output; S^- and S^+ are the slack variables; and λ_j is the weighting coefficient. An efficiency value of IGT higher than 1 indicates that it is in a relatively effective state, otherwise, it is in an ineffective state. The input and output indicators of IGTare shown in Table 1.

3.3.2. Core explanatory variable

Electricity price distortion (DIS) is a way to measure the deviation of factor market prices from their opportunity costs. Major common measures of factor price distortions include cost (production) functions, stochastic frontier analysis (SFA), data envelopment analysis (DEA), shadow prices, and computable general equilibrium methods. Specifically, SFA and DEA are based on the principle of characterizing price distortions by calculating the distance between the actual production point and the optimal production point, which leads to the degree of technological distortion and the degree of allocation distortion (Zhao et al., 2022). The disadvantage of stochastic frontier and data envelopment analysis is that they cannot quantify absolute factor distortions. The computable general equilibrium method usually incorporates factor price distortions into a system characterized by large samples and complex calculations (Wang et al., 2022a). The production function approach describes factor price distortions by calculating the ratio of marginal output to real prices of factors. Specifically, the marginal output of electricity to the economy is estimated based on the regression results of the production function, which is used as a reference for the optimal price of electricity and energy (Ai et al., 2020). Then, by comparing the actual price of a factor of production with its marginal production return, the degree of price distortion of that factor is determined based on the commonly used marginal rule (Shi and Sun, 2017). Following Yang et al. (2022) and Wu et al. (2023), this study constructs a C-D function with constant returns to scale to measure DIS:

$$Y_{it}=AK_{it}^{\beta_{Ki}}L_{it}^{\beta_{Li}}E_{it}^{\beta_{Ei}} \tag{16}$$

where Y_{it}, E_{it}, K_{it}, and L_{it} denote GDP, electricity consumption, capital, and labour, respectively; and β_{Ki}, β_{Ei}, and β_{Li} are the elasticity coefficients of capital, electricity consumption, and labour, respectively. GDP is calculated using constant 2006 prices. The perpetual inventory method uses the capital stock to represent the amount of capital input. The calculation formula is: $K_{it}=I_{it}/P_{it}+(1-\delta)K_{it-1}$, where K_{it}, I_{it} and P_{it} are the fixed capital stock, total nominal fixed capital formation, and fixed asset investment price index in time t of province i, respectively; and δ denotes the depreciation rate. Both δ and the base period fixed capital stock K_{2006} are determined by referring to Yang et al. (2022) , in which the depreciation rate is set to 9.6% and converted to the 2006 base period using the regional GDP deflator. The average number of employees at the end of the year reflects labour. Electricity consumption indicators are characterized using social electricity consumption.

To yield the marginal effects of each factor, let $\beta_{Ki}+\beta_{Ei}+\beta_{Li}=1$. Dividing both sides by L_{it}, taking the logarithm, and introducing the individual effect i, the time effect t, and the random disturbance term ε_{it}, we obtain the electricity output elasticity β_{Ei} of province i:

$$ln\left(\frac{Y_{it}}{L_{it}}\right)=\ln A+\beta_{Ki}ln\left(\frac{K_{it}}{L_{it}}\right)+\beta_{Ei}ln\left(\frac{E_{it}}{L_{it}}\right)+\mu_i+\lambda_t+\varepsilon_{it} \tag{17}$$

By regressing this equation, the values of β_{Ei} and can be calculated. As a result, the marginal output MP(t) of electricity price can be expressed as:

$$MP_{it}=\beta_{Ei}AK_{it}^{\beta_{Ki}}L_{it}^{\beta_{Li}}E_{it}^{\beta_{Ei}-1}=\beta_{Ei}\frac{Y_{it}}{E_{it}} \tag{18}$$

Lastly, the degree of electricity price distortion (DIS_{it}) can be calculated for each province over the years:

$$DIS_{it}=(PE_{it}-MP_{it})/MP_{it} \tag{19}$$

where PE_{it} is actual electricity price; MP_{it} is marginal production return; and DIS_{it} implies that production units lower their demand for electricity and switch to relying on other production sources such as capital and labour, and electricity prices are negatively distorted. If the real average electricity sales price is greater than the marginal return to electricity production, electricity prices are positively distorted. To reflect the real situation of electricity price distortion, we take the absolute value of DIS_{it}.

3.3.3. Mechanism variables

This study investigates the mechanism of DIS on IGT from the

Table 1
Industrial green transformation measurement system.

Variable name	Variable symbol	Variable definition
Output	Desired output	Gross industrial product (deflated by the industrial output price index and taking 2006 as the base period)
	Undesired output	Selected industrial wastewater, industrial sulphur dioxide, industrial solid waste, and industrial carbon emissions
Capital input	K	Net investment in fixed assets of industrial enterprises (deflated by the price of investment in fixed assets and taking 2006 as the base period)
Labour input	L	The average number of employees in industrial enterprises
Energy input	E	Consumption of raw coal, coke, crude oil, gasoline, kerosene, diesel, fuel oil, and natural gas

perspectives of technology spillover and structure effects. The mechanism test employs R&D input intensity and energy mix effects as technology spillover effect and structure effect proxy variables, respectively. The R&D investment intensity is expressed as the share of R&D expenditure in GDP. The energy mix has denoted the proportion of coal consumption to total energy consumption.

