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Environmental forcing and policy synergy: A multidimensional approach in the governance of air pollution and carbon emission

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ABSTRACT

Policy synergies effectively contribute to the integrated management of air pollution and carbon emissions, which is crucial for safeguarding ecosystem stability and public health. This study uses the causal network model of Gaussian process regression to analyze the combined impacts of dynamic and static carbon emission reduction and air quality policies on carbon emissions and air quality. The causal effects of policy measures and their synergistic effects are also examined. The study results indicate: (1) There is significant geographical heterogeneity in the implementation of environmental policies and regional economic development, with the economically developed eastern coastal regions adopting more stringent carbon emission and air pollution control measures, while the western provinces adopt relatively lax environmental policies. (2) The synergistic effect of carbon emission reduction policies and air quality policies exists, and the two types of static policies are substitutable for managing carbon dioxide emissions and air pollution. (3) Policies' forced effect exists, where the exacerbation of environmental problems leads to the formation and implementation of policies. (4) The value added by the secondary industry is a key motivation for forming carbon emission reduction policies and air quality control policies. Additionally, the value added by the secondary industry directly impacts the incidence of respiratory diseases (e.g., tuberculosis). Finally, dynamic and synergistic policy recommendations are proposed based on the study's findings.

1. Introduction

The rapid development of China's secondary industry has significantly boosted economic growth. The value added by the secondary industry increased by 84.2 percent in 2023 compared to 2013, with an average annual growth rate of more than 6 percent (National Bureau of Statistics of China, 2024). However, the secondary industry, characterized by energy-intensive and highly polluting sectors, has become a major source of air pollutants (Yi et al., 2022). In 2022, 37.2 percent of cities in China still had substandard air quality, ranking the country 160th out of 180 in terms of environmental performance (Xu et al., 2024). PM2.5 has become the world's fifth deadliest risk agent, causing about three million deaths per year from air pollution-related diseases, with China being particularly affected (Wei et al., 2021).

The large-scale expansion of the secondary industry has triggered serious air pollution and exacerbated carbon emissions (Liu et al., 2020). In 2023, China's carbon emissions reached 12.6 billion tonnes, exceeding one-third of the global total (IEA, 2024). Excessive carbon dioxide emissions are a major driver of global warming (Kılkış et al., 2020) and have significant impacts on the economy, environment, and food security, threatening human survival [8˗9]. Currently, China, as the world's largest carbon emitter (Zhang and Yang, 2024), is committed to achieving its "dual carbon" goals but continues to face many challenges [11,12].

The Chinese government has implemented several important policies to address the dual pressures of reducing carbon emissions and mitigating air pollution (Sun et al., 2023). In 2012, environmental performance was included in appraisals, and a national ambient air quality monitoring network was established to incentivize local governments to control air pollution (Lu et al., 2023). In 2013, the Air Pollution Prevention and Control Action Plan was implemented to limit the emission of air pollutants from the industrial sector (Zhang et al., 2019). In 2018,

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the Three-Year Action Plan to Win the Battle for a Blue Sky further called for the reduction of air pollution (Xiao et al., 2021). Regarding carbon emission reduction, the government enacted the Nationally Appropriate Mitigation Actions (NAMAs) and the National Autonomous Contribution Plan (NACP), setting mandatory energy and carbon intensity reduction targets in various five-year plans (Liu et al., 2022). Additionally, the carbon trading policy was piloted in Beijing, Tianjin, Shanghai, Chongqing, and other provinces and cities [18]. The national carbon trading market was officially launched in 2021, and local governments have introduced relevant carbon emission reduction policies and regulations (Liu et al., 2020) in a concerted effort to alleviate China's carbon emission problems.

Due to the homologous nature of carbon emissions and air pollution (Zheng et al., 2018), there is a close link between the two in terms of governance strategies. Carbon emission reduction policy measures can indirectly reduce air pollutant emissions, realizing the synergistic benefits of carbon emission reduction and air quality improvement. Adopting source control strategies, such as replacing fossil energy with cleaner energy sources, improving industrial production processes, and optimizing the industrial structure in air pollution control policy, can also effectively reduce carbon emissions and form a synergistic effect (Zhang et al., 2023b). In view of this, the Chinese government has begun to focus on the synergistic management of air pollution and carbon emissions. The "Implementation Plan for Synergistic Effectiveness of Pollution Reduction and Carbon Emission Reduction" was issued in 2022, marking the substantive stage of promoting synergistic management of environmental pollution reduction and carbon emission reduction(Xian et al., 2024a).

The innovativeness of this study is mainly reflected in (1) classifying air quality and carbon emission reduction policies into two categories: static and dynamic policies, considering the interaction and synergistic effects among policies, and incorporating respiratory-related disease data to further analyze the policy influence mechanism, which provides the theoretical basis for formulating more accurate and comprehensive environmental policies. (2) Combining Gaussian process regression and causal network models to effectively deal with nonlinearity and dynamic uncertainty, revealing the interaction and causal effects among policies through network topology, and improving the explanatory power and precision of the model, which provides a new methodological path for evaluating and optimizing environmental policies.

The subsequent chapters of this study are arranged as follows: the second part consists of a literature review on the study of carbon emission and air pollution under industrial development, the role of policies in carbon emission reduction and air quality, and the study of the causal effect model. The third and fourth parts use the causal network model, constructed via Gaussian process regression, to explore the causal effects and the synergistic nature of policies related to carbon emission reduction and air pollution. The fifth part presents the results based on the theoretical model, discussing both the outcomes of the model and their real-world implications. Part VI offers recommendations for the synergistic management of carbon emissions and air pollution based on the conclusions.

2. Literature review

2.1. Study on carbon emissions and air pollution under industrial development

Carbon emission and air pollution issues have been the focus of academic research. The development of the secondary industry impacts carbon emissions and PM2.5 concentrations [22-23]. Air pollution not only increases the environmental burden (You et al., 2024) but also negatively affects human health (Huang et al., 2018). When exploring the relationship between industrial development and carbon emissions, studies usually focus on industrial agglomeration and transfer, technological progress, industrial structure upgrading, and the impact of industrial trade on regional carbon emissions.

The relationship between industrial agglomeration and carbon productivity shows an inverted "U" shape, and technology plays a prominent role at the inflection point (Liu and Zhang, 2021). In the long run, industrial labor and capital agglomeration will increase carbon emissions; industrial output agglomeration also significantly contributes to regional carbon emissions, while industrial technology agglomeration has a significant inhibitory effect on regional carbon emissions (Tang et al., 2022). Luan et al. (2023) empirically found that industrial transfer exacerbates inter-city carbon transfer (Luan et al., 2023). Pan et al. (2024) found that circular economy agglomeration in urban manufacturing effectively reduces carbon emissions at the city level (Pan et al., 2024).

Xia et al. (2022) assessed the relationship of implied carbon emission flows between industrial sectors in China and found significant carbon leakage (Xia et al., 2022). Wang et al. (2022) studied the relationship between participation in GVCs, industrial upgrading, and carbon emissions in different countries. The results showed that the transformation and upgrading of industrial structure when participating in GVCs mitigate carbon emissions in developing countries (Wang et al., 2022). Wang et al., 2024b found that low carbon emissions in southern China come at the expense of high trade-implied carbon emissions in the north and that carbon emission intensity and bilateral trade-industry linkages are the dominant factors of implied carbon emissions (Wang et al., 2024a).

Carbon dioxide mainly comes from industrial economic activities, making industrial structure upgrading particularly important for carbon emission reduction (Gu et al., 2022). Technological upgrading can effectively correct the distorting effect of resource dependence on the rationalization of industrial structure (Zheng et al., 2023). Zhao et al. (2023) found that fiscal decentralization and industrial structure upgrading inhibit carbon emissions (Zhao et al., 2023). In addition, the digital economy and industrial intelligence reshape the industrial structure, which in turn reduces carbon emissions-a fact confirmed by research [36-38].

