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Impact of air pollution prevention and control on urban green economy efficiency: evidence from China

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One of the Sustainable Development Goals is to enable cities to thrive, improve resource efficiency, and reduce pollution. However, balancing economic development with pollution control and fostering green growth remains a major challenge for developing countries. This study, using panel data from 284 prefecture-level and above cities in China from 2006 to 2020, evaluates urban green economy efficiency (GEE). Then, adopting implementation of "12th Five-Year Plan for Key Regional Air Pollution Prevention and Control" in China as a quasi-natural experiment, this study investigates the impact of air pollution prevention and control (APPC) on urban GEE. Findings reveal an overall upward trajectory in urban GEE across China, marked by discernible regional differentiations following implementation of national Plan. Considering the "hysteresis effect" and spatially "pollution halo effect", APPC notably improves urban GEE, particularly within cities of eastern zone, high-population density cities, large-sized cities, non resource-based cities and major-APPC cities. Importantly, APPC acts as a catalyst for both enhancing green innovation quality and optimizing industrial structures, ultimately fostering urban GEE in China. These findings are significant and also provide a valuable supplement to the existing study.

Keywords Air pollution prevention and control, Plan, Urban green economy efficiency, Green innovation, Industrial structure

Amidst the rapid industrialization and urbanization in China, environmental pollution has experienced a discernible uptick. Notably, air pollution has emerged as a significant impediment to the high-quality and sustainable development of the regional economy. The intricate challenges posed by regional atmospheric environmental issues present formidable obstacles to environmental governance in China. Compounding this, the prevailing industrial structure is strong reliant on fossil fuel resources, with coal being a primary contributor. Urgency surrounds the imperative to expedite the shift from energy and resource intensive systems to renewable alternatives[1–3]. In response to rigorous environmental protection inspections and the pursuit of environmental assessment objectives, certain regions in China have implemented stringent measures, including power outages, work stoppages, and business closures. These measures are particularly pronounced in areas characterized by key industries such as steel, cement, coal power, and chemicals.

Some literature indicate that environmental regulations significantly increase enterprises' production costs and reduce their operational efficiency. Under the constraint of short-term profit goals, companies may abandon local research and development or technological innovation and move to areas with relatively lax environmental regulations, thereby causing the transfer of environmental pollution and creating a "pollution refuge effect"[4–6].

Therefore, balancing resource utilization with economic stability, while designing effective tools to improve environmental quality and achieve green economic growth, is not only a critical issue for China but also a key challenge for developing and emerging countries, particularly those dealing with geopolitical risks and economic uncertainty[7–11]. In 2012, China approved the "12th Five-Year Plan for Key Regions' Air Pollution Prevention and Control (Hereinafter referred to as Plan)," its first comprehensive national plan targeting air pollution. This marked a significant shift in focus from merely controlling the total amount of pollutants to improving overall environmental quality, addressing both primary and secondary air pollution.

Since then, this plan has been implemented as a stringent environmental regulation policy for many years. In particular, in the middle and late periods of China's "12th Five-Year Plan" (2013–2015) and the entire period

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of “13th Five-Year Plan” (2016–2020), has the issuance of these Plans helped China achieve its dual goals of economic development and environmental governance? Did this improve China’s GEE? Therefore, it is important to scientifically evaluate the economic effects of this plan from an efficiency perspective, and examine its impact on the GEE through specific channels. Addressing the above questions is crucial for China to realize the green transformation of its industrial structure and the high-quality development of its economy and developing countries to achieve sustainable economic growth under environmental constraints.

While scholars have extensively examined the environmental impact of China’s atmospheric measures and policies, much of the existing literature primarily focuses on the direct environmental effects of these regulations, typically measured by individual indicators like PM2.5/PM10 concentrations, or CO_2, SO_2, O_3, and NO_x emissions, as well as composite indicators such as the Air Quality Index (AQI) and Air Pollution Index (API). However, there is comparatively less research assessing the economic impacts of these measures, particularly from an efficiency perspective.

Accordingly, utilizing panel data encompassing 284 prefecture-level and above cities spanning from 2006–2020, this study establishes an evaluation index system that integrates energy consumption and various environmental constraints to systematically assess urban GEE in China. The study rigorously analyzes China’s APPC tool, the Plan, released in 2012, treating it as a quasi-natural experiment, and employs the DID method to evaluate the benchmark and spatial ATE (Average Treatment Effect) of the Plan urban GEE. Furthermore, the study endeavors to elucidate the pathways through which the Plan influences urban GEE, considering green innovation or industrial structure as potential mediators. The overarching goal is to furnish practical references for developing countries aiming to advance a green economy.

The study reveals that the Plan contributes to the enhancement of urban GEE in China, epitomizing the achievement of a “win-win” scenario for APPC and economic development. Furthermore, it demonstrates a positive spatial spillover effect, coined the “pollution halo effect,” extending to neighboring areas. This empirical evidence offers valuable insights to support coordinated inter-regional or joint APPC efforts. In comparison to existing research, this study makes marginal contributions in four key dimensions:

① Empirical evidence for the “Porter hypothesis”: In the realm of prefecture-level and above cities, this study provides empirical evidence supporting the “Porter hypothesis” by recognizing the positive impact of China’s APPC on urban GEE. Unlike prior studies relying on proxy variables for environmental regulations, this study treats the Plan issuance as an exogenous shock, employing the DID method to estimate GEE differences between cities in key regions implementing the Plan and those in non-key regions that did not. This quasi-experimental approach effectively mitigates endogeneity bias.

② Identification of spatial ATE: Addressing the oversight in prior studies regarding spatial externalities, this study captures the spatial ATE arising from the Plan China’s Plan on urban GEE. Through the incorporation of a spatial DID model with heterogeneity, the study includes the “spatial” ATE of the Plan implemented in local areas on the GEE of geographically neighboring areas—an aspect less frequently highlighted in previous studies.

③ Comparison of different ATEs: In contrast to previous studies focusing on provincial levels, this study precisely identifies and compares various ATEs exerted by China’s Plan on GEE in different cities. The emphasis on cities, as pivotal spatial carriers of environmental regulation and economic development, enhances the practical relevance of clarifying the heterogeneity performance of environmental regulatory tools.

④ Impact mechanism analysis: The study delves into the impact mechanism by which China’s APPC influences urban GEE from two perspectives: green innovation and industrial structure. By considering green innovation quantity and quality, as well as advanced and rationalized industrial structures, the study proposes and empirically verifies corresponding research hypotheses. The insights contribute to a more comprehensive understanding of the internal mechanisms of environmental air regulation and green economic development, providing theoretical and practical references for formulating targeted regional environmental air regulation strategies.

The remainder of this paper is organized as follows: Section “Literature review” reviews relevant literature. Section “Policy background and mechanism analysis” introduces the background of the Plan. Section “Measurement and analysis of urban GEE in China” measures and analyzes the features of the urban GEE in China. Section “Methodology and variables” sets up the models, selects variables, and presents statistical descriptions. Section “Empirical analysis” includes the benchmark test, robustness checks, heterogeneity tests, spatial spillover tests, and mechanism tests. The final Section concludes the paper, presents policy implications and research limitations.

Literature review

In the academic realm, a consensus remains elusive regarding the economic effects of environmental regulations on economic efficiency or total factor productivity (TFP). Originally, extensive studies posit that stringent environmental policy tend to elevate production and operational costs, displace productive investment, and diminish firms’ standing and competitiveness in international markets. This outcome is commonly referred to as the “cost compliance effect”[12,13]. However, Porter[14] puts forth a noteworthy departure from conventional viewpoints with the introduction of the “Porter hypothesis.” According to this hypothesis, more stringent regulations can enhance productivity growth by compelling firms to rationalize their operations. For instance, Bhowmik et al.[15] highlights the role of stringent policies in promoting sustainable resource use and reducing dependency on emissions for economic growth. The study of Caijuan et al.[16] also underscores stringent environmental policies not only support sustainable green economic growth but also mitigate the adverse effects of external uncertainties. Moreover, some literature has delved into this issue, scrutinizing the hypothesis from an economic efficiency or TFP standpoint[17,18].

Due to variations in research objects, dimensions, types of environmental regulatory tools, and institutional backgrounds, several studies have uncovered an uncertain or nonlinear relationship between environmental air regulation and economic efficiency or productivity. Notably, Wu et al.[19] provided evidence for a significant U-shaped relationship between environmental regulation and green energy efficiency, dependent on the type of environmental decentralization. Plus, Pan et al.[20], Guo and Yuan[21] reported diverse effects of different environmental regulations (command-and-control, market-based, voluntary compliance, etc.) on energy efficiency or green productivity across various industries. These findings underscore the nuanced and context-specific nature of the relationship between environmental air regulation and economic efficiency or productivity, emphasizing the need for a comprehensive understanding that considers multiple variables and dimensions.

Recently, among excessive literature on China, scholars have evaluated the impact of various China's air regulation policy, such as the "Two Control Zones" (Control Zone for SO_2 Pollution and Control Zone for Acid Rain) policy[22], the "Low-carbon City Pilot," the "Air Quality Standards"[23–26], the "Air Pollution Prevention and Control Action Plan"[27,28], the "Clean Air Action"[29], and so forth. Moreover, the regulatory effects of China's ambient air policies on TFP or economic efficiency are diverse and inconclusive. For example, on one side, using the panel dataset of industrial enterprises, Tang et al.[30] found that the "Two Control Zone" policy has a lagging and continuous negative effect on the growth of enterprise TFP because of increased costs and resource misallocation. The empirical results of Wang and Yuan[31] showed that, in the short term, air pollution control has a significant inhibitory effect on industrial ecological total-factor energy efficiency; however, in the long run, the influence is significantly heterogeneous.

On the flip side, findings of Zhang et al.[32] reveal that the "Carbon Emission Trading Market" policy not only augments economic dividends but also diminishes industrial CO_2 emissions across all trading pilots. Concurrently, Peng et al.[33] indicate that China's "SO_2 Emissions Trading Pilot" policy has yielded significant productivity-enhancing effects. Besides, Bai et al.[34] highlighted that China's market-driven environmental regulation, in the form of the "Carbon Market Pilots," effectively promoted TFP of enterprises in the pilot areas.