3.3.4. Control variables

The following control variables are selected to eliminate the effect of other factors on the regression analysis: fiscal structure, urbanization ratio, human capital, population density, and technological inputs. Public spending favours environmental goods, and financial support encouraging enterprises to undergo technological innovation can positively influence IGT. Fiscal structure (FIN) is characterized using the ratio of local fiscal expenditure to local fiscal revenue. Urbanization expansion requires large amounts of resources and energy, while how resources and energy are processed directly determine the IGT level. The urbanization ratio (URB) is characterized by the ratio of the resident population to the total population (Wu et al., 2019). A good human capital structure provides industrial enterprises with continuous talent (Tong et al., 2020). Human capital (HUM) is characterized by years of education per capita. With population growth, the demand for industrial products grows, influencing IGT (Wang et al., 2021). Population density (POP) is characterized by the ratio of the total population to the jurisdiction area. Technological output (TEO) directly reflects the technological innovation activity from R&D to application and the ability to apply mature technology to industrial production. Following Wang and Yi (2022), technological output (TEO) is expressed using technology market turnover.

3.4. Data

This paper selects 30 provincial-level administrative regions in China from 2006 to 2019 as a research sample to test the impact of electricity price distortion on IGT.

Among the variables, electricity price data are collected from the Annual Electricity Price Implementation Supervision Report and Electricity Price Situation Supervision Circular issued by the State Electricity Regulatory Commission and the National Energy Administration. Since the electricity supply in Hebei Province is divided into the northern and southern networks, and the electricity supply in Inner Mongolia Autonomous Region is divided into the eastern and western networks with different grid operations, the electricity-related data of these two provinces are replaced by the average value taken from the data of the two major power grids in each province. The rest of the data are from the China Industrial Statistical Yearbook, various local statistical bureaus, and the EPS database. Some missing data are replaced by the moving average method and interpolation method. Table 2 shows descriptive statistics. To avoid disturbance of the results by multicollinearity among the variables, this study tested for multicollinearity and correlation coefficient among the variables. Tables 3 and 4 report that the DIS negatively correlate with IGT, and the values of variance inflation factors for all variables are <10, indicating an acceptable level of multicollinearity.

Table 2
Descriptive statistics.

Variable	Obs	Mean	Std Dev	Min	Max
IGT	420	0.436	0.241	0.176	1.315
DIS	420	0.275	1.697	−5.675	4.54
FIN	420	0.037	0.016	0.012	0.119
HUM	420	8.868	0.991	6.59	12.78
TEO	420	4.105	1.857	−0.635	8.647
POP	420	5.464	1.265	2.036	8.256
URB	420	54.646	13.584	27.49	89.6
RD	420	1.505	1.087	0.2	6.31
ENE	420	0.424	0.154	0.012	0.748

4. Results and discussion

4.1. Baseline regression results and discussion

Based on the benchmark model above, this paper conducts a preliminary investigation of the impact of DIS on IGT. Table 5 presents the results of the OLS model based on individual and time-fixed effects. Control variables are continuously added in step-wise regression to ensure the rigor and consistency of the estimation results. With the addition of control variables, the coefficient of DIS remains consistent with values of −0.064 to −0.057 (p-value <0.01), indicating that the influence of DIS on IGT always presents an inhibitory effect. It confirms the Hypothesis. When DIS increases by 1%, IGT decreases by 0.057%. Our investigation supports the findings of Ai et al. (2020), Wang et al. (2022b) and Sha et al. (2022). Ai et al. (2020) argue that DIS inhibits enterprise technological innovation, negatively impedes IGT. Wang et al. (2022a) suggest that energy price distortion negatively affects the energy efficiency of energy-intensive industries, with heterogeneous characteristics across cities. Sha et al. (2022) arrive at a similar finding, arguing that energy price distortion is a key factor contributing to increased carbon emissions and slowing economic growth. As the degree of DIS rises, enterprises seek primary energy sources such as coal and oil for economic benefits, directly forcing IGT in the reverse direction (Li et al., 2022c). DIS directly elevates enterprise production costs. Inevitably, production cost hikes squeeze enterprise profits, which may require reducing green investments to preserve overall profit.