In the study of the relationship between industrial development and air pollution, Yan et al. (2021) confirmed the relationship between industrial structure, economic development, and PM2.5. (Yan et al., 2021). Wang et al. (2021) found that optimizing industrial structure significantly reduces haze in Western China while improving energy efficiency is more significant in the east (Wang et al., 2021). Yan et al. (2022) found that industrial structure upgrading significantly improves air quality (Yan et al., 2022). Tan et al. (2022) found that the relationship between industrial agglomeration and urban haze pollution is not purely linear or inverted U-shaped but dynamically N-shaped, with heterogeneous effects of agglomeration type on haze pollution (Tan et al., 2022).

2.2. Study on the policy role of carbon emission reduction and air quality

The Chinese government has introduced policies to regulate carbon emissions and air pollution, and academics have conducted corresponding research. In terms of carbon emission reduction, Danish et al. (2020) confirmed that environmental regulations effectively boosted carbon emission reduction (Danish et al., 2020). Dai et al. (2022) analyzed the spatial spillover effect of carbon trading policy on industrial carbon intensity reduction through a spatial double-difference model and found that it effectively lowered the carbon intensity in the pilot area, while technological progress played an intermediary role (Dai et al., 2022). Shen et al. (2023) empirically found that the pilot carbon emissions trading policy reduced carbon emissions and promoted the adjustment of industrial low-carbon structure (Shen et al., 2023).

In terms of mitigating air pollution, He et al. (2021) showed that pollution rights trading policies are effective in promoting the "decoupling" of industrial pollution from economic growth. Low-carbon city policies and carbon emissions trading policies play an important role in reducing industrial smog emissions and carbon emissions (He et al., 2021). Guo et al. (2024) also found that healthy city pilot policies significantly curbed industrial pollutant emissions and improved air quality (Guo and Zhang, 2024). Xie et al. (2024) found that air pollution regulation policies not only improved regional air quality but also increased health and welfare benefits in the policy area (Xie et al., 2024).

In carbon-air pollution synergistic governance, key technological innovations play a driving role (Tian et al., 2023). Carbon-biased technological advances can promote synergistic governance through energy savings or hinder it due to rebound effects (Zhang et al., 2023a). Technology-biased energy can significantly mitigate carbon emissions and PM2.5 pollution. Bollen et al. (2014) investigated the interactions of climate change policies with greenhouse gases and air pollutants (Bollen and Brink, 2014). Yi et al. (2022) analyzed the impacts of urbanization, industry, economy, energy, and innovation on the synergistic management of carbon-air pollution from a spatio-temporal perspective (Yi et al., 2022), and these factors are mediators of the environmental policies' role in the pathway of synergistic management of carbon-air pollution [52-54]. Shao et al. (2023) found that low-carbon policies can improve the atmospheric environment by promoting the upgrading of the industrial structure and optimization of the energy structure (Shao et al., 2023). Xian et al. (2024) found that carbon trading policies improved air quality in pilot areas by studying the relationship between carbon trading policies and pollutant emissions from power and industrial sectors (Xian et al., 2024b).

In summary, carbon emissions and air pollution are closely related to the development of the secondary industry, while government policies have been effective in reducing carbon emissions and mitigating air pollution. Since carbon emissions and air pollution have a certain homologous nature (Wang et al., 2023), government regulation of one aspect will have a synergistic effect on the governance of the other. However, existing studies mostly focus on the synergistic governance of a single policy, and the synergistic governance mechanism between the two types of policies is still to be explored.

2.3. Causal effects modelling studies

At present, the causality assessment for policy effects mostly adopts methods such as Regression Discontinuity Design, Synthetic Control Methods, and Difference in Differences. For example, Bronzini R. et al. (2014) assessed the effect of R&D policy through Regression Discontinuity Design (Bronzini and Iachini, 2014). Chen and Lin, 2021 and Xian et al. (2024) used Synthetic Control Methods and Difference in Differences, respectively, to assess the effects of carbon emissions trading policy from different perspectives [56,59]. The basic logic of these methods is to derive the causal relationship of X on Y by constructing a counterfactual control group and comparing it with the policy intervention group. This involves comparing the outcome of the hypothetical research subject Y, after receiving policy intervention X, with the outcome without policy intervention. Its data types can be divided into the assessment of dichotomous variables and the assessment of continuous variables (Pearl, 2000). However, in actual research, relevant policies and data are non-experimental, making it impossible to set up control results to identify causality through experimental interventions.

To account for the dynamic, complex, and nonlinear relationships among the actual data, studies have combined network analysis models with causal identification (He and Song, 2023). The linear non-Gaussian acyclic model (LiNGAM) proposed by Shohei Shimizu et al. (2006) is the most basic method for causal function modeling (Shimizu et al., 2006). On this basis, Hoyer and Shimizu designed an additive noise model (ANM) and a linear non-Gaussian acyclic model based on Bayesian estimation, respectively [63,64]. Liu et al. (2023) further constructed the Gaussian nonlinear additive noise model and combined it with graphical complex analysis, offering flexibility, adaptability to the amount of data, and the ability to handle high-dimensional data. This makes its causal identification results better than those of the traditional causal analysis model (Liu et al., 2023).

3. Material and methods

3.1. Data

This study collected datasets from 2003 to 2024 for each province in China from various sources, including the National Bureau of Statistics (NBS), CEADs China Carbon Accounting Database, Atmospheric Composition Analysis Group of Washington University in St. Louis, Public Health Science Data Centre, China Cause of Death Surveillance Dataset, National Disease Surveillance System Cause of Death Surveillance Dataset, Peking University Law Database, and provincial ecological environment departments.

In the selection of relevant policies, a combination of dynamic and static policy frameworks was adopted. Dynamic policies, which are long-term sustainable penalties based on laws and regulations, better reflect the effects of policy implementation. Static policies, which are laws and regulations of the central government and individual provinces, demonstrate the intensity of policy formulation and areas of focus. Firstly, under static policy statistics, air pollution and low-carbon policies were retrieved based on keywords and synonyms. The number of central and provincial policies was manually verified and counted. The data were then divided into two groups: cumulative values and newly added values. When calculating the cumulative value, two rules were followed: first, the cumulative value for 2003 included all relevant policies and regulations before that year; second, the policy or regulation was removed when it lapsed or was repealed in a cumulative year. Secondly, in calculating dynamic policies, policy implementation data from the ecological environment departments of each province were manually screened and identified. Finally, after repeated verification and comparison, two sets of data were obtained for each type of policy: static (new and cumulative) and dynamic values for the year. The specific breakdown of static and dynamic policies is illustrated in Table 1.

The data collected was categorized into several groups: The first group on air pollution included air quality indicators (PM2.5, PM10, CO, SO_2, NO_2, O_3) and air quality policy (dynamic and static). The second group on carbon emissions included CO_2 emissions and carbon emission reduction policy (dynamic and static). The third group on the development of the secondary industry included secondary industry added value, energy industry investment, industrial policies (dynamic and static), and total energy consumption. The fourth group concerned human health impacted by air pollution, including data on respiratory disease deaths, mortality rates, tuberculosis incidence, and incidence rates. Additional control variables included Gross Regional Product (economic data of each province), resident population at year-end (demographic data of each province), number of R&D projects, and R&D expenditure of industrial enterprises (reflecting the innovation activities of major carbon-emitting enterprises), along with total energy consumption.

Due to the large number of missing actual data, some variables with too many missing years and poor interpolation fit were deleted. The panel data from 2004 to 2022 was selected as the final dataset, with the remaining missing years filled in using linear interpolation (Newton interpolation, Lagrangian interpolation, KNN interpolation, and other interpolation methods were considered but found to be negative and not realistic).

3.2. Descriptive analysis

To visualize the air pollution and carbon emissions among provinces, ArcGIS is used to plot the mean values of PM2.5 and CO_2 for each province for the complete dataset from 2004 to 2022.