Summarily, while existing research has provided valuable insights, certain limitations persist. Firstly, there remains a dearth of research on the potential impact of the Plan on urban GEE China. Secondly, the majority of existing studies solely rely on provincial data from China when analyzing the effects of ambient air policies on green efficiency or TFP, lacking a nuanced examination of heterogeneity across different pilot areas.

Policy background and mechanism analysis

Policy background

Since the beginning of the twenty-first century, China's economy has maintained a high growth rate. As the Fig. 1 shows, data from the *China Statistics Yearbook*, China's GDP has increased from 11 trillion yuan in 2001 to 101 trillion yuan in 2020, with an average annual growth rate of 12.4%. However, this rapid economic growth has also led to environmental air pollution issues. Also, according to global average annual PM2.5 concentration data provided by the *CGEG* (*Center on Global Economy and Governance*) of Columbia University, for the same period, the annual average concentration of PM2.5 fell from 37 to 22 μg/m³, with an average annual deceleration rate 1.2%.

During the China's "11th Five-Year Plan" period (from 2006–2010), regional air pollution became increasingly severe. According to data from the *China Environmental Statistics Yearbook*, the annual average volume of industrial waste gas emissions and SO_2 emissions in China were 42 trillion tons and 24 million tons respectively

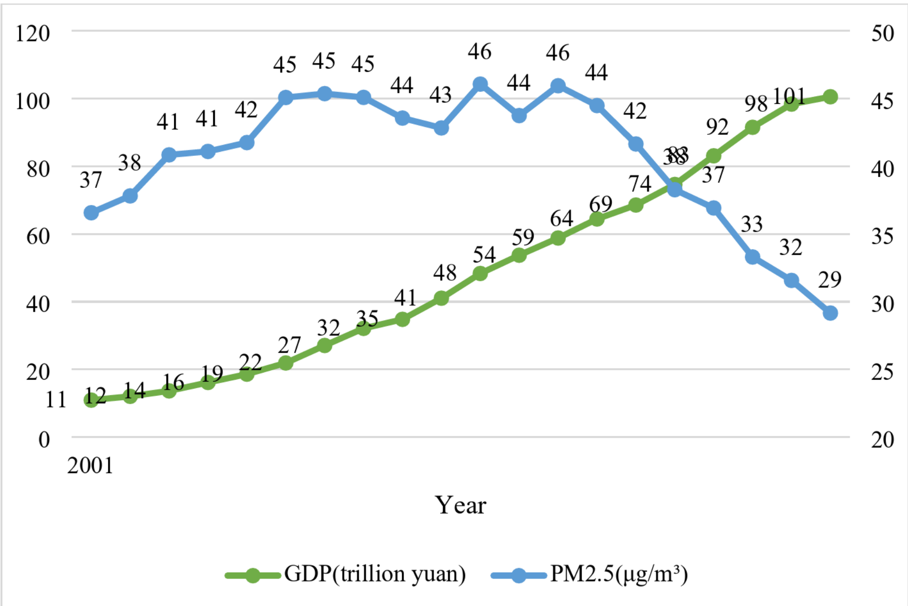

Fig. 1. Trends in China's GDP and PM2.5 from 2001–2020.

and the annual average concentration of PM2.5 remained high as well, which was about 44 μg/m^3 from 2006–2010. Furthermore, moving into the "12th Five-Year Plan" period (from 2011–2015), China's industrialization and urbanization continued to develop rapidly, leading to increased consumption of resources and energy. This put unprecedented pressure on the atmospheric environment.

From an administrative perspective, it is difficult for a single city to effectively solve the problem of air pollution. Therefore, as a new regional APPC system, and based on the "Air Pollution Prevention and Control Law of the People's Republic of China" and the "12th Five-Year Plan for National Economic and Social Development of the People's Republic of China", on December 5, 2012, the "12th Five-Year Plan for Key Regional Air Pollution Prevention and Control", i.e., the Plan, was jointly issued by the Ministry of Ecology and Environmental, the National Development and Reform Commission and the Ministry of Finance, and approved by the State Council. This is China's first comprehensive plan for APPC, marking a shift from the goal of controlling total pollutant emissions to improving environmental quality, and a shift from mainly addressing primary pollution to addressing both primary and secondary pollution.

The Plan, aims to improve the ambient air quality in China by taking the lead in promoting joint APPC in key regions. It includes strict environmental access, promoting clean energy utilization, accelerating the elimination of outdated production capacity, implementing coordinated control of multiple pollutants, significantly reducing pollutant emissions, and establishing an "inducement mechanism" to coordinate China's regional economy and environment, promote the transformation of development mode, and meet the requirements for air environmental quality in building a moderately prosperous society by 2020. The Plan covers a total of 13 key regions for APPC, known as the "Three Zones and Ten Clusters" (The "Three Zones" include the Beijing-Tianjin-Hebei region, the Yangtze River Delta, and the Pearl River Delta; The "Ten Clusters" include the Central Liaoning Cluster, Shandong Cluster, Wuhan and its surrounding Cluster, Changsha-Zhuzhou-Xiangtan Cluster, Chengdu-Chongqing Cluster, the west coast of the Taiwan Strait Cluster, the central and northern parts of Shanxi Province Cluster, the Guanzhong Plain (or Weihe Plain) in Shaanxi Cluster, Gansu-Ningxia Cluster, and the Xinjiang Urumqi Cluster), which involve a total of 19 provinces, autonomous regions, and municipalities directly under the central government, 118 prefecture-level cities, and 6 county-level cities, covering an area of approximately 1.33 million square kilometers, accounting for 13.81% of China's land area.

Just as shown in Fig. 1, since the issuance of the Plan, that is, since 2013, the average annual PM2.5 concentration in China has begun to decrease significantly, indicating that China's ambient air quality has been gradually improved, which also provides a factual basis for this study to empirically identify the "quasi-experimental" effect of the Plan on urban GEE in China.

Mechanism analysis

Some studies have confirmed that China's ambient air governance can promote environmental awareness[35] and FDI, induce industrial structure upgrades and technological innovation, and stimulate the willingness and motivation of local and central governments for environmental governance[36]. This study captures the impact mechanism by which China's Plan influences urban GEE from two perspectives: green innovation and industrial structure.

Green innovation mechanism

Environmental regulations or policies are acknowledged as catalysts for innovation[37,38]. Precisely, these regulations compel companies to internalize the costs associated with pollution control and reduction, prompting increased investments in Research and Development (R&D), the adoption of cleaner technologies, and the stimulation of green innovation. This not only diminishes tax payments related to pollution but also alleviates environmental degradation, fostering a trajectory towards green and productive growth[39,40]. In the context of China, empirical studies have corroborated these insights. For instance, utilizing panel data from the industrial sectors of OECD countries, Wang et al.[24] demonstrated that, within a certain level of stringency, environmental policies contribute to the growth of green productivity by inducing the "innovation offset effect" or "innovation compensation effect." Furthermore, Wang et al.[41] revealed that technological innovation in renewable energy significantly enhances the regional green TFP.

Contrarily, Chen et al.[42] suggests that air pollution serves as a significant factor influencing population movements within China. Regions characterized by poor air quality impede the influx of high-end human capital and markedly suppress urban innovation vitality. Additionally, some scholars posit that the promotion of green innovation or clean technologies, while fostering economic expansion, can also create new energy demands. Consequently, the positive effects of green innovation may be partially or entirely offset, potentially leading to environmental degradation and decreased efficiency—a phenomenon referred to as the "rebound effect."

Empirical studies have further indicated that environmental regulations might not always provide incentives for innovation; in some cases, they may even pose obstacles or lead to technical inefficiency[43]. In the context of China, for instance, Shi et al.[44] concluded that China's "carbon emissions and trading pilot" policy significantly hinders innovation, resulting in a reduction in enterprise productivity. In light of the above analysis, Hypothesis 1 (H1) is posited.

> H1: Green innovation is a non-ignorable mediating factor between the Plan and urban GEE. However, the direction of its impact depends on which need to be tested empirically.

Industrial structure mechanism

Strong evidence has been provided to support that China's environmental regulations can affect production and change industrial structure[21,45,46]. On the one hand, environmental regulations or policies not only help transform energy-intensive industries, especially tertiary and clean industries, but also eliminate resource-based industries and cultivates environment-friendly industries, ultimately upgrading or modernizing industrial structure and improving production efficiency in China[47–51]. On the other hand, although environmental regulations may lead to changes or optimizations in industrial structure, it does not necessarily improve economic efficiency, as its "cost compliance effect," "squeezing out effect on investment," and the resulting industrial redistribution, or regional disparities, all of which possibly reduce the economic or production efficiency of some industries[52,53]. Based on the above analysis, Hypothesis 2 (H2) is proposed.

H2: Industrial structure acts as a positive channel between the Plan and urban GEE when factors shift from energy-consuming and pollution-intensive industries to technological-driven and environment-friendly industries. Otherwise, the urban GEE might be impeded.

Measurement and analysis of urban GEE in China

Measurement of urban GEE

Methods for measuring the GEE can be broadly classified into two main categories: parametric and non-parametric approaches. The parametric approach, typically represented by Stochastic Frontier Analysis (SFA), requires the specification of a production function, along with distribution assumptions, and focuses on a single output factor. In contrast, the non-parametric approach, exemplified by Data Envelopment Analysis (DEA), does not require predefined functional forms and can accommodate multiple output factors. Given that urban GEE involves both desirable outputs (e.g., economic growth) and undesirable outputs (e.g., environmental pollution), DEA is more commonly employed for GEE evaluation, using a total-factor analytical framework[54].

In this study, we adopt the Slack-Based Measure-Global Malmquist Luenberger (SBM-GML) model, as proposed by Salman et al.[55] and Wang et al.[49], to assess GEE. The SBM-GML model comprehensively accounts for resource inputs, desirable outputs, and undesirable outputs, providing a more holistic reflection of urban GEE across economic, environmental, and resource dimensions. Unlike traditional DEA models, the SBM-GML model addresses non-radial slacks, effectively managing non-zero slacks in inputs and outputs. This enhances measurement accuracy and helps avoid potential biases. Furthermore, the SBM-GML model is highly flexible, allowing it to be applied across various cities, industries, and countries, and can be customized to meet specific research needs, making it a robust tool for diverse scenarios[56,57].

