Spatial and nonlinear effects of new-type urbanization and technological innovation on industrial carbon dioxide emission in the Yangtze River Delta

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Abstract
The purpose of this paper is to quantify the level of new-type urbanization and unravel the spatial and nonlinear effects of new-type urbanization and technological innovation on industrial carbon emissions. Although the impact of traditional urbanization levels on carbon emissions has been widely studied, there is still a huge room for optimization, and the impact of new-type urbanization on carbon emissions has not yet been clarified. Selecting 37 cities in the Yangtze River Delta as a research sample, this paper measures the new-type urbanization based on an evaluation system we build. Consequently, we assess the spatial and nonlinear effects of new-type urbanization and technological innovation on carbon emissions by the spatial Durbin model and non-parameter additive model, respectively. The results indicate that the new-type urbanization and low-carbon city pilot policy have significant spatial spillover effects on reducing carbon dioxide emissions, while the economic growth plays a positive role in increasing carbon emission. As for nonlinear effects, there is a significant inverted “N”-shaped relationship between the level of new-type urbanization and carbon dioxide emissions, while the nexus between technological innovation and carbon emissions is an inverted “U”-shaped relationship. This paper provides a new perspective for confirming the mechanism of the new-type urbanization on carbon emissions. Meanwhile, these findings are of significance for the relevant authorities in China to develop appropriate policy in carbon dioxide emission reduction.

Keywords Industrial carbon dioxide emissions · New-type urbanization · Low-carbon technological innovation · Spatial spillover effect · Nonlinear relationship

Introduction

Due to the huge volume of global carbon emissions, carbon dioxide emission is an important issue for a shared future for the world. As the world’s largest energy consumer and carbon dioxide emitter (Xu and Lin 2016a), the energy conservation and emission reduction task of China are still arduous. Therefore, in this context, many studies have put forward corresponding policy recommendations for carbon dioxide emission reduction tasks from the perspectives of urbanization level, technological innovation (Safi et al. 2021), and policy (Fu et al. 2021). There are still limitations for further improvement.

First, from the perspective of urbanization, China is currently in the process of rapid development. It is estimated that by 2030, China’s urbanization rate will reach 70.12% (Sun et al. 2017), and by 2050, it will reach more than 90% (Mignamissi and Djuefack 2021). The coordinated development between urbanization and the environment plays an important role in the construction of ecological civilization (Wang et al. 2020). Under the background that the overall impact of urban expansion on climate warming is positive and significant, there are problems in the evaluation of urbanization, such as single and one-sided quantification. At present, most studies use the proportion of the urban population to describe the level of urbanization (Wu et al. 2021; Liu and Han 2021). The first manifestation of urban expansion is the growth of the urban population, but when the urbanization rates of two cities are identical, it does not mean that the urbanization levels are the same. The main reason...
is that there may be a large gap between them in terms of economic level, technological innovation, energy efficiency, infrastructure construction, transportation convenience, and environmental friendliness. The classical urbanization rate cannot sufficiently quantify the overall level of urban development. Consequently, it is vital to explore a comprehensive evaluation system for measuring the level of new-type urbanization under this background (Ding et al. 2021). In March 2014, China published the National New-type Urbanization Plan 2014–2020 (Fang et al. 2015), which proposed specific requirements for new-type urbanization. Based on this, this paper proposes an evaluation system for new-type urbanization. The new-type urbanization effect that the plan calls for in the Yangtze River Delta is significant (Peng et al. 2021), so we measure the new-type urbanization level in the Yangtze River Delta and study how it affects carbon dioxide emissions.

Second, the technological innovation that plays a key part in decreasing environmental pollution has received considerable attention (Hao et al. 2021), and the total number of patent applications is generally used as a quantitative indicator (Erdogan 2021). Nonetheless, among all the patents applied, the proportion of patents for reducing environmental pollution is comparatively small. Including all the patent applications will overestimate the effect of technological innovation in upgrading the environment. Accordingly, this paper further refines this indicator and selects low-carbon technology patents as an explanatory variable to accurately extract the relationship between technological innovation and carbon emissions.

Finally, considering the important role of government policy and regulation in carbon dioxide emission reduction (Ma et al. 2021), we take China’s low-carbon city pilot policy (LCCP) into consideration. The low-carbon pilot city policy announced the first batch of pilot cities in 2010 and announced the second and third batches of pilot cities in 2012 and 2017, respectively. In this study, we try to figure out whether the LCCP can reduce the carbon emission and whether the LCCP can get the spillover effects to neighboring cities.