From Fig. 1, it is evident that air pollution is mainly concentrated in North China, especially in Hebei (HB1) and Shandong (SD) provinces. Surrounding provinces, such as Beijing (BJ), Tianjin (TJ), Shanxi (SX2),

Table 1
Static - Dynamic Policy list (Part).

policy	Air quality policy		Carbon emissions reduction policy	
	Static: laws and regulations	Dynamic: Reward and punishment implementation	Static: laws and regulations	Dynamic: Reward and punishment implementation
The central government	Air Pollution Prevention Law of the People's Republic of China (2018 Amendment)	None	Notice of The General Office of the State Council on issuing the 2014–2015 Action Plan for Energy Conservation, Emission Reduction and Low-carbon Development	None
The provincial government	Regulations of Guizhou Province on the Prevention and Control of Air Pollution (Amended in 2023)	Case of Suspected Failure to set up air pollutant discharge Outlets following regulations (No. 2102321006)	Interim Measures of Hubei Province for the Administration of Carbon Emission Rights Trading	Zhejiang Huajia Thermal Power Group Co., Ltd. is suspected of key emission units did not pay carbon emission quotas on time and in full (Shao City Huan Penalty Word [2022] No. 9 (new))
	Regulations of Shaanxi Province on Air Pollution Prevention and Control (Amended in 2023)	Pujiang Hangbiao Material Packaging Co., LTD. + Excessive emission of air pollutants (Jinpu Huan penalty Word [2020]28)	Trial Measures for Carbon Emission Management of Guangdong Province	Chongqing Ecological Environmental Protection Comprehensive Administrative Law Enforcement Corps Administrative Punishment Decision No. 86 (Chongqing Hechuan Salt Chemical Industry Co., LTD.)
	Regulations of Guangdong Province on the Prevention and Control of Air Pollution (Revised in 2022)	Shanghai Xiangzhe International Cargo Transport Agency Co., LTD. Motor vehicles, ships, and non-road mobile machinery exceeding the standard emission of air pollutants	Trial Measures of Shanghai Municipality for Carbon Emission Management	Inner Mongolia Autonomous Region Department of Ecology and Environment Administrative punishment Decision (Inner Ring punishment Word (2022) No. 9)
	Regulations of Jilin Province on Prevention and Control of Air Pollution (Revised in 2022)	About the case of Zaozhuang Longxiang Furnace Material Co., Ltd. suspected of discharging air pollutants in excess of pollutant discharge standards	Interim Measures of Shenzhen Municipality for the Administration of Carbon Emission Rights Trading	Hengsheng Energy Co., Ltd. suspected of false reporting of greenhouse gas report (Quhuan Longyou Penalty [2022] No. 14)

Note: The data come from the Peking University Law Database (https://www.pkulaw.com/) and provincial ecological environment departments.

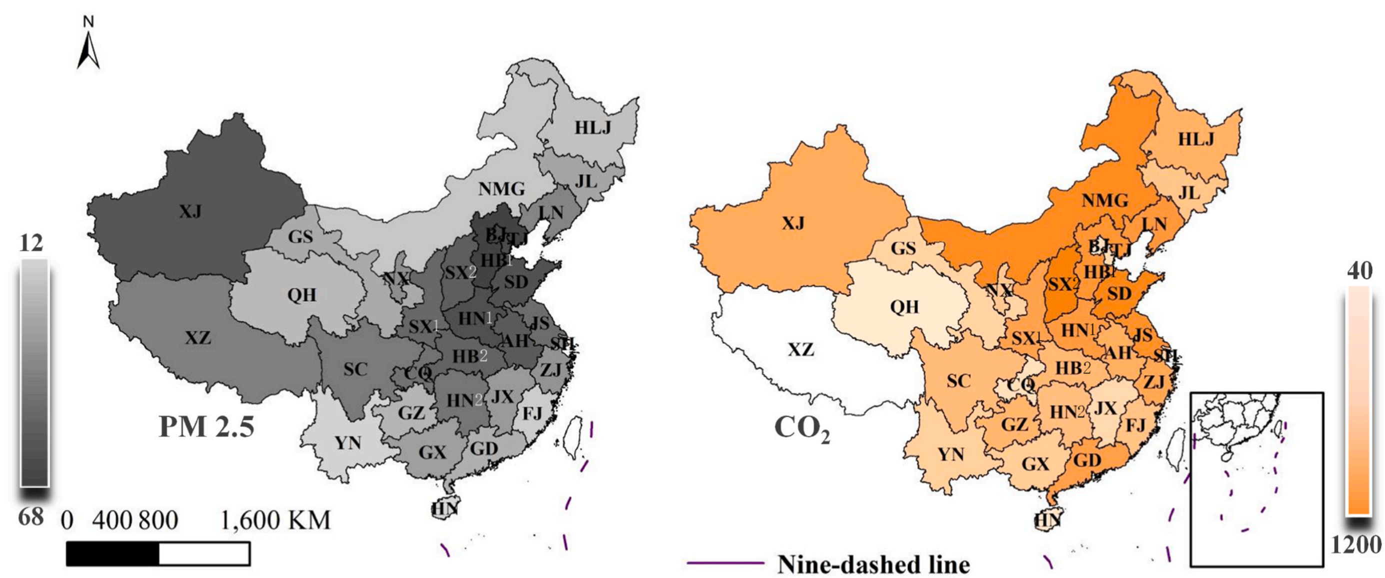

Fig. 1. Average PM2.5 and CO_2 in China from 2004 to 2022. Note: Tibet appears white in the right panel due to the lack of data; each province's name is capitalized in the Chinese context. To effectively differentiate between provinces with the same abbreviation, numerical labels have been added after the abbreviation.

Henan (HN1), and Jiangsu (JS), also exhibit relatively high levels of air pollution. The provinces with high carbon emissions have shifted northwards from the PM2.5 center, primarily in the central and eastern provinces, including Shanxi (SX2), Shandong (SD), Hebei (HB1), Henan (HN1), and Jiangsu (JS). In contrast, regions like Tibet (XZ) and Qinghai (QH) in the west have relatively low levels of both air pollution and carbon emissions. This distribution may reflect the degree of industrialization and population density in each province. Additionally, the consistency in the depth of color distribution in the figure suggests a potential positive correlation between the concentrations of PM2.5 and CO_2 emissions.

As depicted in Fig. 2, the GDP per capita and the secondary industry added value are higher in the coastal regions, particularly in the eastern provinces of Jiangsu (JS), Shanghai (SH), and Guangdong (GD). Conversely, the western provinces such as Gansu (GS), Qinghai (QH), and Tibet (XZ) exhibit lower GDP per capita and smaller secondary industry added value. Overall, regions with more advanced development in the secondary industry also demonstrate relatively higher GDP per capita.

A joint analysis with Fig. 1 shows a potential link between economic development, industrialization, and environmental pollution. Regions with higher levels of economic development and industrialization often experience greater levels of environmental pollution. The secondary sector (including manufacturing, construction, electricity, mining, etc.)

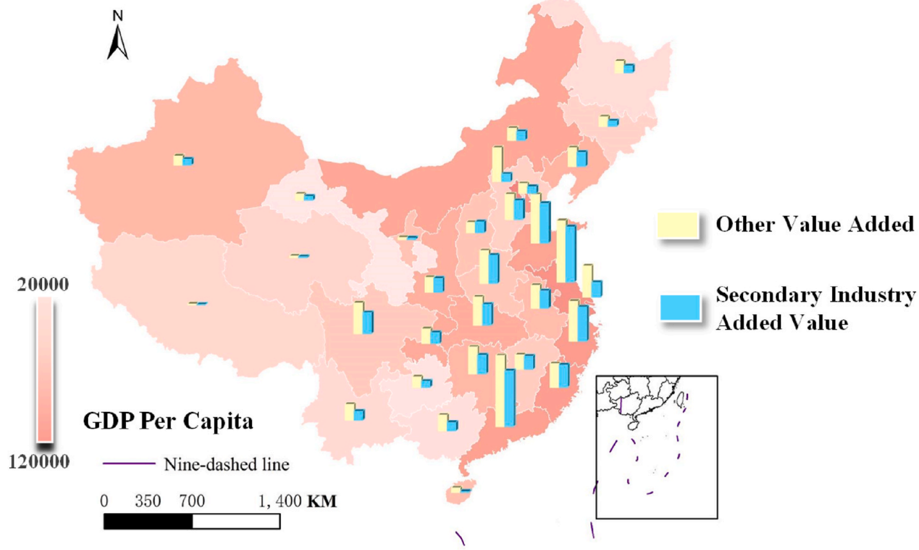

Fig. 2. Average GDP per capita and value added of industries by province in China, 2004–2022.

is an important part of the industrialization and modernization process and is usually associated with higher energy consumption and higher pollutant emissions (including PM2.5 and CO_2). Coastal provinces, especially economically developed regions, bring higher value added in the secondary sector and corresponding pollutant emissions. In contrast, regions such as Tibet (XZ) and Qinghai (QH), which are sparsely populated and have relatively few industrial activities, have relatively low pollutant emissions.