In the SBM-GML model for measuring urban GEE in China from 2005–2020, the decision-making units (DMU) is 284 cities at and above the prefectural level in China. Thus, the GEE of the city i is identified as the ratio of the theoretical minimum input factor X ($x_{i1}, x_{i2}, \ldots, x_{iM}$) to the actual input when the undesirable output factor Z ($z_{i1}, z_{i2}, \ldots, z_{iO}$) is minimized under the given constraints of the desirable economic output factor Y ($y_{i1}, y_{i2}, \ldots, y_{iN}$).

First, the basic production possibility set $P(X)$ is constructed:

$$P\left(X\right)=\left\{\left(Y,Z\right):\ X\to\left(Y,Z\right)\right\},\ X\in R^{+},\ Y\in R^{+},\ Z\in R^{+} \tag{1}$$

Also, in period T ($t = 1, 2, \ldots, t$), the $P(X)$ of city i is expressed as $P(X)_i = (x^t_i, y^t_i, z^t_i)$ and the production possibility set $P(X)$ is expressed:

$$P\left(X^{T}\right)=\left\{\begin{array}{c}\left(Y^{T},\ Z^{T}\right):\sum\lambda^{T}Y^{T}\geq Y^{T};\ \sum\lambda^{T}Z^{T}\geq Z^{T}\\ \sum\lambda^{T}X^{T}\geq X^{T}\end{array}\right. \tag{2}$$

where λ^T represents cross-section observations.

Then, following Tone[58], the SBM model is defined as:

$$\begin{aligned}&\vec{S}_{C}^{T}(X^{T'},\ Y^{T'},\ Z^{T'},\ G^{X},\ G^{Y},\ G^{Z})=\max\frac{\frac{1}{M}\cdot\sum\frac{S^{X}}{G^{X}}+\frac{1}{N+O}\cdot\left(\sum\frac{S^{Y}}{G^{Y}}+\sum\frac{S^{Z}}{G^{Z}}\right)}{2}\\&s.t.\sum\lambda^{T}X^{T}+S^{X}=X^{T};\ \sum\lambda^{T}Y^{T}-S^{Y}=Y^{T};\ \sum\lambda^{T}Z^{T}-S^{Z}=Z^{T};\\&where\quad\sum\lambda^{T}=1;\ \lambda^{T}\geq0;\ S^{X}\geq0;\ S^{Y}\geq0;\ S^{Z}\geq0\end{aligned} \tag{3}$$

where $\vec{S}_{C}^{T}$ denotes the directional distance function based on constant returns to scale; $X^{T'}$, $Y^{T'}$, $Z^{T'}$ denotes input factors, desirable output factors, and undesirable output factors, respectively; G^X, G^Y, G^Z denotes the direction vector of input decrease, desirable output increase, undesirable output decrease, respectively; S^X, S^Y, S^Z denotes the slack vector of input factors, desirable output factors and undesirable output factors, respectively.

Finally, the GML (Global Malmquist Luenberger) index is established:

$$GML^{T\sim T+1}=\frac{1+D^{G}\left(X^{T},\ Y^{T},\ Z^{T}\right)}{1+D^{G}\left(X^{T+1},\ Y^{T+1},\ Z^{T+1}\right)} \tag{4}$$

where, D^G (X^T, Y^T, Z^T) and D^G (X^{T+1}, Y^{T+1}, Z^{T+1}) denotes global directional distance function for periods T and $T+1$, respectively. A value of $GML > 1$ indicates an increase in GEE of city i from period T to $T+1$. $GML = 1$ indicates unchanged; $GML < 1$ indicates a decrease.

Furtherly, the GML index can be decomposed into the *GEC* (global efficiency change) index, which mean and *GTP* (global technology progress) index. In this case, formula (4) can be transformed into formula (5) as following:

$$GML^{T\sim T+1} = GEC^{T\sim T+1} \cdot GTP^{T\sim T+1}$$
$$= \frac{1 + D^T\left(X^T,\ Y^T,\ Z^T\right)}{1 + D^{T+1}\left(X^{T+1},\ Y^{T+1},\ Z^{T+1}\right)} \cdot \left[\frac{1 + D^G\left(X^T,\ Y^T,\ Z^T\right)/1 + D^T\left(X^T,\ Y^T,\ Z^T\right)}{1 + D^G\left(X^{T+1},\ Y^{T+1},\ Z^{T+1}\right)/1 + D^{T+1}\left(X^{T+1},\ Y^{T+1},\ Z^{T+1}\right)}\right] \quad (5)$$

where, $GEC^{T\sim T+1}$ indicates the technical progress changes or technical innovation improvement from period T to $T+1$; $GTP^{T\sim T+1}$ indicates the distance between the gap from the optimal production front in period T and the one in period $T+1$.

Specifically, the SBM-GML model under environmental air constraints contained three input factors, i.e., labor (L), capital stock (K) and energy consumption (E); one desirable output factor, i.e., gross domestic product (GDP); and three undesirable output factors, i.e., industrial smoke (powder) dust emissions (SD), industrial SO_2 emissions (SO_2) and annual average concentration of PM2.5 (PM2.5).

Input factors of urban GEE
(1) Capital stock (K): is calculated by the method called "perpetual inventory"[19,59], with formula as the following:

$$K_{i,t} = E_{i,t-1} + (1-d) * K_{i,t-1}\ (2005 < t \le 2020);\quad K_{i,2005} = E_{i,2005}/(g+d) \quad (6)$$

where $K_{i,t}$ is the capital stock of city i in year t, and $E_{i,}\ t$ is the total investment in fixed assets on the city i in year t, δ is the depreciation rate (5% set in here); g is the geometric average growth rate of investment in fixed assets in city i from 2005 to 2020.

(2) Labor (L): is measured by total employment at year-end of each city.

(3) Energy consumption (E): is measured by total calorific value calculation (10^4 tce) of each city, which is converted by total supply of gas (i.e., coal gas, natural gas), liquefied petroleum gas, and annual electricity consumption.

Output factor of urban GEE
(1) Desirable output factor is: GDP of each city is regarded as the desirable output factor of SBM-GML model, after being deflated based on the price index of year 2000.

(2) Undesirable output factors are as follows: ① industrial smoke (powder) dust emissions (SD); ② industrial SO_2 emissions (SO_2); ③ annual average concentration of PM2.5 (PM2.5) .

The data of both input factors and output factors is obtained from the *China Urban Statistical Yearbook* and *the China Statistical Yearbook*.

Analysis of urban GEE

Overall analysis
Based on the calculation of the SBM-GML model, the GEE of 284 prefectural levels and above cities in China were obtained for 2006–2020. As shown in Fig. 2, the average value of urban GEE in China shows a general growth trend, increasing from 0.991 in 2006 to 1.014 in 2020, with an average value of 1.003 and a growth rate of 0.17%. Based on the timing of the plan issuance, we divided the sample into two periods: 2006–2012 and 2013–2020. It can be observed that before the issuance of China's Plan, from 2006–2012, the urban GEE exhibited a fluctuating trend resembling an M-shape, with an average value of 1.001 and a growth rate of 0.13%; after the issuance of the Plan, from 2013–2020, the urban GEE shows a growth trend resembling a W-shape, with an average value of 1.004 and a growth rate of 0.29%.

Regional analysis
On the one hand, Fig. 3 shows the average value of urban GEE in China's four economic zones (Eastern, Northeast, Central, and Western) from 2006–2020, reflecting that generally, the GEE trends of cities in China's four zones are similar to that in Fig. 1. Specifically, based on the average value of GEE, the ranking from highest to lowest is as follows: Eastern zone (1.005), Central zone (1.002), Western zone (1.002), and Northeast zone (1.000). Based on the growth rate, the ranking from highest to lowest is as follows: Eastern zone (0.23%), Central zone (0.21%), Western zone (0.12%), and Northeastern zone (0.03%). Before the issuance of the Plan, based on the average level, the ranking from high to low is as follows: Eastern zone (1.002), Western zone (1.002), Northeast zone (1.001), and Central zone (1.000). Based on the growth rate, the ranking from highest to lowest is as follows: Eastern zone (0.18%), Western zone (0.15%), Central zone (0.14%), and Northeastern zone (−0.05%).

Notably, the analysis implies that China's Plan, as an environmental regulation for APPC, may widen the gap in urban GEE between the Eastern/Central zone and Western/Northeast zone and bring more incentives for green economic development and transformation for cities in Eastern/Central zone than Western/Northeast zone thus exhibiting a potential "Matthew effect." Consistent with Shuai and Fan[60], our findings reveal a rising trend in GEE across China's eastern, central, and western zones, accompanied by pronounced spatial inequalities. While environmental policies, such as the Plan, can broadly enhance GEE, they may also intensify regional disparities.

On the other hand, Fig. 4 shows the average value of urban GEE in China's key regions and non-key regions from 2006–2020, reflecting that generally the GEE trends of cities in key and non-key regions are similar to that

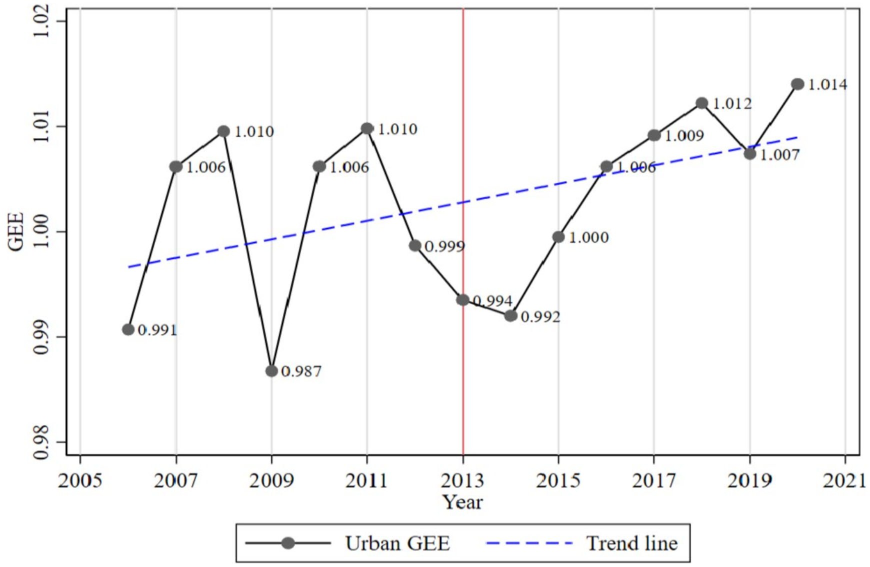

Fig. 2. Trends of urban GEE in China from 2006–2020.