4.2. Mechanism results and discussion

Table 6 shows the estimated results for the role mechanism of DIS on IGT using the OLS model with time and individual effects fixed. Columns 1 and 2 of Table 6 suggest that DIS can significantly inhibit R&D input intensity, affecting IGT. It is not difficult to understand that DIS causes enterprises to produce huge fluctuations in production costs if other factor prices are constant. In contrast, enterprises conducting R&D activities require large capital investment and have long and risky cycles (Zhao and Zhang, 2023). Reducing electricity expenditure for technological innovation may not necessarily cover the R&D investment in innovation activities. If the increase in electricity prices is less than the cost to enterprises promoting green R&D investments, they cut back on R&D investment in green technologies (Lin and Chen, 2019). This is not enough to threaten the cost of technological innovation, and enterprises maintain the high energy consumption status quo (Sha et al., 2021), which does not motivate them to increase the intensity of R&D capital investment and adversely affects IGT. In addition, the DIS enables enterprises to secure production factors at a lower cost to earn excessive profits. Profits driven enterprises reduce investment in R&D, which hinders IGT (Zhang et al., 2022).

Columns 2 and 3 of Table 6 suggest that DIS can significantly promote energy mix, affecting IGT. DIS brings about price differences within the energy factor, which gives the consumption of electricity and other energy sources the elasticity of substitution (Gracia et al., 2012). Compared to coal, oil, and other highly polluting energy sources, the price of secondary energy represented by electricity lacks a price advantage, and the energy consumption mix has changed (Hosseini and Abdul Wahid, 2014). DIS hinders energy mix upgrading. At the micro level, it leads enterprises to opt for cheaper energy, often low in heat or high in pollution. Enterprises invest in equipment based on current energy prices, resulting in a continuum of energy consumption (Jamil and Ahmad, 2010). Enterprises weigh re-investment in equipment or continued use of non-clean energy sources, making future energy mix upgrades subject to greater resistance, thus hindering IGT (Zhu et al., 2020). Thus, DIS can inhibit the IGT by promoting the energy mix. It validates the Hypothesis 2.

Table 3
Correlation coefficient of each variable.

	IGT	DIS	FIN	HUM	TEO	POP	URB
IGT	1						
DIS	−0.056	1					
FIN	0.161***	−0.086*	1				
HUM	0.120**	−0.241***	0.363***	1			
TEO	0.006	−0.428***	0.439***	0.626***	1		
POP	0.205***	−0.291***	0.315***	0.489***	0.525***	1	
URB	0.188***	−0.231***	0.462***	0.874***	0.661***	0.553***	1

* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

Table 4
Multicollinearity test results.

Test	DIS	FIN	HUM	TEO	POP	URB	Mean VIF
VIF	1.27	1.36	4.39	2.30	1.57	5.24	2.69

4.3. Robustness and endogeneity

Several checks are implemented to confirm the robustness and endogeneity of the estimated results, i.e., whether DIS manifests significant dampening effects on IGT.

Firstly, to verify the existence of within-group correlation causing biased results, we re-regress the results using clustering robust standard errors ((See column 1 of Table 7). Secondly, considering the potential endogeneity of the OLS model, the baseline regression model is re-estimated using two-stage least squares (TSLS) (See columns 2 of Table 7). This study constructs instrumental variables based on the historical case of DIS. Regarding China's electricity reform process, thermal power generation is the main form of electricity production in China. The previous thermal power generation in each region can reflect the development of DIS to a certain extent. However, with the diversification of the forms of power generation in China and the gradual development of renewable energy sources etc., the reliance on thermal power generation has gradually decreased. Therefore, this study suggests that thermal power generation in 1997 may be an appropriate instrumental variable. Since this data is cross-sectional, it cannot be used directly as an instrumental variable.

This study considers the lagged 2-period of coal consumption (considering that thermal power generation mainly uses coal as the major source) as a relevant time trend, and multiplies it by the thermal power generation in 1997 to obtain an instrumental variable in the form of a panel. Bootstrap sampling simulates only a relatively accurate result for quantifying the uncertainty associated with the estimates. The bootstrap sampling technique forms a different data set by repeatedly taking samples from the original data set and returning them to converge as closely as possible to a normal distribution. The bootstrap sampling method is used to re-estimate the baseline regression results' standard errors and confidence intervals (See column 3 of Table 7). Lastly, the System generalized method of moments (SYS-GMM) can

Table 6
Mechanism results.

Variable	(1)	(2)	(3)
	IGT	RD	ENE
DIS	−0.057***	−0.105***	0.024***
	(0.010)	(0.019)	(0.005)
FIN	2.791***	7.941***	−0.489**
	(0.484)	(0.919)	(0.226)
HUM	0.087***	0.002	0.005
	(0.027)	(0.051)	(0.013)
TEO	−0.002	−0.049***	−0.002
	(0.009)	(0.017)	(0.004)
POP	0.026	1.220***	−0.174**
	(0.145)	(0.275)	(0.068)
URB	−0.019***	−0.007	−0.004***
	(0.002)	(0.005)	(0.001)
_cons	1.315	−2.916	1.796***
	(1.126)	(2.139)	(0.527)
Individual effect	YES	YES	YES
Time effect	YES	YES	YES
N	420	420	420
R^2	0.875	0.978	0.934

Table 5
Benchmark regression results and discussion.