Note: Fig. A represents the mean value of new air quality-related policies (static) for each province in the year 2004–2022, while Fig. B represents the cumulative value of air quality penalties (dynamic) for that province during the same period. Similarly, Fig. C represents the mean value of new carbon emission reduction-related policies (static) for each province in the year 2004–2022, and Fig. D represents the cumulative value of new carbon emission reduction-related penalties (dynamic) for each province over the same period. To effectively differentiate between provinces with the same abbreviation, numerical labels have been added after the abbreviation.

Fig. 3 shows the implementation of air quality policies and carbon emission reduction policies in each province of China from 2004 to 2022, from both static and dynamic policy perspectives. Fig. 3A indicates that a relatively large number of air quality policies have been implemented in the central and eastern regions from 2004 to 2022, especially in Henan (HN1), Shandong (SD), and Jiangsu (JS). Conversely, the northwestern regions, such as Qinghai (QH), Xinjiang (XJ), Gansu (GS), and Tibet (XZ), have a relatively small number of new air quality-related policies. Fig. 3B shows that Hebei (HB1), Shandong (SD), and Jiangsu (JS) have a high number of environmental violations from 2004 to 2022, based on the cumulative value of air pollution-related penalties.

In terms of carbon emission reduction policies, Fig. 3C indicates that the number of new policies in the central and eastern regions is higher from 2004 to 2022, with Shandong (SD), Jiangsu (JS), and Guangdong (GD) formulating more policies to promote carbon emission reduction. Fig. 3D shows that the cumulative value of penalties for carbon emissions is relatively high in the eastern region from 2004 to 2022, with Guangdong (GD), Shandong (SD), and Zhejiang (ZJ) imposing severe penalties for non-compliance with regulations.

Taken together, some provinces in East and South China have been more active and stringent in implementing environmental protection policies and penalties. This may be related to the local level of economic development and industrial structure, as these provinces are highly industrialized with intensive industrial activities, leading to relatively high air pollutants and carbon emissions. Consequently, they face greater environmental pressure. To cope with this pressure and promote environmental quality improvement, the number of policies and penalties is also relatively large.

3.3. Model

Based on the above, this study finally selects the causal network model of Gaussian process regression (Hoyer et al., 2008) based on the relevant literature in section 2.3 and the characteristics of the actual data, and explores the impacts of carbon emission reduction policies (dynamic and static) on carbon emissions, and the interactive impacts on air pollution, respectively. Meanwhile, the effects of air quality policies (dynamic and static) on air pollution and the interaction effects on carbon emissions are explored. In addition, this study explores the mutual causality between industrial development, respiratory-related diseases, and other control variables.

Firstly, the input data $X = \{x_1, x_2, ..., x_n\}$, which is the final dataset after cleaning, and the corresponding output data is $y = \{y_1, y_2, ..., y_n\}$, where x_i is the input vector and y_i is the corresponding output vector. Gaussian process regression first assumes that $f(x)$ obeys a Gaussian distribution and later predicts a new input x_* and provides the probability distribution of its corresponding output y_*.

$$f(x) \sim \mathrm{GP}(m(x), k(x, x')) \tag{1}$$

Where N denotes the Gaussian distribution, $m(x)$ is the mean function, and $k(x, x')$ is the covariance function. Given the observed data X and the corresponding output y, it can be obtained:

$$\begin{pmatrix} y \\ f(X_*) \end{pmatrix} \sim N\left(\begin{pmatrix} m(X) \\ m(X_*) \end{pmatrix}, \begin{pmatrix} K(X,X) + \sigma_n^2 I & K(X,X_*) \\ K(X_*,X) & K(X_*,X_*) \end{pmatrix} \right) \tag{2}$$

Where $f(x)$ and y are identically distributed, $K(X,X)$ is the covariance matrix between the sample points in the observed data X, $K(X_*,X_*)$ is the covariance matrix between the sample points in the new input data X_*, $K(X,X_*)$ is the covariance matrix between the observed data X and the new input data X_*, σ_n^2 is the noise variance of the observed data, and I is the unit matrix.

In the choice of kernel function, there are three types of commonly used kernel functions: firstly, the linear kernel; secondly, the RBF (Radial Basis Function); and lastly, the polynomial kernel. The RBF

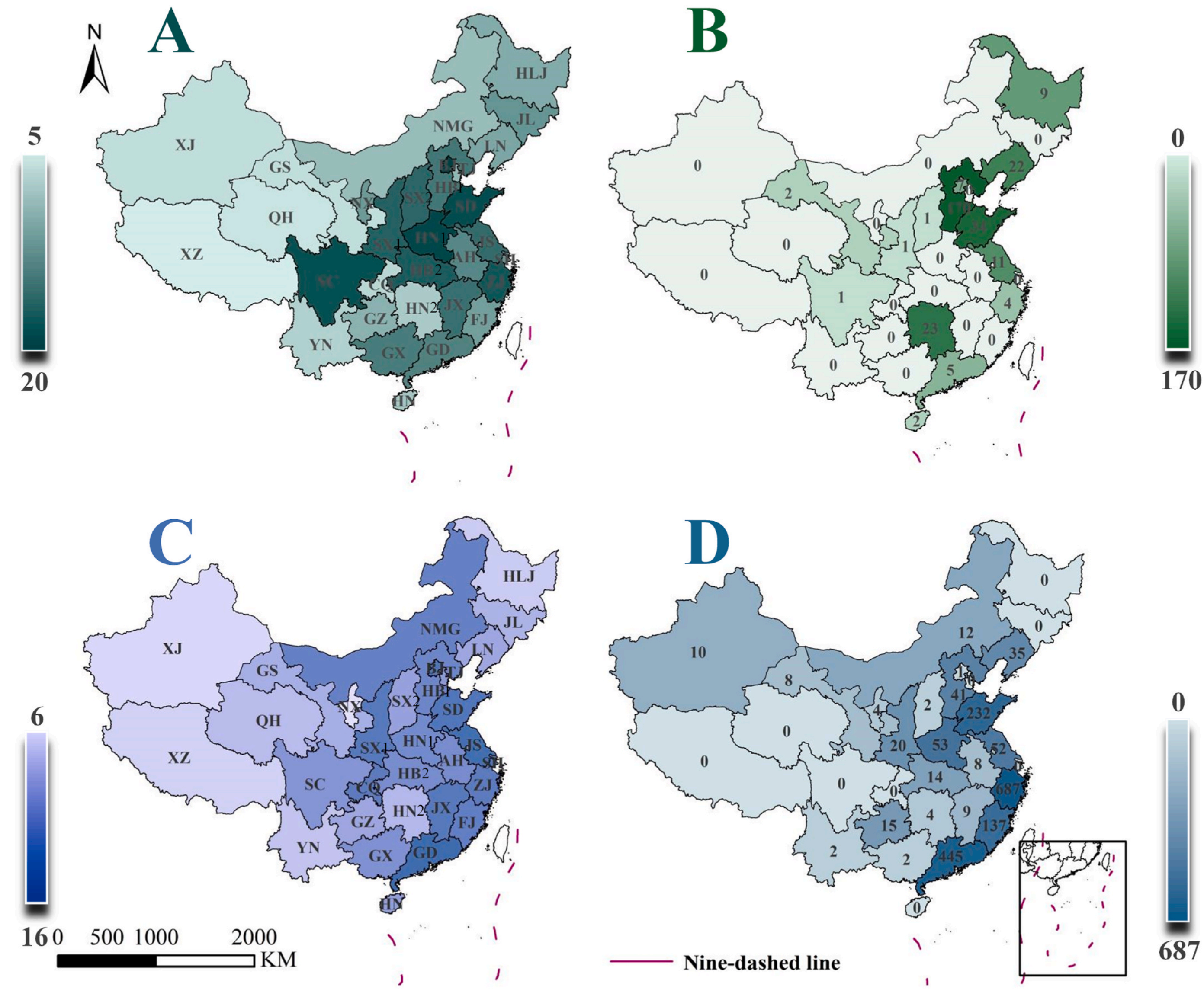

Fig. 3. Distribution of air quality and carbon emission reduction policies across provinces in China from 2004 to 2022.