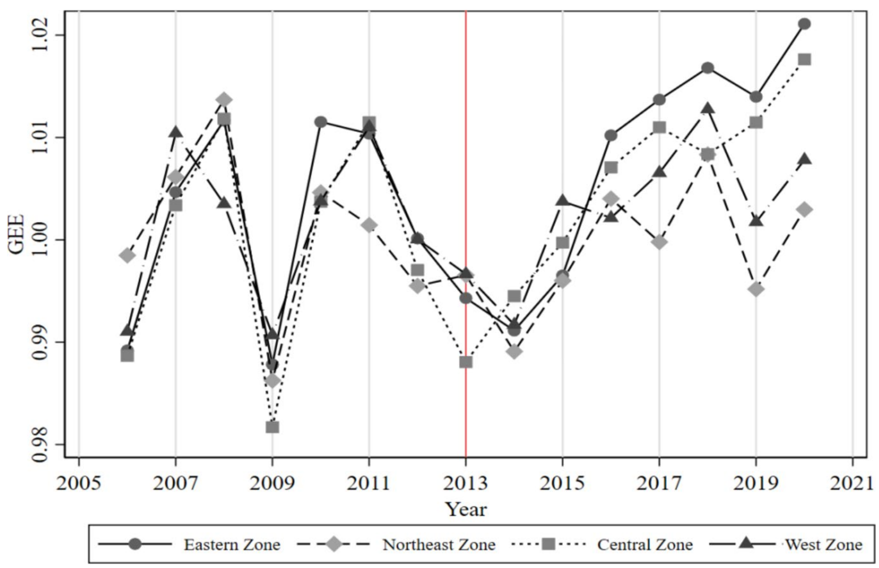

Fig. 3. Trends of urban GEE in four economic zones from 2006–2020.

in Fig. 1 as well. Specifically: ① The average value of urban GEE in key regions and non-key regions is 1.004, with a growth rate of 0.22% and 1.002, with a growth rate of 0.13%, respectively. ② Before the issuance of the Plan, the average value of urban GEE in key regions and non-key regions is 1.001, with a growth rate of 0.19% and 1.001, with a growth rate of 0.10%, respectively. ③ After the issuance of the Plan, the average value of urban GEE in key regions and non-key regions is 1.007, with a growth rate of 0.35% and 1.002, with a growth rate of 0.25%, respectively.

Furthermore, to reflect the urban differences and trends in GEE, Fig. 5 shows the average GEE of the top 10 cities with its average growth rate in China from 2006–2020, indicating that all of top 10 cities are located in key regions. Specifically, based on the average value of GEE, the ranking from high to low is as follows: Beijing (1.040) with a growth rate of 0.52%, Xi'an (1.037) with a growth rate of 0.52%, Chengdu (1.033) with a growth rate of 1.37%, Guangzhou (1.032) with a growth rate of 0.63%,Changsha (1.029) with a growth rate of 1.22%, Hangzhou (1.024) with a growth rate of 0.55%,Xiamen (1.022) with a growth rate of 1.25%, Xianyang (1.018) with a growth rate of − 0.04%, Ningbo (1.018) with a growth rate of 0.48%, Fuzhou (1.017) with a growth rate of − 1.30%. Summarily, the above results imply that the Plan might widen gap of GEE between the key regions and non-key regions, thus presenting a potential environmental regulating effect on key regions, where the air pollutant was effectively controlled with the continuous development of the economy.

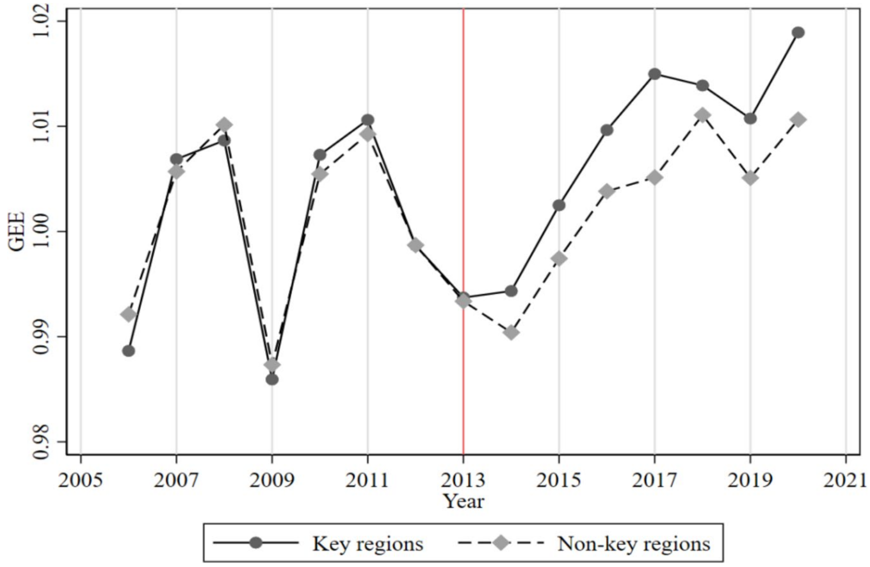

Fig. 4. Trends of urban GEE in key regions and non-key regions from 2006–2020.

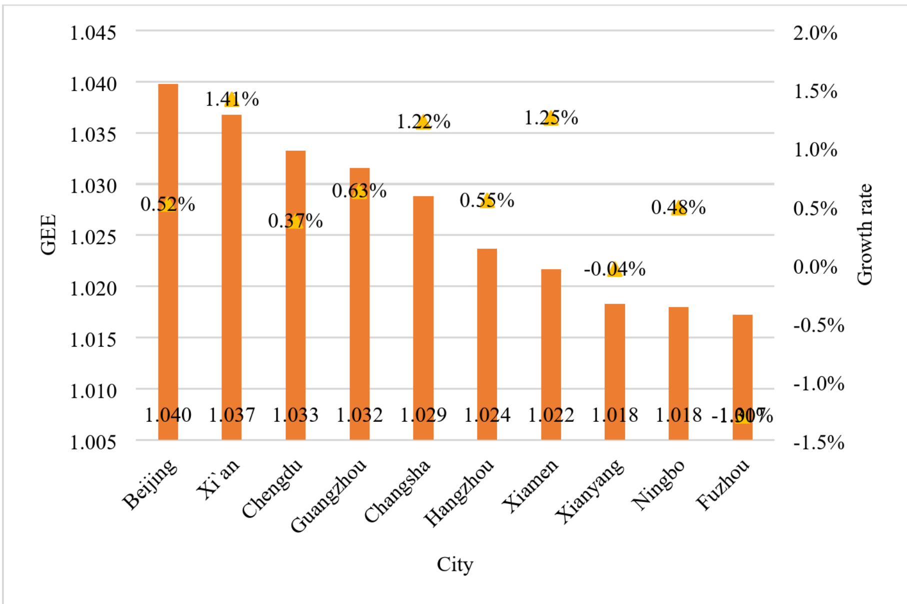

Fig. 5. Top 10 cities in terms of average GEE with growth rate from 2006–2020.

Methodology and variables

Model design and variable definition

As a robust quasi-experimental approach, the DID model addresses endogeneity concerns. Given that urban GEE is influenced by unobserved factors beyond APPC policies, treating the Plan as a quasi-natural experiment allows for a clearer identification of its causal impact on GEE by comparing pre- and post-policy periods across treatment group and control group. Furthermore, the DID model effectively controls for potential confounding from time-variant factors and city-specific characteristics, enhancing estimate robustness, ensuring a more precise assessment of Average Treatment Effect (ATE) derived from APPC on urban GEE. Therefore, referring to the Zhang and Zhang[61], we regard construct a DID model given by following equation:

$$GEE_{it} = \alpha + \beta TR_{it} + \sum \lambda X_{it} + \mu_i + \delta_t + \varepsilon_{it} \quad (7)$$

where, the subscript, *i* and *t*, denotes the city and the year, respectively.

The dependent variable, GEE_{it}, denotes the green economy efficiency of city i at year t, which is measured by the value of prefecture-level and above cities calculated by the SBM-GML model in section "Measurement and analysis of urban GEE in China".

The treatment variable, TR_{it}, is dummy variable to measure whether city i has been affected by the issuance of China's Plan in year t. Knowing that issued in December, 2012, China's Plan is implemented in 13 key region, covering 4 municipalities directly under the central Government, 112 prefecture-level cities, 6 county-level cities, which compose the treatment group. Other cities located in the non-key regions compose the control group. Moreover, considering that the issuance time of the Plan is the end of 2012, governments at all levels and relevant plants need a certain amount of time to give feedback or take action, so here we set treatment time is 2013. That is, we set $TR=1$ for the city i located in key regions (i.e., treatment group) after 2012 (i.e., from 2013–2020). Otherwise, if the city i located in non-key regions (i.e., control group) from 2006–2020 and city i located in key regions from 2006–2012 cannot be influenced by the Plan, thus $TR=0$. Notably, the coefficient β of variable TR can capture the ATE of the Plan on urban GEE, which means that if β is significantly positive, there will be a positive ATE made by China's plan on urban GEE.

The control variables, X, encompass ① Development level (DL), which is measured by the average salary of the working staff in each city; ② Financial level (FL). which is measured by the proportion of total deposits and loans of financial institutions in GDP of each city; ③ Urbanization rate (UR) , which is measured by the proportion of urban resident population in total resident population (urban resident population and rural resident population) of each city.

Other variables, μ_i and δ_t, denotes the city-fixed and year-fixed effects, respectively, controlling for city-level factors that do not vary with time and year-level characteristics that do not vary with city; ε_{it} is the residuals. To relieve potential heteroscedasticity and serial correlation, we clustered the standard errors at the city-year level.