Variable	(1)	(2)	(3)	(4)	(5)	(6)
DIS	−0.061***	−0.064***	−0.063***	−0.064***	−0.061***	−0.057***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.010)
FIN		1.992***	2.026***	2.355***	2.273***	2.791***
		(0.505)	(0.503)	(0.519)	(0.516)	(0.484)
HUM			0.060**	0.059**	0.060**	0.087***
			(0.029)	(0.029)	(0.029)	(0.027)
TEO				−0.022**	−0.017*	−0.002
				(0.009)	(0.010)	(0.009)
POP					0.386***	0.026
					(0.148)	(0.145)
URB						−0.019***
						(0.002)
_cons	1.091***	0.966***	0.306	0.433	−2.320**	1.315
	(0.032)	(0.045)	(0.328)	(0.331)	(1.105)	(1.126)
Individual effect	YES	YES	YES	YES	YES	YES
Time effect	YES	YES	YES	YES	YES	YES
N	420	420	420	420	420	420
R^2	0.844	0.850	0.851	0.853	0.855	0.875

Note: Standard errors in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ (as below).

Table 7
Robustness check result.

Variable	(1) Clustering robust standard error	(2) TSLS	(3) Bootstrap sampling	(4) SYS-GMM	(5) Driscoll -Kraay standard error
L.IGT				0.9092***	
				(0.064)	
DIS	−0.0575**	−0.0762**	−0.0575***	−0.0697**	−0.0575***
	(0.024)	(0.034)	(0.017)	(0.031)	(0.011)
Other variables	YES	YES	YES	YES	YES
Individual effect	YES	YES	YES	YES	YES
Time effect	YES	YES	YES	YES	YES
AR(2)				1.22	
				[0.222]	
Hansen test				7.68	
				[1.000]	
N	420	360	420		420
r2_a	0.890	0.859	0.875		0.890

Note: “[]” denotes the *P* value. The other contents are characterized as in Table 5. Underidentification, Weak identification, and Sargan statistic tests validated the instrumental variables.

correct for unobserved individual heterogeneity issues, omitted variable bias, measurement error, and potential endogeneity issues that often affect estimation results when OLS models are used (Luo et al., 2022). The SYS-GMM method reduces the potential bias and imprecision due to using first-order difference GMM estimation methods. To minimize endogeneity, following Zhao et al. (2023) and Pan et al. (2023), SYS-GMM is employed to explore the effect of DIS on IGT (See column 4 of Table 7). Lastly, to address the endogeneity problems caused by heteroskedasticity, autocorrelation and cross-sectional correlation, following Ramzan et al. (2023), Driscoll-Kraay standard error is employed to explore the effect of DIS on IGT (See column 5 of Table 7). The subsample statistics are compared to the statistics of the total sample to verify the robustness (see Table 7). Table 7 shows that the directionality and significance of the core explanatory variables remain consistent with Table 5 after re-estimating the results using the clustering robust standard errors, TSLS, and bootstrap sampling method, SYS-GMM, and Driscoll -Kraay standard error, i.e., the empirical results are robust.

4.4. Heterogeneity results and discussion

4.4.1. Regional heterogeneity

Due to resource endowment and geographical conditions, industrial development level, electricity price control, and economic development mode among various regions in China may lead to the distinct influence of regressors. Following Yue and Zhang (2022), this paper divides the sample into eastern, central, and western regions to examine the heterogeneous effects of DIS on IGT (see Table 8).

Table 8
Regional heterogeneity results.

Variable	(9) Eastern	(10) Central	(11) Western
FIN	2.820***	2.794***	2.566***
	(0.468)	(0.496)	(0.504)
HUM	0.084***	0.095***	0.093***
	(0.026)	(0.028)	(0.028)
TEO	−0.001	−0.000	0.002
	(0.009)	(0.009)	(0.009)
POP	0.225	−0.039	0.095
	(0.141)	(0.151)	(0.151)
URB	−0.008***	−0.022***	−0.020***
	(0.003)	(0.003)	(0.003)
DIS	−0.176***		
	(0.022)		
DIS		−0.071***	
		(0.018)	
DIS			−0.006
			(0.015)
_cons	−1.049	1.949*	0.879
	(1.190)	(1.236)	(1.231)
Individual effect	YES	YES	YES
Time effect	YES	YES	YES
N	420	420	420
R^2	0.883	0.870	0.864