kernel function, which can handle high-dimensional and non-linear data, and has good generalization ability, is therefore chosen. The function that measures the similarity of any two points in the input space is equivalent to the inner product of a nonlinear mapping to an infinite dimensional space. The RBF kernel is formulated as:

$$k(x, x') = \exp\left(-\|x - x'\|^2 / 2\sigma^2\right) \tag{3}$$

Where x and x' are two points in the input space, $\|x - x'\|^2$ is the square of the Euclidean distance between these two points. σ is the width parameter of the kernel function, which controls the smoothness of the function. The smaller the value of σ , the narrower and sharper the function, implying that only points that are very close to each other are considered similar.

Regression between variables through the Gaussian process, after which the residuals between the two variables are calculated, and the residuals e_i are specified as follows:

$$e_i = y_i - \widehat{y}_i \tag{4}$$

Where i denotes each observation, y_i denotes the actual observation, and $\widehat{y}_i$ denotes the predicted mean.

Causality is inferred by determining whether the residuals and the independent variables are independent of each other, thus constituting a causal network. Causal inference follows these rules: (1) If x and x' are independent of each other, it is inferred that there is no causal relationship between the two; (2) If x is not independent of x', x is independent of residual n, x' is not independent of residual n', it is inferred that x is the cause of x'; (3) If x is not independent x', x is not independent of residual n, and x' is independent of residual n', it is inferred that x' is the cause of x; (4) The fact that x is not independent of x', x is not independent of residual n, and x' is not independent of residual n' suggests that the generating mechanism is too complex to be directly inferred. It can be reasonably explored by introducing other variables; (5) If x is not independent of x', x is independent of residual n, and x' is independent of residual n', then one direction with a higher independence score is chosen.

Considering the Maximum Mean Discrepancy (MMD) between the distribution of the residuals and the distribution of the independent variables, MMD as a basic kernel method has been widely used in distributional inference as well as in transfer learning. In this study, refer to HSIC (Hilbert-Schmidt independence criterion) to infer the independence between variables through this kernel method, to deduce the causal relationship. The specific framework of the idea is as follows(see Fig. 4).

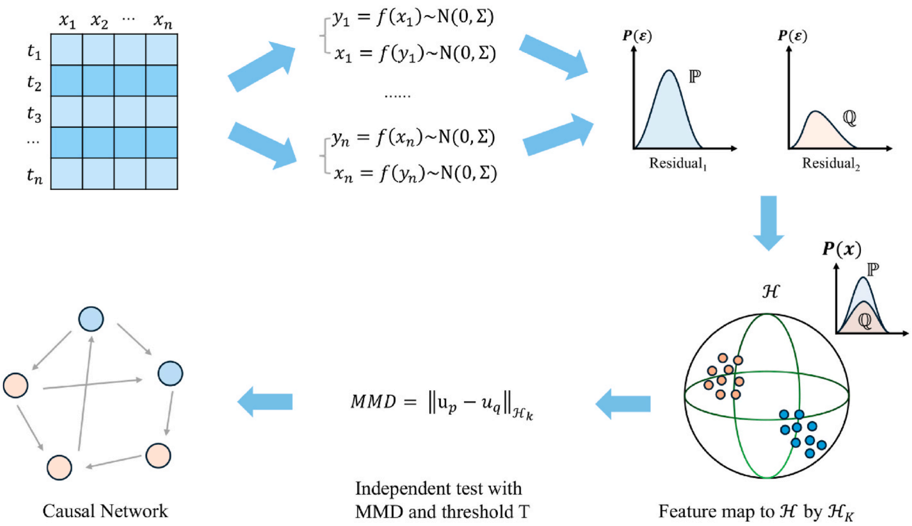

Fig. 4. Frame of thought figure.

4. Results

4.1. Causal analysis of carbon emission reduction policies

To explore the dynamic-static policy impacts related to carbon emission reduction, the residuals of carbon emission reduction policies and carbon emission variables, and the residuals of carbon emission reduction policies and air pollution variables were measured, totaling 32 groups, of which only 4 groups are shown below.

Fig. 5 shows significant differences in the distribution of the residuals of each group of variables. To more accurately identify the causal relationship of carbon emission reduction policy related to the multi-

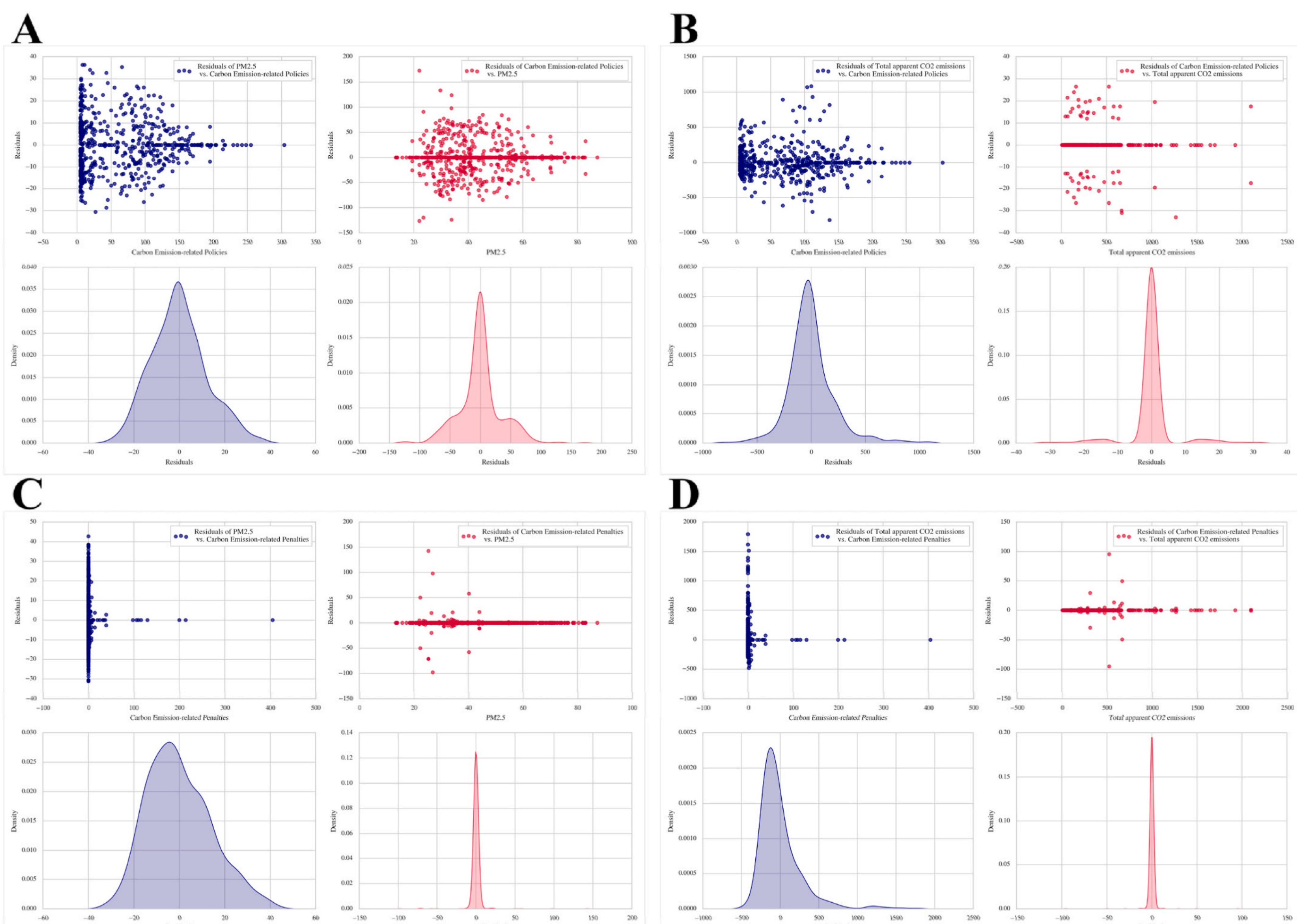

Fig. 5. Residual and scatter plots and probability density plots between variables related to carbon emission reduction policy (partial).

dimensional assessment of policy synergy, the Maximum Mean Discrepancy value between each variable was calculated. The results are shown in Table 2.