Statistical description of variables

The final sample consisted of 284 cities at the prefecture level and above in China from 2006–2020, covering three periods (i.e., the 11th Five-Year Plan, the 12th Five-Year Plan, and the 13th Five-Year Plan). Missing values were filled by linear interpolation. To avoid potential heteroscedasticity and dependence on the DID model setting, we took control variables as their natural logarithms. To avoid the influence of extreme values, all variables were winsorized by 1% in the empirical analysis. All relevant data were obtained from the *China Statistical Yearbook*, *China Urban Statistical Yearbook*, and *China Environmental Statistical Yearbook*. Table 1 presents the descriptive statistical of all variables.

Empirical analysis

Benchmark tests

Table 2 reports the ATE of issuing China's Plan on urban GEE in line with Eq. (7). The results of DID estimation are shown in columns (1)–(5). Column (1) and (2) represents the estimated result of DID model based on both the city-fixed effect and the year-fixed effect, without and with control variables, respectively. Column (3), (4), and (5) represents the result the estimated result of DID model with only on the city-fixed effect, with only the year-fixed effect, and without city-fixed effect or the year-fixed, respectively. Obviously, all the coefficients β of the variable TR are positive, and crucially, the coefficients β in Column (2) passed the significance test at a 1% confidence level. That is, after issuing the Plan, urban GEE of treatment group is significantly higher than that of control group cities, indicating that China's Plan is conducive for improving urban GEE. This finding aligns with the studies of Zhou and Qi[62], Guo and Hu[63], which highlight the role of environmental regulations in promoting green growth, and gives evidence to support the "Porter hypothesis."

Robustness checks

Parallel trend test

Ensuring the presence of a parallel trend between the treatment group and the control group is crucial for the proper estimation of the DID model. Therefore, we establish model (8) to investigate the parallel trend of the ATE driven by the Plan on urban GEE. This is formulated through the following equation:

$$GEE_{it} = \alpha_0 + \sum_{j=-4}^{5} \gamma_t \cdot TR_{i\,t_0+j} + \sum \lambda X_{it} + \mu_i + \delta_t + \varepsilon_{it} \tag{8}$$

where TR_{ito+j} is a year dummy variable representing whether the city i has been subject to the Plan for j years since the reference year t_0. Specifically, it takes the value of 1 for the city i that has been issued the Plan for j years

Variables	Meaning (units)	Obs	Mean	Sd	Min	Max
GEE	Green economy efficiency (–)	4260	1.003	0.034	0.847	1.168
TR	Whether be affected by the "Plan" (–)	4260	0.408	0.492	0.000	1.000
ln_DL	Logarithm of development level (Yuan)	4260	10.628	0.514	9.479	11.616
ln_FL	Logarithm of financial level (–)	4260	0.730	0.424	−0.143	1.910
ln_UR	Logarithm of urbanization rate (%)	4260	3.886	0.350	2.721	4.549

Table 1. Statistical description of variables.

Variables	(1)	(2)	(3)	(4)	(5)
	DID	DID	DID	DID	DID
TR	0.006***	0.005***	0.001	0.004**	0.001
	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)
ln_DL		0.004	0.010***	0.005*	0.005***
		(0.005)	(0.002)	(0.003)	(0.001)
ln_FL		−0.012***	−0.009***	0.003*	0.003*
		(0.004)	(0.003)	(0.002)	(0.002)
ln_UR		0.005	0.003	0.004**	0.004**
		(0.005)	(0.005)	(0.002)	(0.002)
_cons	1.002***	0.971***	0.907***	0.945***	0.946***
	(0.001)	(0.056)	(0.024)	(0.032)	(0.014)
City-Fixed Effect	YES	YES	YES	NO	NO
Year-Fixed Effect	YES	YES	NO	YES	NO
Obs	4260	4260	4260	4260	4260
R^2	0.116	0.118	0.067	0.070	0.019

Table 2. Benchmark results. The standard error value of coefficients is in parentheses; *, **, and *** denotes the significance levels of 10%, 5%, and 1%, respectively.

before or after the reference year, and 0 otherwise. The coefficient γ estimated the ATE of the Plan in the jth year before and after its issuance. If the significance of coefficient γ coefficient is confirmed through statistical tests, it implies a statistically significant difference in GEE between the treatment group and control group. All control variables X remain consistent with those in Eq. (7).

As shown in Fig. 6, before the issuance of China's Plan ($j < 0$), the coefficients γ of variable TR are not significant, reflecting no significant difference in GEE between the treatment and control groups. After the issuance of China's Plan ($j > 0$), the coefficients γ of variable TR are all positive, yet significant only in the third, fourth and fifth years ($j = 3, 4, 5$). The results manifest the "hysteresis" ATE of the Plan on urban GEE, possibly because there is path dependence on traditional production mode, therefore a lag in the ATE.

Placebo test

To ensure the validity of employing the DID method, it is crucial to establish that there are no significant differences in the trends of urban GEE between the treatment and control groups before the issuance of the Plan. Following the methodology outlined by Cai et al.[64], a placebo test is conducted. In this test, one year is randomly selected as the time-point for the issuance of the Plan for a new treatment group, consisting of cities randomly chosen from the sample. To enhance the statistical power of the placebo test, this random generation process is repeated 500 times.

As illustrated in Fig. 7, the Kernel density estimated coefficients β of the variable TR with corresponding P values exhibit a normal distribution centered around 0. Importantly, these observations suggest that the ATE value (0.005) of the issuing Plan significantly deviates from the placebo test results (0). This outcome rules out the possibility that differences in the ATE of environmental air regulation between the treatment and control groups are caused by random factors. It underscores the robustness of the benchmark results.

PSM-DID estimation

To mitigate potential systematic differences between the treatment group and the control group, the PSM (Propensity Score Matching) method is employed. This involves selecting control variables, such as DL, FL, UR) in Eq. (7), as matching covariates. Cities with the closest matching scores are then chosen as the control group for the subsequent DID estimation. The outcomes of the PSM-DID estimation are presented in columns (1) of Table 3 and the positive value of the coefficient β is consistent with estimated results of the benchmark DID regression in Table 2, reflecting that the Plan is conductive to urban GEE robustly.

Deleting sample of municipalities and provincial capitals

Considering that there are some cities with higher administrative level in APPC regions, which have higher air quality and better economic foundation, we exclude the samples of 4 municipalities directly under the Central government of China and 29 provincial capitals and then makes DID estimation, further eliminating the interference of "non-random" factors on the DID regression results. According to the report in Column (2) of Table 3, the coefficient β is still significantly positive.

Excluding the interference of other regulatory policy

Issued in 2010, the China "Low-Carbon Pilot Projects" (LCPP) in provinces, regions, and cities, identifying the first batch of LCCP in five provinces and eight cities. In 2012, the LCPP extended to a second batch in other cities or provinces, including Beijing, Shanghai, and Shijiazhuang. To account for the potential impact of China's LCPP

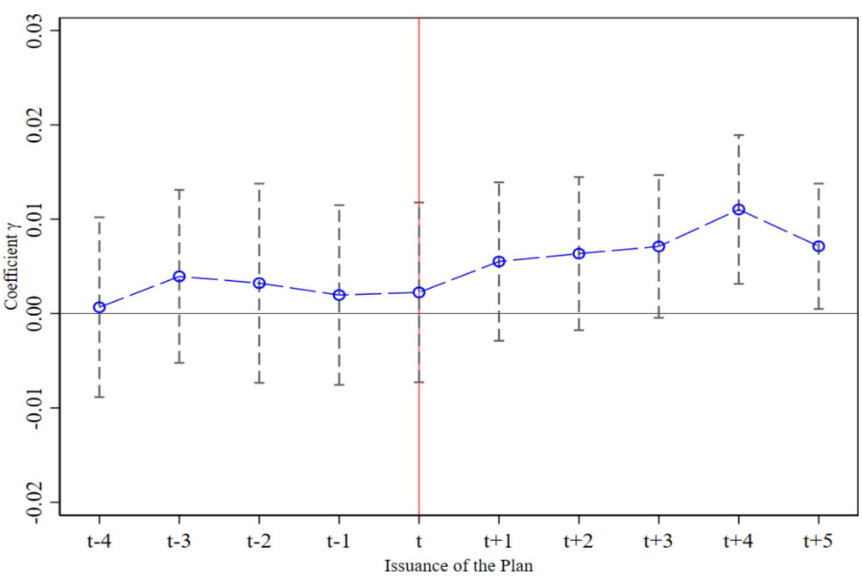

Fig. 6. The dynamic ATE of China`s Plan on urban GEE.

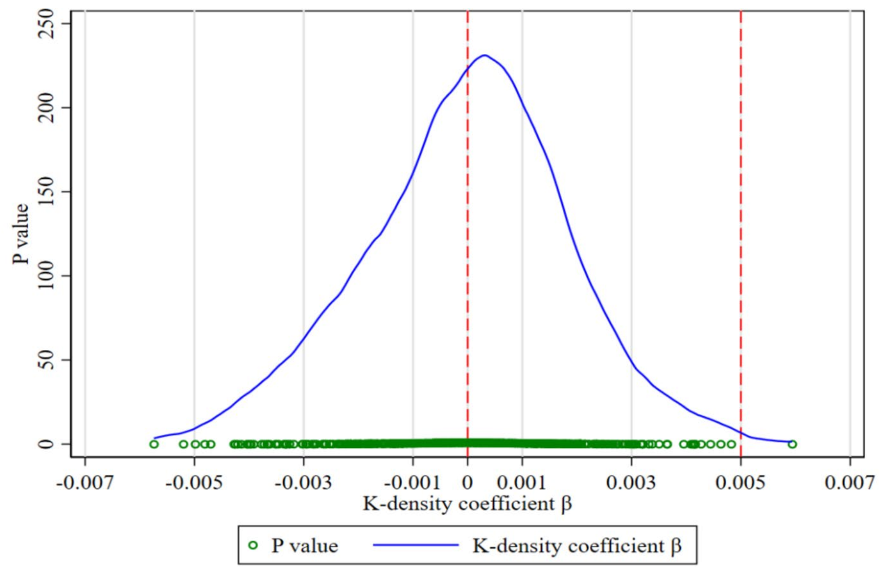

Fig. 7. The kernel density of 500 estimates in placebo test. Notes: The X-axis represents the coefficient β of the variable *TR* from 500 random estimation of placebo test; the Y-axis represents the P values and K-density coefficients from each random regression. The gray solid line is the kernel density distribution curve of all 500 estimated coefficients, whereas the gray dots are corresponding P values. The left and the right red vertical dash line is the value of zero and coefficient β in Column (2) of Table 2, respectively.