Compared with the aforementioned studies, the measurement of urbanization is simple by using the ratio of urbanization population which is no longer suitable to present the overall development level of a city, and using the total number of patent applications may overestimate the effects of technology innovation (Wu et al. 2021; Erdogan 2021). Hence, the marginal contributions of this paper are threefold. First, on the basis of panel data, we build a novel evaluation system to measure the level of new-type urbanization in a clear and comprehensive way. Second, traditional literature focuses on extracting the linear relationship between carbon emissions and related variables, while ignoring the nonlinear relationship that may exist in economic variables. Consequently, this paper applies both the spatial econometric model and the non-spatial econometric model to extract the spatial relationship and nonlinear relationship between variables. Finally, the impacts of economic level, new-type urbanization, low-carbon technology patents, and low-carbon pilot city policy on carbon emissions are thoroughly considered, and corresponding suggestions are given.

The rest of this dissertation is structured as follows: In the next section, previous research on carbon dioxide emission, new-type urbanization, technology innovation, low-carbon city pilot policy, and method theories are reviewed. “Model specification” presents the research steps we utilized, including methodology and data sources. “Results and discussions” present the empirical results, and the last section presents the conclusion and points out the policy implications.

**Literature review**

At present, research on carbon dioxide emissions is mainly focused on two aspects. One is to estimate carbon dioxide emission, and the other is to study the influencing factors of carbon dioxide emission. First, among the methods for estimating carbon emissions, there are fractional grey Riccati model (Gao et al. 2021a), Scope-1 carbon emission inventories city-level input–output table (Wiedmann et al. 2020), non-competitive input–output models that consider intermediate production and consumption (Gao et al. 2021b), etc.

On the other hand, the research on the influencing factors of carbon dioxide emissions is mainly carried out with different methods for different objects. The main research objects include agriculture (Koondhar et al. 2021), manufacturing (Lan et al. 2021), transportation (Lin and Wang 2022), and urban agglomeration (Cheng et al. 2021). After identifying the specific research objects, literatures from the perspective of economic growth (Zhang et al. 2021a), technological progress (Xie et al. 2021), energy structure (Liu et al. 2021), renewable energy (Khan et al. 2022), green investment or green technology innovation (Dong et al. 2022), the COVID-19 (Wang et al. 2022a), and other important factors use quantile regression analysis (Rehman et al. 2021), structural decomposition analysis (Fang and Yang 2021), Tapio decoupling method (Du et al. 2021), the auto-regressive distribution lag model (Tarazkar et al. 2021), and asymmetry analysis (Mahmood et al. 2020; Mahmood et al. 2022) to identify factors that play significant roles in affecting emissions. In addition, in order to achieve carbon neutrality and carbon peaking (Zhou et al. 2022b), some literatures also put forward theoretical suggestions on policies such as carbon emission trading system (Cui et al. 2021) and carbon tax (Green 2021).
As one of the strongest CO₂ source regions in China (Fang et al. 2022), the overall performance level of energy consumption reduction in the Yangtze River Delta region (YRD) is relatively average (Sun et al. 2022). Under these circumstances, many studies focus on this region to perform their opinions over the low-carbon or environmental friendliness issues. Sheng et al. applied the spatial autocorrelation analysis to conclude that the high-high agglomeration region is located in YRD in terms of carbon emissions (Zheng et al. 2022b). Yu et al. examine the carbon emission from land use and their intensity in the YRD by using a modified gravity model (Yu et al. 2022b). Xia et al. qualified the carbon footprint to capture the socioeconomic driving forces by structural decomposition analysis (Xia et al. 2022). As for urbanization, Min holds the idea that the living standard of the YRD is high and the corresponding resources and energy consumption is large, causing the increase of carbon emissions (Min 2022). As for economic growth, Yu et al. studied the nexus between economic agglomeration and carbon emissions in YRD, and the outcome shows an inverted “U-shaped” type (Yu et al. 2022a). Wen et al. used the spatial Durbin model to conclude that the financial agglomeration promotes the green development in YRD (Wen et al. 2022). Meanwhile, the innovation level and government planning play a significant role in stimulating urban green development in YRD (Li et al. 2022).