From the table, it can be seen that the Maximum Mean Discrepancy values between most of the variables are large, indicating that the variables are independent of each other and there is no causal relationship. However, Secondary Industry Added Value has a causal relationship with PM2.5 and Carbon Emission Reduction Policy; Carbon Emission Reduction Policy has a causal relationship with CO_2 Emissions and PM2.5; the Incidence Rate of Tuberculosis has a causal relationship with Carbon Emission Reduction Policy and PM2.5. Dynamic Policies (related penalties) may have no relevant causal relationship with other variables due to their low timeliness, incomplete coverage, and small scope of influence (see the discussion section in Chapter 4 for specific analyses). To further analyze causality, the causal diagram below was obtained by categorizing it using the five categories of causal inference.

Fig. 6A shows that total apparent CO_2 emissions, secondary industry added value, and the incidence rate of tuberculosis have led to the introduction of carbon emission reduction policy, which is a form of enforced environmental policy. (Environmental policies are often shaped and implemented as a result of the intensification of environmental pressures and problems, particularly in the areas of climate change and environmental pollution, where high levels of carbon dioxide emissions not only exacerbate global warming, but also have direct and indirect negative impacts on ecosystems, human health and economic activity, and such pressures prompt Governments to act proactively to shape and implement carbon reduction policy to mitigate or reverse these adverse impacts.) Secondly, the fact that the value added of the secondary sector leads to carbon emission reduction policy suggests that industrial production activities also influence carbon emission reduction policy and that the aforementioned "forced" policies affect carbon emissions by first influencing the value added of the secondary sector.

The fact that secondary industry added value and total apparent CO_2 emissions also contribute to the incidence rate of tuberculosis suggests that industrial activities may lead to a deterioration in air quality, thereby increasing the risk of respiratory diseases such as tuberculosis. At the same time, increased carbon dioxide emissions may be a sign of increased air pollution, and deterioration of air quality is closely related to respiratory health problems. The incidence of respiratory diseases such as tuberculosis contributes to PM2.5 in Fig. 6B, which may be due to incomplete respiratory data. The incidence of tuberculosis is related to PM2.5 but is also affected by multiple factors, such as poverty, migration (Ponticiello et al., 2005), and COVID-19 (Namgung et al., 2023), among others. Finally, Fig. 6A and B share similar causal logic, suggesting that carbon emission reduction policies have similar impacts on PM2.5 and total CO_2 emissions and that there are synergistic effects of carbon emission reduction policies.

4.2. Causal analyses of air quality policies

To explore the impact of dynamic-static policies related to air quality, the residuals of the related variables were measured. The residuals of the variables related to air quality policy and carbon emission, as well as the residuals of the variables related to air quality policy and air pollution, totaled 32 groups, but only 4 groups are shown below.

Fig. 7 shows significant differences in the distribution of residuals for each group of variables. To more accurately identify the causality related to air quality policy and assess policy synergy in multiple dimensions, the value of Maximum Mean Discrepancy between each variable is calculated. The results are shown in Table 3.

From the table, it can be seen that the Maximum Mean Discrepancy values between most variables are large, indicating that the variables are independent of each other and there is no causal relationship. However, Secondary Industry Added Value has a causal relationship with PM2.5 and Air Quality Policy; Air Quality Policy has a causal relationship with CO_2 Emissions, PM2.5, and the Incidence Rate of Tuberculosis. To further analyze causality, the causal diagram below was obtained by categorizing it using the five categories of causal inference and obtaining Fig. 8.

The causal paths of Figs. 6 and 8 are the same, showing consistency in the roles of carbon emission policy and air quality policy, and indicating that policy synergy exists for both types of policies.

4.3. Multidimensional causal analysis of the other variables

Since carbon emissions and air pollution are also affected by many indirect factors, the relationship between the remaining variables and the value added by the secondary industry is analyzed to explore indirect causation. The Maximum Mean Discrepancy value between each variable is calculated, and the results are shown in Table 4.

From the table, it can be seen that the Maximum Mean Discrepancy values between most variables are large, indicating that the variables are independent of each other and there is no causal relationship. Total Industrial Energy Consumption and Total Energy Consumption both have a causal relationship with Secondary Industry Added Value, Resident Population at Year-End, Number of R&D Projects, R&D Expenditure of Industrial Enterprises, and Energy Industry Investment; There is a causal relationship between Total Energy Consumption and several factors: Secondary Industry Added Value, Resident Population at Year-End, Number of R&D Projects, R&D Expenditure of Industrial Enterprises, and Energy Industry Investment. To further analyze causality, the causal diagram below was obtained by categorizing it using the five categories of causal inference (see Fig. 9).

From a research and innovation perspective, R&D Expenditure of Industrial Enterprises directly impacts the Number of R&D Projects that a firm can initiate and sustain. Higher R&D investment usually means more R&D projects can be financed, and an increase in the number of R&D projects tends to be closely related to secondary industry added value (manufacturing, construction, etc.). Higher value in the secondary sector, in turn, feeds back into overall investment in the energy sector. Additionally, firms in the secondary sector are likely to invest in energy efficiency improvements and new energy technologies, further

Table 2
Maximum mean discrepancy for carbon emission reduction policies.

	Secondary Industry Added Value	Carbon Emission Reduction Policy	Carbon Emission-related Penalties	CO_2 Emissions	PM2.5	Incidence Rate of Tuberculosis
Secondary Industry Added Value	0	0.994843425	1.001842502	0.994843425	0.994843428	0.999915824
Carbon Emission Reduction Policy	0.058655652	0	0.872166393	0.05834799	0.06180144	0.060806139
Carbon Emission-related Penalties	0.766711264	0.807041759	0	0.769271957	0.72502523	0.750758242
CO_2 Emissions	0.805230263	0.805878503	0.88068809	0	/	1.004689008
PM2.5	0.157644704	0.176826079	0.835534051	/	0	0.179020181
Incidence Rate of Tuberculosis	0.727992433	0.743420854	0.839292417	0.743117797	0.847275329	0

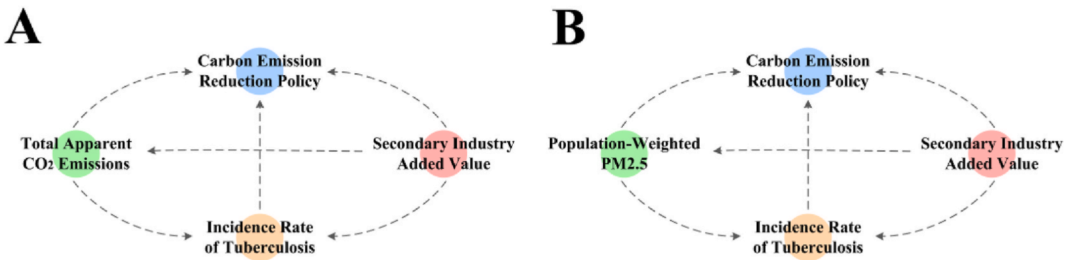

Fig. 6. Causal network diagram under carbon emission reduction policies.