	PSM-DID estimation	Delete sample of municipalities and provincial capitals	Eliminate interference of the LCPP	Eliminate interference of the AAQS
Variables	(1)	(2)	(3)	(4)
TR	0.006***	0.006***	0.006***	0.004*
	(0.002)	(0.002)	(0.002)	(0.002)
LC× *TM*			−0.0003	
			(0.000)	
AS× *TM*				0.0004
				(0.000)
L1.GEE				
L2.GEE				
_cons	0.914***	0.936***	1.158***	0.557**
	(0.078)	(0.057)	(0.195)	(0.255)
Control variables	YES	YES	YES	YES
City-Fixed Effect	YES	YES	YES	YES
Year-Fixed Effect	YES	YES	YES	YES
Obs	3591	3795	4260	4260
R^2	0.126	0.115	0.119	0.119

Table 3. Robustness checks results. The standard error value of coefficients is in parentheses; *, **, and *** denotes the significance levels of 10%, 5%, and 1%, respectively.

on urban GEE, the interaction term *LC*× *TM* of the LCPP dummy variable (*LC*) and the time trend variable (*TM*) for the low-carbon pilot cities is added in Eq. (7). As indicated in Column (3) of Table 3, the coefficient β of variable *TR* remains significantly positive, while the coefficient of the interaction term *LC*× *TM* is negative and statistically insignificant. This suggests that the Plan is the dominant policy influencing urban GEE in China.

Furthermore, in 2012, to enhance ambient air quality, the Ministry of Environmental Protection of China and the General Administration of Quality Supervision, Inspection, and Quarantine jointly released stricter "Ambient Air Quality Standards" (AAQS), which was gradually implemented in 74 key cities in 2012, and later in 113 another key cities in 2013. Thus, the interaction term *AS*× *TM* of the dummy variable (*AS*) and the time trend variable (*TM*) for the key cities is incorporated into Eq. (7). The results in Column (4) of Table 3 show that the coefficient β of variable *TR* remains significantly positive, and the coefficient of the interaction term *AS*× *TM*

Variables	Economic zone				Population density	
	Eastern zone (1)	Central zone (2)	Western zone (3)	Northeast zone (4)	High-density (5)	Low-density (6)
TR	0.018**	0.003	0.001	0.008	0.005**	− 0.000
	(0.008)	(0.005)	(0.005)	(0.005)	(0.002)	(0.007)
_cons	1.285***	0.731***	0.860***	0.936***	0.968***	0.856***
	(0.151)	(0.113)	(0.088)	(0.117)	(0.057)	(0.173)
Control variables	YES	YES	YES	YES	YES	YES
City-Fixed Effect	YES	YES	YES	YES	YES	YES
Year-Fixed Effect	YES	YES	YES	YES	YES	YES
Obs	1290	1200	1260	510	3900	360
R^2	0.161	0.147	0.096	0.144	0.126	0.103

Table 4. Heterogeneity test of economic zones and population density. The standard error value of coefficients is in parentheses; *, **, and *** denotes the significance levels of 10%, 5%, and 1%, respectively.

Variables	City size		Resource constraint		Regulation intensity	
	Large-sized (1)	Small-sized (2)	Non resource-based (3)	Resource-based (4)	Major-APPC (5)	General-APPC (6)
TR	0.007*	0.004	0.008***	− 0.002	0.007**	0.005*
	(0.004)	(0.002)	(0.003)	(0.003)	(0.003)	(0.002)
_cons	0.953***	0.931***	0.997***	0.875***	0.904***	0.866***
	(0.122)	(0.064)	(0.074)	(0.083)	(0.061)	(0.059)
Control variables	YES	YES	YES	YES	YES	YES
City-Fixed Effect	YES	YES	YES	YES	YES	YES
Year-Fixed Effect	YES	YES	YES	YES	YES	YES
Obs	1515	2745	2550	1710	3225	3585
R^2	0.149	0.096	0.139	0.093	0.114	0.104

Table 5. Heterogeneity test of city size, resource constraints, and regulation intensity. The standard error value of coefficients is in parentheses; *, **, and *** denotes the significance levels of 10%, 5%, and 1%, respectively.

is statistically insignificant. This implies that the Plan continues to be the predominant policy improving urban GEE.

Heterogeneity tests

Note that the regions of China exhibit distinct characteristics in terms of economic conditions, urban population, resource endowment, and environmental constraints. These variations can influence the effectiveness of environmental air regulations on green economy[41,62,65,66]. Consequently, this section aims to validate the heterogenous ATEs of issuing a plan on urban GEE, considering four aspects: cities in the four economic zones, population density, city size, resource constraints, and regulation intensity (see Tables 4 and 5).

Heterogeneity of economic zones

The analysis, segmented by China's economic zones, divides the overall samples into four sub-samples, including eastern cities, western cities, central cities, and northeast cities. This segmentation aims to explore whether there are heterogeneous ATEs of the Plan. The coefficients β of columns (1)–(4) in Table 4 indicate that the Plan leads to a significant improvement in urban GEE specifically for the eastern economic zone. Possibly, compared to other economic zones, the eastern region has faster economic growth and is generally dominated by technology- and capital-intensive industries. It has relatively strong innovation capabilities and abundant innovation resources, providing favorable conditions for industries to transform, upgrade, or eliminate outdated production capacity. In addition, residents in the eastern zone have a higher awareness of environmental protection and requirements for environmental quality. Therefore, the "innovation incentive effect" brought by the Plan is higher than its "cost compliance effect," ultimately helping increase urban GEE in the eastern zone. Contrarily, the central and northeastern economic zones are focused on heavy or resource-intensive industries lacking in technology and path dependence, while the western region has a relatively backward economy and weak innovation and industrial foundations. It is labor-intensive and has a relatively extensive production pattern. Most cities in these zones have long faced talent outflow. Moreover, they have taken on high-energy-consuming and high-polluting industries from other zones for local economic development. The issuance of the Plan might accelerate the transfer of polluting plants to cities of western zone.

Heterogeneity of population density
The Aihui-Tengchong Line, or Hu Line, is a boundary that separates China's population level from its economic and social structure. The eastern side of Hu Line accounts for only 43.8% of China's territory, with over 90% of the population. This region primarily consists of plains, water networks, and gentle hills. It has a relatively high average temperature and has historically relied on agricultural economies. In contrast, the western side of Hu Line has a population of less than 10% and a very low population density. This region is characterized by grasslands, deserts, and snow-covered plateaus. It has a cold and harsh climate and has relied on nomadic economies. Thus, the Hu Line is also known as China's ecological and environmental boundary. The overall sample is divided into two subsamples: cities on the eastern side of the Hu Line (i.e., the high-population density cities) and cities on the western side of the Hu Line (i.e., the low-population density cities). The coefficients β of columns (5)–(6) in Table 4 show that national Plan significantly benefits the GEE of cities on the eastern side of the Hu Line, namely, the high-population density cities. This is possible because compared to cities on the western side of the Hu Line, those on the eastern side have a large pool of innovative talent. Communicating and aggregating continually, they achieved knowledge spillovers and economies of scale. This provides a strong labor force and technological reserve for green innovation and industrial upgrading in that region. Plus, the intensity of China's environmental information supervision has gradually weakened from east to west[67,68]. In this sense, under the stimulation and promotion of China's APPC they could have a higher urban GEE.

Heterogeneity of city size
Based on household population size, the overall sample is divided into two sub-samples: large-sized cities (household population > 5 million) and small-sized cities (household population ≤ 5 million). According to the value of coefficients β in columns (1)–(2) of Table 5, implementing national Plan has a positive effect on the GEE of large-sized cities, but no significant effect on small-sized cities. A possible explanation is that China's large-sized cities tend to have more diversified industrial sectors and relatively complete industrial systems, making the transition from pollution-heavy production to green, intensive growth more efficient with economies of scale[63]. In contrast, small-sized cities often have a more homogeneous industrial structure and face higher levels of industrial isomorphism, which limits the effectiveness of the APPC in boosting their GEE.

Heterogeneity of resources constraints
Recognizing that various resource constraints can influence the impact of environmental regulations[69], a segmentation based on resource constraints is considered. Referring to the *National Plan for Sustainable Development of Resource-based Cities (2013–2020)* (The website of the file is: http://english.www.gov.cn/archive/state_council_gazette/2015/06/08/content_281475123321157.htm) issued by the State Council of China in 2013, the resource-based cities were identified. Thus, the overall samples are divided into two sub-samples: non-resource-based cities and resource-based cities. The coefficients β of variable TR in columns (3)–(4) of Table 5 reveal that China's APPC exerts a significant positive ATE on GEE of non-resource-based cities, while the insignificant ATE on GEE was observed in non-resource-based cities. Conversely, an insignificant ATE on GEE is observed in resource-based cities. This discrepancy may be attributed to the fact that, compared to resource-based cities, non-resource-based cities have lower dependence on resources and lower costs associated with environmental air regulation. Faced with the environmental pressure induced by the Plan, non-resource-based cities are compelled to upgrade green technology or explore new energy sources to address air pollution. Plants with high energy consumption or significant pollution in these cities have a strong incentive to invest in green R&D and enhance green innovation. Inversely, resource-based cities face a serious "resource curse" and even "race to the bottom" among governments at all levels for the depletion of resources[70–73]. This has added resistance to green economic transformation and development, ultimately resulting in the inability of the Plan to effectively promote the GEE of resource-based cities.