Table 8 shows that the coefficient of DIS is negative (significant) in the eastern and central regions, i.e., it significantly inhibits IGT in this region, while it is negative (insignificant) in the central and western regions. Moreover, this paper finds that the absolute value of DIS is in order from high to low: eastern, central, and western. One interesting explanation is that the eastern region is highly market-oriented, where industrial enterprises are directly exposed to the moderation of market institutions and their behaviour reacts quickly to electricity price fluctuations (Liu et al., 2013). Enterprises seek primary energy sources such as coal and oil when DIS is higher for economic benefit. Moreover, a higher DIS has a stronger crowding-out effect on enterprises' green investment, inhibiting IGT. The eastern and central regions have more high-pollution and high-energy-consumption industrial companies since they are home to heavy industries (Sha et al., 2021). As a result, the slow speed and process of industrial upgrading and energy-saving transformation, the high cost of IGT, and the distortion of electricity prices hinder the green transformation of polluting industries by adversely affecting the financing and management costs of enterprises (Xin-gang and Shu-ran, 2020). Compared to the eastern and central regions, the marketization of the economy in the western region is relatively weak, and the role of the government's visible hand is stronger, which is responsible for low DIS, and the inhibiting effect is not significant (Ai et al., 2020). There are fewer high-polluting and heavy industries in the western regions, the resistance to the green transformation of enterprises is smaller, and their response to DIS is also lower; thus, the inhibitory effect is relatively weak (Xie et al., 2015).

4.4.2. Industrial green transformation level heterogeneity

This paper introduces quantile regression models to verify the two relationships at different conditional quantiles of the explanatory variables to investigate whether DIS has a long-tail effect on IGT. The quantile regression model comprehensively carves out the effect of independent variables on the dependent variable distribution's location, scale, and shape. Table 9 presents the model estimation results at five quantiles: 10, 25, 50, 75, and 90. Table 9 confirms that the coefficient signs of DIS are largely consistent with Eq. (3), indicating that the regression results of Eq. (1) have high credibility and that DIS can inhibit IGT. Specifically, the coefficients of DIS at the five quantile positions 10, 25, 50, 75, and 90 are −0.024, −0.029, −0.042, −0.062, and − 0.071, respectively, indicating that DIS has an inhibitory effect at different stages of IGT. At higher quantiles, the inhibition of IGT by DIS generally follows an upward trend, with the highest coefficient value and the

Table 9
Quantile regression results.

Variable	(1)	(2)	(3)	(4)	(5)
	Q = 10	Q = 25	Q = 50	Q = 75	Q = 90
DIS	−0.024***	−0.029***	−0.042***	−0.062***	−0.071***
	(0.009)	(0.007)	(0.010)	(0.011)	(0.018)
FIN	0.806*	1.294***	2.047***	2.282***	1.263
	(0.429)	(0.337)	(0.496)	(0.559)	(0.915)
HUM	0.067***	0.076***	0.086***	0.058*	0.041
	(0.024)	(0.019)	(0.028)	(0.031)	(0.051)
TEO	0.003	0.004	0.002	0.003	0.001
	(0.008)	(0.006)	(0.009)	(0.011)	(0.017)
POP	0.370***	0.345***	0.176	−0.002	−0.195
	(0.128)	(0.101)	(0.148)	(0.167)	(0.274)
URB	−0.008***	−0.009***	−0.010***	−0.014***	−0.015***
	(0.002)	(0.002)	(0.003)	(0.003)	(0.005)
_cons	−1.751*	−1.641**	−0.395	1.434	3.237
	(0.999)	(0.784)	(1.155)	(1.301)	(2.129)
Individual effect	YES	YES	YES	YES	YES
Time effect	YES	YES	YES	YES	YES
N	420	420	420	420	420

strongest marginal contribution at the 90 quantiles. Because regions with a high level of IGT usually have more reasonable economic structures and higher shares of industrialization (Li et al., 2022a).

On the contrary, regions that experience higher levels of IGT are generally poorer in power resources and experience higher electricity demand, which results in an inverse relationship between power resources and industrial green development levels (Maboshe et al., 2019). Consequently, electricity prices are usually higher in regions with high IGT. Higher electricity prices increase energy costs, squeeze out enterprises' profits (compliance cost effect), shatter the original cost minimization constraints, and compel enterprises to make new production decisions, thus causing a reduction in enterprise output (Lin and Chen, 2019). This is consistent with the national situation in China in recent years, in which energy costs have risen in regions with high levels of IGT, high electricity prices, and frequent electricity curtailment.

4.5. Further analysis: spatial characteristics

This paper adopts the SDE method for additional exploration to explore the shift of IGT and its spatial distribution. Table 10 and Fig. 3 display that the gravity centre of IGT over the past 14 years is distributed between 111° 24′ 54.392“ - 113° 33′ 46.661” E, and 32° 14′ 49.528“ N - 33° 53′ 6.773” N, located to the southeast of the geometric centre of China, indicating that IGT is more successful in the eastern and southern regions. Judging from factors such as economic level and population concentration, the south-eastern region has higher economic development. Rapid economic development has been accompanied by the migration and iterative upgrading of massive industries, thus promoting the IGT level. Fig. 2 demonstrates that the spatial dynamic migration trajectory of the gravity centre of IGT moves to the southwest from 2006 to 2007, continues to move eastward in 2007, and then gradually moves northward. Overall, the centre of gravity of IGT shows a southwest-northeast-southeast directional migration. From 2006 to 2019, the ellipse and azimuth of IGT varied significantly, in the range of 8.862°-32.854°. The gravity centre of IGT is distributed at the junction of Henan and Hubei. Between 2006 and 2019, the location of the gravity centre changes by 19.340 km. Judging from the long and short semi-axes of the ellipse, the short semi-axis decreases over time, while the long semi-axis shows a significant trend of first increasing and then decreasing. It implies that the IGT gradually develops from discrete to concentrated.