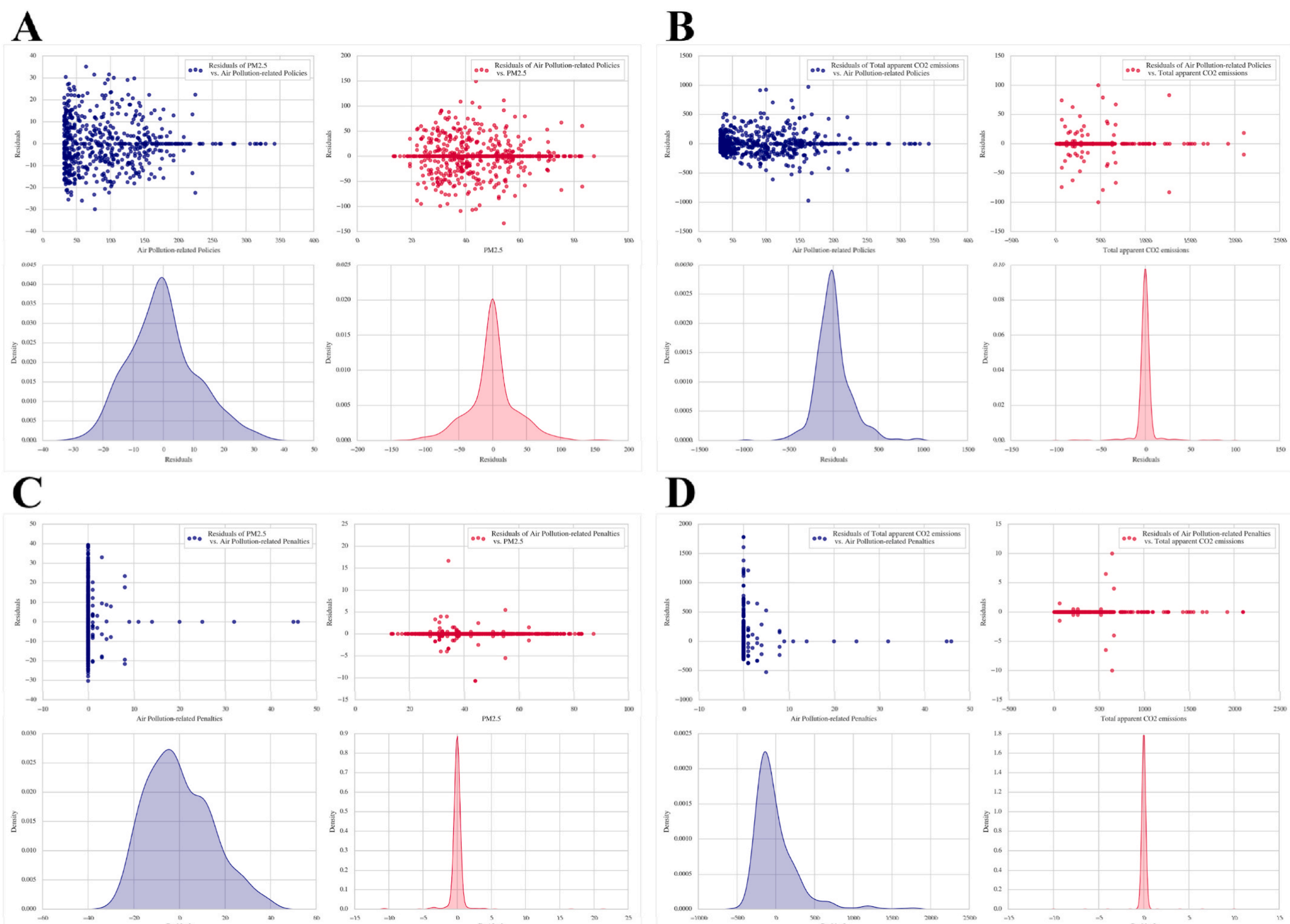

Fig. 7. Residual and scatter plots and probability density plots between variables related to air quality policy (partial).

Table 3
Maximum mean discrepancy of air quality policy.

	Secondary Industry Added Value	Air Quality Policy	Air Pollution-related Penalties	CO_2 Emissions	PM2.5	Incidence Rate of Tuberculosis
Secondary Industry Added Value	0	1.000291782	1.001842502	0.994843425	0.994843428	0.999915824
Air Quality Policy	0.035232142	0	0.8703987	0.034146348	0.077638773	0.057274512
Air Pollution-related Penalties	0.858730417	0.854157011	0	0.861120574	0.815736197	0.844405234
CO_2 Emissions	0.805230263	0.821543913	0.972995338	0	/	1.004689008
PM2.5	0.157644704	0.159453634	0.914921226	/	0	0.179020181
Incidence Rate of Tuberculosis	0.727992433	0.740117478	0.9437172	0.743117797	0.847275329	0

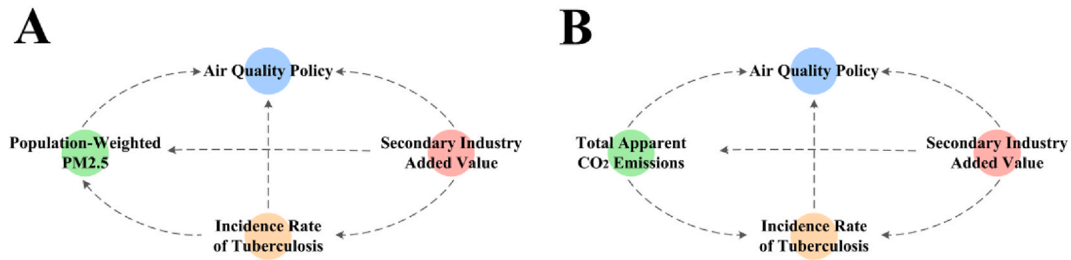

Fig. 8. Causal network diagram under air quality policy.

Table 4
Maximum Mean Discrepancy of the other variables.

	Secondary Industry Added Value	Resident Population at Year-End	Number of R&D Projects	R&D Expenditure of Industrial Enterprises	Energy Industry Investment	Total Industrial Energy Consumption	Total Energy Consumption
Secondary Industry Added Value	0.000000	0.994843	0.994843	0.994843	0.994843	0.994843	0.994838
Resident Population at Year-End	0.873221	0.000000	0.875655	0.871707	0.896400	0.873225	0.873184
Number of R&D Projects	0.753423	0.788433	0.000000	0.753433	0.946792	0.946745	0.758763
R&D Expenditure of Industrial Enterprises	1.001755	1.001755	1.001755	0.000000	1.001755	1.001755	1.001755
Energy Industry Investment	0.469389	0.488818	0.469410	0.469484	0.000000	0.491054	0.485429
Total Industrial Energy Consumption	0.060025	0.060283	0.060194	0.059926	0.063617	0.000000	0.864266
Total Energy Consumption	0.054460	0.054753	0.054611	0.054386	0.058077	1.052632	0.000000

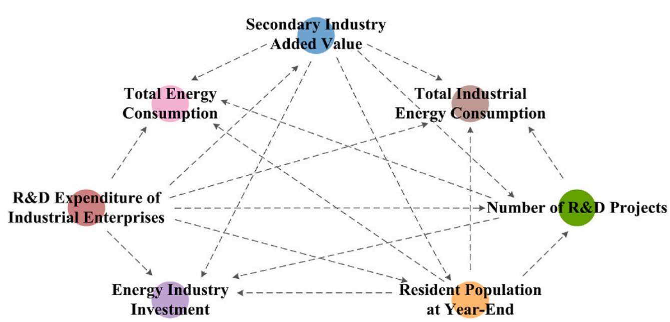

Fig. 9. Causal network figure of other variables.

contributing to investment in the energy sector.

In terms of energy consumption, an increase in the secondary industry added value usually leads to higher energy consumption, as more productive activity requires additional energy. Similarly, heightened industrial activity boosts energy demand, directly increasing total energy consumption. Furthermore, a growing population, implying more residential, commercial, and industrial activities, also escalates total energy consumption.