Heterogeneity of regulation intensity
Based on geographical features, socio-economic development level, atmospheric pollution level, urban spatial distribution, and the regional transport law of atmospheric pollutants, all key regions mentioned in China's Plan (i.e., the "Three Zones and Ten Clusters") is divided into two types: major-APPC cities and general-APPC cities. For different regions, the differentiated control requirements are implemented, and targeted APPC strategies are formulated. Thus, the overall samples are divided into two sub-samples: cities in major APPC cities (i.e., cities with high regulation intensity) and cities in general APPC cities (i.e., cities with low regulation intensity). The coefficients β of variable TR in columns (5)–(6) of Table 5 reveal that China's Plan exerts a significant positive impact on GEE of both major-APPC and general-APPC cities, especially the high ones. Possibly because for cities with high regulation intensity or major-APPC cities, more stringent environmental access conditions are implemented, and special emission limits for targeted industry pollutants are enforced, along with more effective pollution control measures. Furthermore, major-APPC cities also possess a high reserve of high-end talent and a relatively strong economic foundation. Additionally, there is a prevalent "race to the top" among various levels of government, which leads to the more efficiency derived from national Plan in promoting GEE of major-APPC cities.

Mechanisms tests
The above analysis demonstrates that implementing China's Plan enhances urban GEE significantly. Then, what are the specific transmission mechanisms or pathways involved? Based on the two hypotheses raised in Section

"Policy background and mechanism analysis" (i.e., *H1* and *H2*), we use green innovation and industrial structure as the two key mediators to construct the Mediating Effects Models (MEM) to identify the mechanisms of China's Plan driving urban GEE, including the roles played by either green innovation or industrial structure in this process. To check *H1* and *H2*, we refer to Hicks and Tingley[74] and derive the following MEM equations:

$$ME_{it} = \alpha_0 + \alpha_1 TR_{it} + \sum \lambda X_{it} + \mu_i + \delta_t + \varepsilon_{it} \tag{9}$$

$$GEE_{it} = \gamma_0 + \gamma_1 TR_{it} + \gamma_2 ME_{it} + \sum \lambda X_{it} + \mu_i + \delta_t + \varepsilon_{it} \tag{10}$$

where *ME* denotes the mediating variable through which the Plan makes the ATE on urban GEE, including ① Green innovation with green innovation quantity, *GIT* and green innovation quality, *GIL* (In the MEM estimation, the values of *GIT* and *GIL* are characterized by adding 1 to the number of green invention patent applications and grants, respectively, and then taken in the logarithmic form. The data on green invention patent applications and grants is obtained from the *Chinese Research Data Services* (CNRDS) Platform.). *GIT* and *GIL* represent the number of green invention patent applications and grants, respectively. ② Industrial structure, comprises two essential components: Industrial Structure Rationalization (*ISR*) (*ISR* is measured by the Thiel index or Theil's entropy measure, the equation of which is $ISR = \sum_{i=1}^{3} (y_i) \ln (y_i/l_i)$, where *yi* means the proportion of the added values of the primary ($i=1$), secondary ($i=2$), or tertiary ($i=3$) industry in GDP, and *li* means the ratio of the employees in the primary ($i=1$), secondary ($i=2$) or tertiary ($i=3$) industry to the total employees. In the MEM estimation, the values of *ISR* are taken in the logarithmic form. The data on *ISR* is obtained from the *China Urban Statistical Yearbook*) and Industrial Structure Optimization (*ISO*) (*ISO* is calculated by the following steps. First, the ratio of value added by the primary, secondary or tertiary industries to GDP is considered a component in the vector, thus getting three-dimensional vectors $X_0=(x_{1,0}, x_{2,0}, x_{3,0})$. Then, calculate the angle θ_j ($j=1, 2, 3$) of each industry between vectors X_0 and the vectors $X_1=(1, 0, 0)$, $X_2=(0, 1, 0)$, $X_3=(0, 0, 1)$ arranged from low to high, as following equation: $\theta_j = \arccos\left(\frac{\sum_{i=1}^{3}(x_{i,j} \cdot x_{i,0})}{\sum_{i=1}^{3}\left(x_{i,j}^2\right)^{1/2} \cdot \sum_{i=1}^{3}\left(x_{i,0}^2\right)^{1/2}}\right)$. Finally, we get the value of *SO* according to the equation $ISO = \sum_{k=1}^{3} \sum_{i=1}^{k} \theta_j$. In the MEM estimation, the values of *ISO* are taken in the logarithmic form. The data of *ISO* is obtained from the *China Urban Statistical Yearbook*). *ISR* gauges the adaptability of industrial structure to shifts in science and technology, and resource conditions. On the other hand, *ISO* reflects the evolution of industrial structure from elementary to advanced stages.

The proportion of total ATE that is mediated by *ME* between the Plan and urban GEE is measured by the equation: The proportion of total ATE mediated = Indirect ATE/Total ATE = Indirect ATE/(Direct ATE + Indirect ATE) = $(\gamma_2 \times \alpha_1)/(\gamma_1 + \gamma_2 \times \alpha_1)$, where γ_1 and $\gamma_2 \times \alpha_1$ denotes Direct ATE and Indirect ATE, respectively (see in Fig. 8). The test results for green innovation and industrial structure mechanisms are presented in Tables 6 and 7, respectively.

Green innovation mechanism tests

Columns (1)–(2) and Columns (3)–(4) of Table 6 report the mediating mechanisms of the *GIT* and *GIL*, respectively, as estimated by MEM. First, according to Eq. (9), the coefficient α_1 of variable *TR* in column (1) is not significant, while coefficient α_1 in column (3) is significantly positive, testifying that China's Plan facilitates green innovation quality rather than green innovation quantity. Next, according to Eq. (10), after adding a mediating variable (i.e., *GIT*/*GIL*), the coefficient γ_1 of variable *TR* in columns (2) and (4) remains significantly positive. Moreover, the coefficients γ_2 of both variable *GIT* in column (2) and *GIL* in column (4), reflecting either green innovation quantity or quality, are conducive to promoting urban GEE in China. In other words, as mentioned in the "Porter Hypothesis," implementing the Plan forces or induces polluting plants in the city to

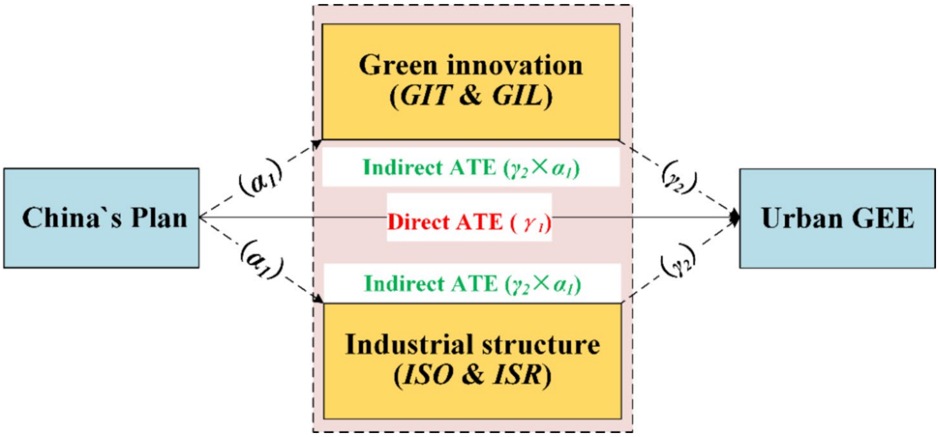

Fig. 8. MEM analysis diagram.

Independent variables	Dependent variables			
	(Plan→GIT→GEE)		(Plan→GIL→GEE)	
	GIT (1)	*GEE* (2)	*GIL* (3)	*GEE* (4)
TR	−0.007	0.005***	0.266***	0.005**
	(0.031)	(0.002)	(0.034)	(0.002)
ME		0.002**		0.002**
		(0.001)		(0.001)
_cons	−0.096	0.974***	3.847***	0.963***
	(0.928)	(0.058)	(1.056)	(0.058)
Control variables	YES	YES	YES	YES
City-Fixed Effect	YES	YES	YES	YES
Year-Fixed Effect	YES	YES	YES	YES
Obs	4260	4260	4260	4260
R2	0.930	0.119	0.907	0.120
Indirect ATE ($\gamma_2 \times \alpha_1$)	0.0000		0.0006**	
	(0.000)		(0.000)	
Proportion of total ATE mediated (%)	−0.27%		11.76%	

Table 6. Results of green innovation mechanism tests. Note: (1) *, **, and *** denote significance levels of 10%, 5%, and 1%, respectively; (2) the standard error values are in parentheses; (3) the Sobel-Goodman Mediation Tests (SGMT) method is used to obtain the standard error and confidence interval of indirect ATE; and (4) the variable *ME* is used to refer uniformly to mediating variables *GIT* and *GIL* in the corresponding MEM.

Independent Variables	Dependent variables			
	(Plan→ISO→GEE)		(Plan→ISR→GEE)	
	ISO (1)	*GEE* (2)	*ISR* (3)	*GEE* (4)
TR	0.008***	0.003**	0.156***	0.006***
	(0.001)	(0.001)	(0.026)	(0.002)
ME		0.033**		−0.001
		(0.016)		(0.001)
_cons	1.567***	0.894***	0.298	0.975***
	(0.034)	(0.028)	(0.944)	(0.058)
Control variables	YES	YES	YES	YES
City-Fixed Effect	YES	YES	YES	YES
Year-Fixed Effect	YES	YES	YES	YES
Obs	4260	4260	4260	4260
R2	0.944	0.071	0.838	0.119
Indirect ATE ($\gamma_2 \times \alpha_1$)	0.0003**		−0.0002	
	(0.000)		(0.000)	
Proportion of total ATE mediated (%)	7.39%		−3.68%	

Table 7. Results of industrial structure mechanism tests. Note: (1) *, **, and *** denotes the significance levels of 10%, 5%, and 1%, respectively; (2) the standard error values are in parentheses; (3) The method of Sobel-Goodman Mediation Tests (SGMT) is used to obtain standard error and confidence interval of indirect ATE; (4) the variable *ME* is used to refer uniformly to mediating variables *ISR* and *ISO* in corresponding MEM.

engage in green R&D or innovation to obtain innovation competitiveness and excess profits. This becomes the driving force for improving urban GEE.