Before using the GTWR model, the variables need to be standardized. We use ArcGIS 10.8 software to perform the GTWR technique on the impact of DIS on IGT. Table 11 presents the minimum, lower quantile, median, upper quantile, and maximum values of the estimated results for descriptive statistics and each test. The effect of DIS on IGT manifests variously, with the minimum value of the coefficient of DIS being −1.311 and the maximum value being 0.062, which indicates that DIS has both positive and negative effects on IGT in different regions in different periods.

Fig. 3 illustrates the effects of DIS on IGT based on the GTWR findings. It shows that DIS inhibits IGT in most regions, 66.7% of the total sample in this case. These regions are mainly concentrated in the east and northwest, and the most significant inhibitory effects are in Fujian, Anhui, Shaanxi, Zhejiang, and Yunnan regions. Firstly, the rapid

Table 10
IGT shift results 2006–2019.

	Centre of gravity attribute				Standard deviation ellipse attribute				
Year	Longitude	Latitude	Travel direction	Distance (km)	Area (km^2)	Short half-axis	Long half-axis	Rotation (°)	Shape index
2006	112° 7′ 32.898″ E	33° 53′ 6.773” N	–	–	3,768,108	1021.65	1174.07	32.85427	0.129821
2007	111° 24′ 54.392″ E	32° 7′ 56.394” N	Southwest	20.813	4,197,001	1046.499	1276.656	8.862078	0.180281
2008	111° 45′ 59.396″ E	32° 29′ 41.576” N	Northeast	16.020	4,032,083	1030.658	1245.341	12.03968	0.172389
2009	111° 47′ 54.355″ E	32° 26′ 12.425” N	Southeast	16.606	3,992,064	1021.591	1243.924	11.75474	0.178735
2010	112° 1′ 23.555″ E	32° 27′ 43.449” N	Northeast	16.075	3,883,817	1000.095	1236.207	12.88657	0.190997
2011	112° 13′ 6.397″ E	32° 23′ 47.095” N	Southeast	16.808	3,791,182	986.7071	1223.095	12.49542	0.19327
2012	112° 23′ 5.264″ E	32° 21′ 58.884” N	Southeast	17.290	3,721,215	973.5274	1216.775	12.86534	0.199912
2013	112° 30′ 10.546″ E	32° 21′ 30.418” N	Southeast	17.559	3,619,803	958.0592	1202.725	13.45182	0.203426
2014	112° 45′ 3.772″ E	32° 34′ 14.292” N	Northeast	15.893	3,466,924	939.5592	1174.611	15.1585	0.20011
2015	112° 51′ 1.978″ E	32° 21′ 47.272” N	Southeast	18.406	3,413,146	929.2641	1169.202	14.32173	0.205215
2016	112° 59′ 30.955″ E	32° 14′ 49.528” N	Southeast	20.109	3,378,543	915.4223	1174.849	14.60872	0.220817
2017	113° 8′ 12.029″ E	32° 22′ 48.658” N	Northeast	19.340	3,320,541	886.9899	1191.696	15.41953	0.255691
2018	113° 30′ 58.760″ E	32° 32′ 25.371” N	Northeast	19.812	3,353,443	894.6762	1193.164	18.22239	0.250165
2019	113° 33′ 46.661″ E	32° 20′ 43.217” N	Southeast	21.806	3,267,666	899.0446	1156.993	17.5294	0.222947