5. Discussion

5.1. Discussion on "policy forced" mechanisms

The enactment and implementation of static policies related to air quality and carbon emission reduction have a "forcing effect", driven by factors such as total apparent CO_2 emissions, PM2.5, secondary industry added value, and the incidence rate of tuberculosis. This “forcing” mechanism arises firstly due to public awareness and pressure (Chai et al., 2024) (Chai et al., 2024). High levels of carbon dioxide and PM2.5 concentrations are closely related to respiratory health problems and affect public production and living activities. With increasing public attention to climate change and air pollution, and growing demand for government action, there is pressure on the government to proactively formulate and implement policies related to carbon emission reduction and air quality to mitigate or reverse these adverse impacts. Secondly, due to the economic impact (Li et al., 2019) [69], carbon emissions and air pollution are closely related to economic activities. Environmental policy affects the economic structure, and the environmental problems caused by industrial production activities also force the generation of environmental policy. The aforementioned reverse policy influences the value added by the secondary industry, impacting carbon emissions and air pollution. Additionally, international cooperation and commitments, including China’s pledges on carbon peaking and neutrality, further drive the formulation and implementation of these policies.

The dynamic policy, including associated penalties, shows no relevant causal relationship with other variables. This may be due to the complexity of the multilevel governance structure, which leads to insufficient enforcement of penalties (Nagel and Bravo-Laguna, 2022) [70]. Consequently, the dynamic policy has a relatively small impact. From 2003 to 2023, only four provinces recorded more than 100 penalties for environmentally non-compliant firms, indicating insufficient enforcement in most provinces. This insufficiency may be influenced by local economic development and political relations (Florackis et al., 2023) [71]. Additionally, income and R&D investment are closely related (Hartmann et al., 2006) [72]. Penalties reduce firms’ revenues, and ex-post penalties that immediately mitigate pollution can have a negative impact (Li et al., 2022) [73]. Firms may engage in symbolic environmental disclosure, which inhibits the effectiveness of environmental penalties in promoting substantive environmental governance activities (Zhou et al., 2024) [74].

The causal network diagrams for air quality policy and carbon emission reduction policy under static policies are structured consistently. Total carbon emissions drive the development of both carbon emission reduction and air quality policy, with PM2.5 concentrations exerting a similar influence on both policy types. This indicates policy synergy between the two static policy types concerning air pollution and carbon emission governance. This synergy stems from the close relationship between carbon emissions and air pollution (Wang et al., 2023) (Shao et al., 2023). Most sources of carbon emissions are significant contributors to air pollution, and vice versa, so static policies targeting both issues share commonalities.

5.2. Causal discussion of secondary industry added value

The development of the secondary industry is closely related to carbon emissions and air pollution. In this study, the secondary industry added value is used to portray its development and verify the impact on carbon emissions and air pollution. The increase in the secondary industry added value implies an increase in size, and the high concentration of heavily polluting and energy-intensive sectors (e.g., iron and steel, cement, chemicals) exacerbates air pollution emissions (Zhu et al., 2019) (Zhu et al., 2019). Simultaneously, the expansion of the secondary industry increases energy consumption, leading to higher carbon dioxide emissions (Xiao et al., 2019) (Xiao et al., 2019).

In the realm of scientific research and innovation, the value added by the secondary industry impacts the number of R&D projects. As the secondary industry develops, the demand for technological innovation rises, aiming to reduce energy consumption rates and enhance production efficiency, product quality, and competitiveness. This demand prompts enterprises to boost R&D investment and expand the number of R&D projects. Tian et al., 2024 and Zhang et al.(2023) express similar views in their studies (Tian et al., 2023; Zhang et al., 2023c).

At the level of energy consumption and energy investment, the secondary industry added value influences total industrial energy consumption, total energy consumption, and energy industry investment. As the production scale of the secondary industry expands, more energy is needed to maintain production, leading to an increase in industrial energy consumption (Wang et al., 2020), which further leads to a rise in total energy consumption. Simultaneously, the energy industry, being a part of the secondary industry, is closely linked to investment in the sector. Thus, investments in the secondary industry also impact the overall investment in the energy industry (Liu et al., 2019).

6. Conclusions and recommendations

6.1. Conclusion

This study applies the causal network model of Gaussian process regression to analyze the combined effects of dynamic and static carbon emission reduction and air quality policies on carbon emissions and air quality, and to evaluate the causal effects of policy measures and their synergies. The following conclusions are drawn.

(1) Regional differences and uneven policy implementation. Significant differences in the correlation between economic development and environmental pollution are demonstrated between the eastern coastal provinces and the western provinces. More economically developed areas, such as Jiangsu and Guangdong, which have higher GDP per capita and value-added in the secondary sector, also exhibit higher levels of environmental pollution. These regions show significant activity and rigor in formulating and implementing carbon emission and air quality policies. In contrast, western provinces like Qinghai and Tibet have relatively lax environmental policies, correlating with their lower industrialization and population density. Furthermore, some of these provinces have zero dynamic policy data (cumulative value of penalties for environmental violations), revealing wide variations in the long-term effects of policy implementation and the actual strength of implementation.

(2) Synergies exist between carbon emission reduction policy and air quality policy. These policies not only share objectives in reducing carbon dioxide emissions and air pollution but also mutually reinforce each other in implementation. The two types of static policies have a certain degree of substitutability in the governance of carbon dioxide emissions and air pollution. By optimizing resource allocation and implementation strategies, these policies can exert a broader positive impact on reducing environmental pollution and enhancing public health.

(3) The existence of an environmental policy forced effect. Causal analysis results indicate that air pollution, carbon dioxide emissions, secondary industry added value, and the incidence rate of tuberculosis are all causes that correlate with two types of policies. This suggests that worsening environmental issues drive the formation and implementation of policies. This effect is especially pronounced in areas with high levels of environmental pollution or significant environmental challenges, where policy formulation and implementation serve not only as direct responses to existing problems but also as strategies to mitigate potential future environmental risks.

(4) Presence of indirect effects of industrial activities. The value added in the secondary sector is a key driver in shaping carbon emission reduction policy and air quality policy. Rising value added in the secondary sector contributes significantly to total carbon dioxide emissions, worsening air quality, and directly increasing the incidence of respiratory diseases such as tuberculosis. Increases in R&D expenditures, often closely associated with value added in the secondary sector, enhance firm profitability and enable higher investments in energy efficiency improvements and new energy technologies. Therefore, effective air quality management policies must consider both the direct and indirect effects of industrial growth.

6.2. Recommendations

Based on the above conclusions, the following feasible recommendations for the synergistic governance of air pollution and carbon emissions are proposed.

(1) Due to the existing synergies between carbon emission reduction-related policies and air quality-related policies, promoting cross-sectoral cooperation is crucial to optimize these synergies. The government should establish a cross-sectoral coordination mechanism to ensure effective coordination between environmental and public health policies. This mechanism should focus on integrating the objectives of carbon emission reduction and air quality control, promoting complementarity and synergy between policies through resource and information sharing.

(2) Given the indirect impacts of industrial activities, strengthening industrial regulation and promoting the research, development, and application of cleaner technologies is crucial. Increasing regulation of secondary industries, particularly those that are highly polluting and energy-intensive, is essential while also encouraging and supporting enterprises to invest in the research and development of clean technologies and energy efficiency improvements. Policy measures could include providing tax incentives, technical assistance, and innovation funds to promote the R&D and commercialization of low-carbon technologies. Additionally, the government could mandate that enterprises disclose their energy consumption and emissions data to enhance transparency and facilitate monitoring by the public and regulatory agencies.

(3) Dynamic evaluation and flexible adjustment of policies are crucial due to regional differences and varying degrees of policy implementation. Governments should regularly evaluate the effectiveness of environmental and public health policies to

ensure they adapt to scientific and technological progress as well as market changes. The evaluation process should incorporate up-to-date data on scientific research, technological developments, and socio-economic factors, allowing for necessary adjustments. Such a dynamic policy adjustment mechanism ensures that policies remain effective and relevant while also enhancing policy synergy.

CRediT authorship contribution statement

Qianwen Li: Writing – original draft, Resources, Methodology, Investigation, Funding acquisition, Formal analysis, Conceptualization. **Tingyu Qian:** Writing – original draft, Visualization, Methodology, Data curation. **Hui Wang:** Writing – review & editing, Visualization, Software, Methodology. **Longhao Bai:** Writing – original draft, Visualization, Data curation. **Ruyin Long:** Writing – review & editing, Supervision, Resources, Funding acquisition.

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.

Data availability

Data will be made available on request.

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