Consequently, China's Plan makes positive ATE on green innovation quality, pushing the urban GEE further. That is, the ATE of the Plan on urban GEE is positively mediated by green innovation quality, which is an indirect or mediating effect of *GIL*, with a value of 0.0006. Correspondingly, the proportion of total ATE mediated by *GIL* is 11.76%. Thus, *H1* is partially verified.

Industrial structure mechanism tests
Columns (1)–(2) and Columns (3)–(4) of Table 7 report the mediating mechanism of the *ISO* and *ISR* estimated by MEM, respectively. First, the coefficients α_1 of variable *TR* in column (1) and column (3) are both significantly positive, expressing that the issuance of China's Plan promotes industrial structure optimization and rationalization. Then, after add mediating variable (i.e., *ISO*/*ISR*), the coefficient γ_1 of variable *TR* in column (2) and (4) still keep significantly positive as well. Plus, the coefficient γ_2 of variable *ISO* in column (2) is significantly positive, while that of variable *ISR* in column (4) did not pass the significance test, demonstrating that urban GEE benefit from industrial structure optimization rather other industrial structure rationalization. In other words, the implementation of the Plan places pressure on the environmental management of air pollution control in cities and provides impetus for the transformation of industrial structure. It effectively guides the flow of factors and resources towards sectors with higher green productivity, and promotes the transition of industrial structure from "low-end, highly pollution, and energy-intensive" to "high-end, green, and intensive." This becomes another driving force for improving urban GEE.

Consequently, the China'2s Plan makes positive ATE on industrial structure optimization, which then helps improve urban GEE. That is, the positive impact of APPC on urban GEE in China is mediated positively by industrial structure optimization, i.e., indirect effect of *ISO*, value of which is 0.0003. Correspondingly, proportion of total ATE mediated by *ISO* is 7.39%. Until now the *H2* is partly testified.

Further analysis: spatial spillover
Additionally, not only the efficiency or TPF per se of different regions may have spatial correlation[25,59], and the regulatory effects of various environmental measures may also have spatial spillover among areas or even countries, which is often overlooked or ignored. Partly because some polluting plants move from areas with stringent environmental regulations to areas with lax or without environmental regulation, then bringing damage to the local environment, i.e., negative externality, which is also known as the "pollution haven effect"[17,75,76]. Correspondingly, the relocation or investment of eco-friendly resource-saving and enterprise, may help improve the local energy conservation and emission reduction via FDI inflows or green innovation, i.e., positive externality, which is also known as the "pollution halo effect"[77–79].

Therefore, taking into account the potential local ATE induced by the Plan on GEE of geographical adjacent cities, i.e., the spatial spillover of ATE, we extend Eq. (7) by constructing a Dynamic Spatial-Dubin DID (DSD-DID) model given by the following equation:

$$GEE_{it} = \xi GEE_{it-1} + \beta TR_{it} + \rho \sum W_{ij} \times GEE_{jt} + \theta \sum W_{ij} \times TR_{jt} + \lambda \sum X_{it} + \mu_i + \delta_t + \varepsilon_{it} \quad (11)$$

In this equation, the coefficient ξ measures the dynamic impact of urban GEE in the $t-1$ year on that in the t year. If $\xi = 0$, the DSD-DID model will transform into a Static Spatial-Durbin DID model (SSD-DID); ρ represents the spatial coefficient, indicating spatial correlation or spillover of GEE among cities; the coefficient θ of the interaction $W \times TR$ measures the spatial spillover of the ATE; Here, W_{ij} denotes the spatial weight matrix, which is the inverse of the spherical geographical distance between cities i and j. Other variables remain the same as Eq. (7).

Columns (1)–(2) and Columns (3)–(4) in Table 8 show the regression results for the SSD-DID model and DSD-DID models. All coefficients β of the variable *TR* are significantly positive. This verifies that after considering the spatial correlation, the issuance of the Plan still benefits urban GEE, confirming the robustness of the benchmark results. Also, the spatial coefficients ρ are significantly positive in all columns of Table 6,

Variables	(1) SDM-DID	(2) SDM-DID	(3) DDM-DID	(4) DDM-DID
L.GEE			−0.012	−0.017
			(0.054)	(0.054)
TR	0.005**	0.006**	0.005*	0.005**
	(0.003)	(0.003)	(0.003)	(0.003)
W×TR	−0.004	−0.011*	−0.005	−0.011*
	(0.004)	(0.006)	(0.004)	(0.006)
Spatial ρ	0.752***	0.718***	0.756***	0.738***
	(0.043)	(0.049)	(0.044)	(0.049)
Control variables	NO	YES	NO	YES
City-Fixed Effect	YES	YES	YES	YES
Year-Fixed Effect	YES	YES	YES	YES
Obs	4260	4260	3976	3976
R^2	0.005	0.010	0.002	0.002

Table 8. Results of spatial spillovers of ATE test. The standard error values of coefficients are in parentheses; *, **, and *** denote the significance at the 10%, 5%, and 1% levels, respectively.

indicating that the GEE among cities produces a positive spatial spillover to neighboring cities. Notably, all the coefficients θ of the interaction term $W \times TR$ are significantly positive, displaying that implementing the Plan locally significantly improves the GEE of neighbors geographically. This suggests that the Plan's implementation can have a positive spatial spillover of ATE on the GEE of nearby cities, demonstrating a "pollution halo effect" and expanding upon the findings of Bhowmik et al.[15], which show that APPC policies can foster GEE spillovers beyond policy boundaries and potentially inspire adjacent regions to adopt greener practices.

According to the plan requirements, the lead in promoting the joint prevention and control of air pollution in key areas is undertaken. Furthermore, taking a holistic perspective, cities in the key regions implement regional strategies for APPC, to improve air quality, and strictly regulate environmental access, promote clean energy utilization, implement coordinated control of multiple pollutants, significantly reduce pollutant emissions, and establish an "incentive mechanism" that promotes environmental optimization and economic development. This facilitates the transformation of economic development and promotes the coordinated development of the regional economy and environment. Consequently, the local issuance of the Plan helps improve not only the local GEE but also the GEE of neighboring cities.

Conclusions, policy implications, and research prospects

Conclusions

The "12th Five-Year Plan for Key Regional Air Pollution Prevention and Control" is China's first comprehensive plan for APPC, initiated in December 2012, serves as a significant environmental air regulatory tool. It represents a shift from the regulatory focus on controlling total pollutant emissions to improving environmental quality, aiming for a harmonious balance between economic development and environmental regulation.

This study, utilizing panel data from 284 prefecture-level and above cities spanning 2006 to 2020 and employing the SBM-GML model, measures and analyzes urban GEE (GEE) in China. The study further employs DID models and mediating effect models to explore whether and how China's APPC policy promotes urban GEE. The key findings include:

① Overall, urban GEE in China shows a general growth trend. The issuance of national Plan for APPC may, however, contribute to widening the gap in urban GEE between the Eastern/Central and Western/Northeast zones and between key APPC regions and non-key APPC regions. ② The Plan significantly improves GEE in cities within key APPC regions, with a noticeable "hysteresis effect." Robustness checks, including placebo tests and PSM-DID, further enhance the objectivity of the conclusions. Also, the positive spatial spillovers of the ATE induced by the Plan on urban GEE are also captured, revealing a "pollution halo effect". ③ Heterogeneity tests indicate that the Plan predominantly benefits GEE in within cities of eastern zone, high-population density cities, large-sized cities, non resource-based cities and major-APPC cities. ④ Mechanism tests reveal that the Plan for APPC can favorably impact GEE through two mediating channel, either by promoting green innovation quality or by optimizing industrial structure in China.

Policy implications

Building on these findings, three policy recommendations are proposed:

① Promoting Multi-Regional and Cross-Regional Collaboration: The study empirically demonstrates that the Plan has a significant positive ATE on urban GEE with a lag and spatial spillover effect. Therefore, there is a need to support collaborative efforts in air pollution prevention and control across multiple regions. Policymakers should discourage the transfer of polluting plants across regions, strictly prohibit practices such as "shifting the burden to others," and establish clear responsibility for environmental pollution based on the principle of "who pollutes, who controls." This collaborative approach can synergistically promote urban air pollution control and enhance green economy efficiency.

② Tailoring Implementation to Regional Characteristics: Acknowledging the heterogeneous ATE of the Plan on GEE across different types of cities, policymakers should implement the Plan in a manner that considers the economic characteristics and environmental constraints of each region. Long-term strategies should be developed to balance sustainable economic development and air pollution prevention. For example, cities in the western and northeastern zones or areas with low population density should establish mechanisms compatible with their incentives and constraints, focusing on environmental protection while ensuring sustainable development. Resource-based cities should accelerate green reforms to upgrade industries and seize opportunities for green development presented by the Plan.

③ Leveraging Environmental Regulatory Tools for Green Innovation and Industrial Upgrading: To address the challenge of short-term environmental deterioration and achieve long-term green development, the positive role of environmental regulatory policy tools should be fully utilized. Cities can introduce fiscal incentives and subsidies to encourage polluting plants to invest in green research and development. This approach aims to stimulate green innovation and achieve energy conservation and emissions reduction. Additionally, diverse industrial support policies should be formulated to promote overall industrial transformation and upgrading, fostering synergistic linkages between different industries. This comprehensive strategy will contribute to a new path of environmental governance that focuses on overall industrial collaboration and upgrading, providing robust support for urban green economies.

Research forecast

The mechanism between environmental air regulation and urban green development is undoubtedly complex. While this study focuses on the mediating effects of green innovation and industrial structure, we recognize the significance of other key factors, such as resource allocation, intergovernmental dynamics, and foreign direct investment. Future research should explore these overlooked mechanisms to offer a more holistic understanding of the relationship, potentially incorporating insights from more finer granularity, such as county-level or micro-level. Additionally, it highlights the need for more comprehensive selection and measurement of control variables, emphasizing the importance of a scientific and cautious approach in subsequent studies, given the limitations of quantitative methods and data availability.

Data availability

The datasets used and/or analyzed during the current study are available from the corresponding author upon reasonable request.

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Author contributions

Han Zhang performed conceptualization, methodology, software, and wrote the main manuscript text; Weijian Dou prepared all figures and tables.

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Declarations

Competing interests

The authors declare no competing interests.

Additional information

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