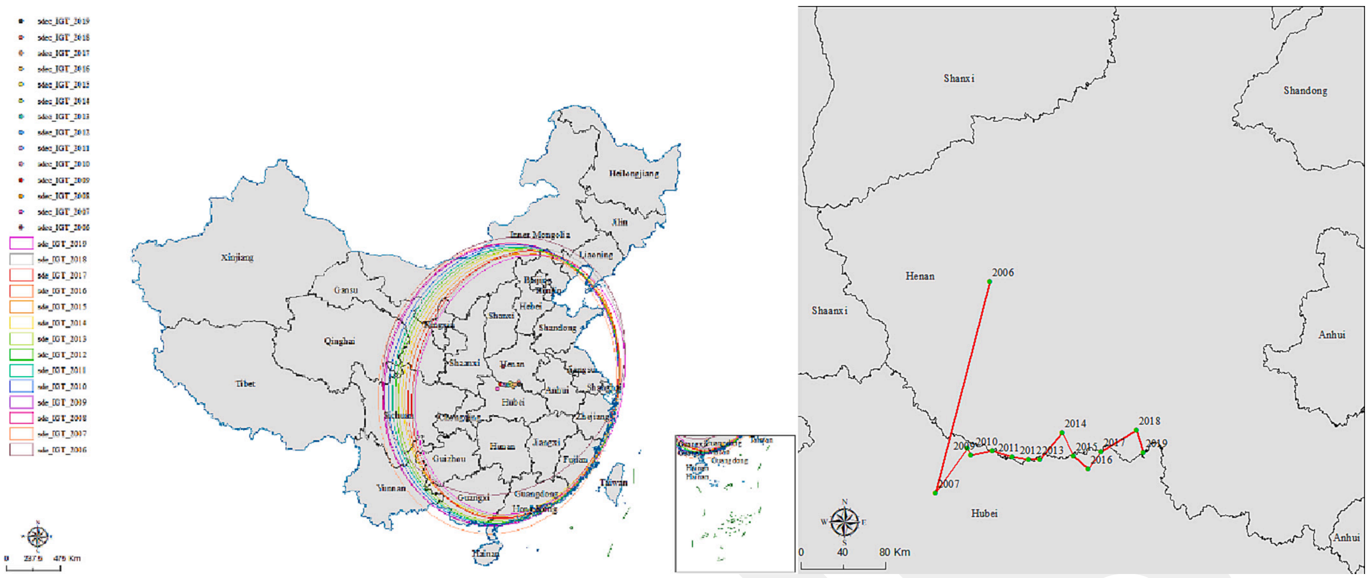

Fig. 2. SDE and centre of gravity shift of IGT.

Table 11
GTWR model estimation results.

Variable	Minimum value	Lower quantile value	Median value	Upper quantile value	Maximum value
DIS	−1.311	−0.008	−0.002	0.005	0.062
FIN	−9.217	−0.985	0.887	1.766	13.674
HUM	−1.035	−0.042	−0.024	−0.003	0.105
TEO	−0.281	−0.067	−0.038	0.002	0.090
POP	−1.471	−0.004	0.005	0.026	0.136
URB	−0.144	0.005	0.008	0.013	0.031
Bandwidth	0.114299				
Sigma	0.144794				
Residual squares	8.80541				
AICc	−228.288				
R^2	0.638044				
Adjusted R^2	0.632785				
Spatio-temporal Distance Ratio	1.87163				

economic development in the eastern region, with strong enterprise production and higher electricity demand but relatively poor resource reserves, means the eastern region must rely heavily on power input from outside, increasing the price of electricity and increasing the energy cost for enterprises. This squeezes profit margins and reduces corporate investment in green technology and innovation, which is detrimental to IGT. Secondly, the northwest and southwest regions have abundant resources and energy.

The newly installed capacity for new energy in the west accounts for more than half the country's total installed capacity. Qinghai, Xinjiang, Gansu, and other western regions have hundreds of millions of kilowatts of grade scenery resources available for development and utilization. Rich power reserves make the power factor prices seriously undervalued. The lower factor price makes the region easily kidnapped by the factor market in the short term and susceptible to the vicious circle of the resource curse. Local governments are less willing to achieve sustainable economic growth by promoting industrial structure upgrading, and enterprises are less motivated to gain a competitive advantage by increasing R&D investment in frontier core technologies, which is not conducive to IGT.

5. Conclusions and policy recommendations

This paper initially examines the impact of DIS on IGT, then empirically investigates its heterogeneous effect using a sample of 30 Chinese provincial-level administrative regions from 2006 to 2019. Moreover, it analyses the intrinsic mechanism between DIS and IGT based on economic development, R&D input intensity, and energy mix. Secondly, a spatial analysis technique inspects the spatial correlation between DIS and IGT. The research finds that DIS on IGT presents an inhibitory effect, i.e., if DIS increases by 1%, IGT decreases by 0.051%. The heterogeneity results indicate that DIS significantly reduces IGT in the eastern and central regions, while it is negative (insignificant) in the central and western regions. DIS inhibits the effect at various stages of IGT, while the inhibition effect generally follows an upward trend when moving to higher quantiles. DIS significantly inhibits R&D input intensity and promotes a coal-based energy mix, inhibiting IGT. Lastly, the gravity centre of IGT gradually shifts to the southeast over time with a tendency for clustering, while the impact of DIS on IGT has prominent individual spatial heterogeneity characteristics.

These findings recommend few policy recommendations. Firstly, policymakers would adequately consider the electricity price-setting system and eliminate DIS when reforming industrial electricity sector affordability. Meanwhile, it is necessary to note that the rising cost of electricity may pressure industries to operate and reduce their profits. To alleviate the burden on industries, policymakers should promote the establishment of electricity spot markets, expand the participation of direct electricity trading market participants and power capacity, institute market-oriented reforms in the industrial electricity security guarantee mechanism, and steer clear of a reform that may appear market-oriented in name but lacks true market orientation.

Policymakers would optimize the spatial layout of electrical

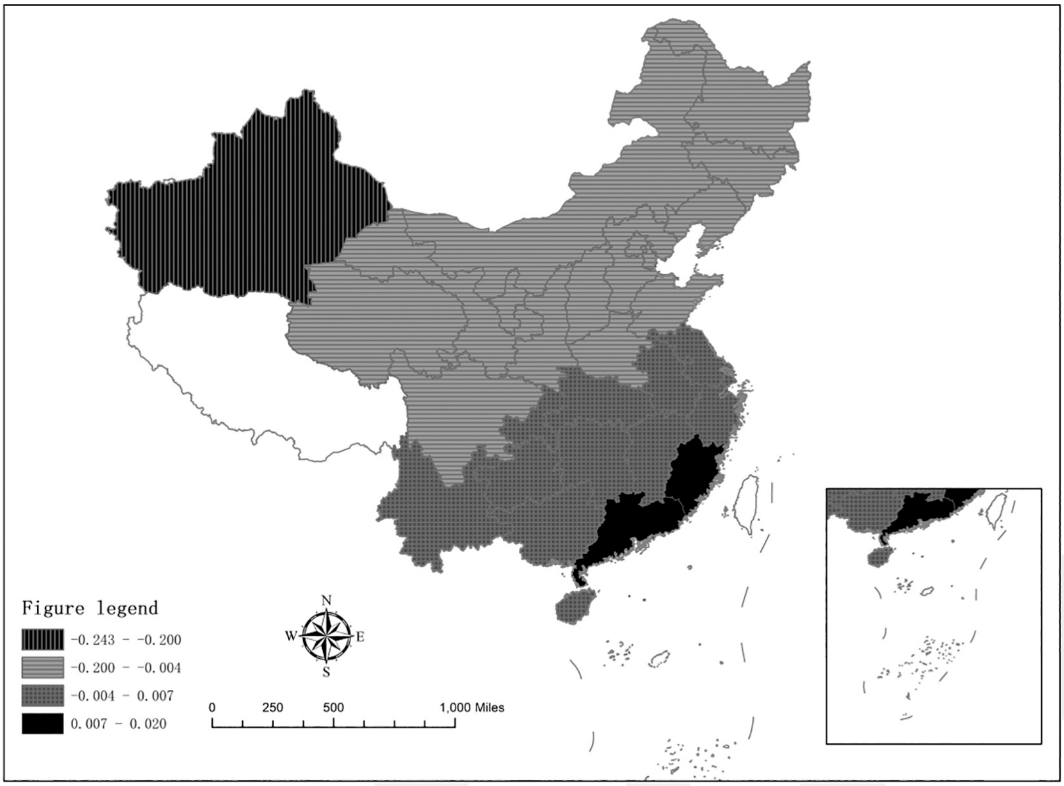

Fig. 3. Spatial heterogeneity of the effect of DIS on IGT.

construction and tariff reform for each area and rebalance the structure and spatial distribution of electricity resources in the eastern, central, and western regions. Electricity tariff policy must not be "one size fits all". They would consider local economic development, electricity price level, industrial structure, and other factors to develop a differentiated tariff policy to maximize electricity price restructuring and boost IGT. For example, the eastern and central regions are the more industrially developed regions, which also coincide with a relative shortage of power resources. The Western region has more abundant power resources and relatively less developed industries. Policymakers should encourage industries to use electricity as their primary energy source and reduce electricity prices to guide them to accelerate IGT for low levels of IGT in the western region. Besides, legislators should increase the construction of national electric power infrastructure, promote the balanced development of power grids, and utilize the abundant power resources in the West to compensate for the poor IGT situation in the east and central regions.

Officials can introduce subsidies and incentives for technological innovation to compensate for the rising production costs due to rising electricity prices. It encourages enterprises to invest more funds in technological innovation activities and reduce the power burden on industrial enterprises. When the intensity of the enterprise's R & D investment is up to a certain degree, policymakers can reduce a certain amount of electricity expenditure for enterprises or give electricity price concessions. Furthermore, DIS contributes to a surge in conventional energy usage. Consequently, it is advisable to raise electricity prices selectively for high-emission industries, encouraging their shift towards low-emission and energy-efficient practices. Reducing electricity costs for low-energy-consumption industries provides them with additional resources to invest in technologies that further curtail energy usage and expedite the process of IGT.

Although this investigation yields few interesting insights into the impact of DIS on IGT, but there are still limitations and scope for further research. Given that the datasets are derived from the provincial level in China, a broader dataset involving multiple cities or counties could facilitate more precise or generalized findings on the impact of DIS. This study only examines two key factors: R&D input intensity and energy mix as mechanism variables. Future researchers will investigate how DIS affects IGT in terms of market level, resource endowment, or institutional quality.

CRediT authorship contribution statement

Asif Razzaq: Writing – review & editing, Writing – original draft, Software. **Arshian Sharif:** Writing – review & editing, Writing – original draft, Methodology. **Xiaodong Yang:** Writing – review & editing, Writing – original draft, Software. **Eyup Dogan:** Validation, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.eneco.2024.107308.

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