Research on new-type urbanization mainly concentrates on two aspects, mainly the measurement method and the impact of new-type urbanization on the ecological environment. First of all, most of the current research attempts to quantify new-type urbanization from the perspectives of population urbanization (Yanna et al. 2022), spatial urbanization (Zhang et al. 2022a), ecological environment (Sun 2017), social indicator (Lin and Zhu 2021), urban–rural coordination (Wu et al. 2022), using the entropy method (Li et al. 2021a), factor analysis and principal component analysis method (Shi et al. 2020), comprehensive index method of fully arranged polygons (Deng 2021), and improved TOPSIS method (Rao and Gao 2022) to quantify new-type urbanization. Second, among the studies of the impact on the ecological environment, the increase of PM2.5 concentration (Wei et al. 2021), the reduction of energy intensity (Lin and Zhu 2021), the reduction of per capita carbon emissions (Wang et al. 2021), and the decreasing of haze pollutions (Han and Cao 2022) are mainly deemed significantly associated with the increase in the level of new-type urbanization. And there are studies focus on the spatial correlation of new-type urbanization. Zhang et al. thought that the Moran’I of the new-type urbanization fluctuates approximately 0.120, showing positive spatial correlation (Zhang et al. 2022a).

In the research of technological innovation, Cheng pointed out that every 1% increase in the technological level of renewable energy can significantly decrease carbon intensity by 0.051% (Cheng and Yao 2021). Solar energy technology (Wang et al. 2021), green technology patent (Chen et al. 2019), and low-carbon energy technology (Zheng et al. 2022a, b) are believed to have a negative impact on carbon emissions in the short or long term. The digital technology development can positively influence carbon abatement through the spillover effect (Liu et al. 2022b). And the spatial spillover of green technology innovation can reduce the carbon emission significantly (Zhang and Liu 2022). However, the qualification of technology is not the same in the research; many studies turn their eyes on the new CPC-Y02 patent classification system to obtain the variable low-carbon technology patent (LCP). Han et al. investigated the mediating relationship between LTP and regional carbon performance (Han and Zhou 2022). Wang et al. performed the spatial Durbin model to test the positive impact of LTP on green total factor productivity in China (Wang et al. 2022a). Zhang et al. got the conclusion that LTP plays a very important role in carbon emission reduction (Zhang and Fan 2022). At the same time, China’s pilot carbon trading system will gradually increase the positive effect on LTP over time (Liu and Sun 2021). In addition, environmental regulation can promote the LTP level to a certain extent (Yang et al. 2021).

In the related literatures of low-carbon pilot city policies, Yu et al. adopted the DID model and SDID model to point out that the low-carbon pilot city policy enhanced carbon emission efficiency by 1.7% (Yu and Zhang 2021). Li utilized the mediation effect model and believed that the policy was an important way to promote China’s low-carbon transition, and the emission reduction effect in East China was significantly higher than that in other regions (Li et al. 2021b). Chen applied the PSM-DID model to demonstrate that the policy can significantly reduce the carbon emissions (Fu et al. 2021) and improve the total factor productivity as well (Chen et al. 2021). Fang applied the capability maturity model to identify weak links in low-carbon pilot city policy and provided recommendations for improving policy efficiency (Fang et al. 2015). Zhou et al. applied the DID methods to conclude that the policy reduces the firm’s coal consumption and coal intensity (Zhou et al. 2022a). Zou et al. concluded that the policy can induce the overall technological innovation capacity of the city especially in terms of utility model patents (Zou et al. 2022a). Still, Shi applied the PSM-DID to get that the implementation of the policy produces positive growth of carbon emission efficiency in industry, especially in the central and eastern regions of China (Shi and Xu 2022). Chen concluded that the policy contributed significantly to a more rational industrial structure (Chen 2022).

As for the methods utilized to analyze the complex nexus between carbon emissions and economic variables, many studies turn their eyes on the spatial models to extract the spillover effects and non-parameter additive regression
to extract the non-linear relationships. Mahmood applied
the spatial Durbin model to conclude the presence of the
environmental Kuznets curves (Mahmood 2022), renew-
able energy consumption can reduce the consumption and
territory-based CO2 emissions in both local and neighboring
countries, financial market development has positive effects
(Mahmood 2020), foreign direct investment is found to be
responsible for local environmental degradation (Mahmood
et al. 2018), and oil rent got the monotonic positive effects
on carbon emissions (Mahmood and Furqan 2020). Ren
et al. utilized a dynamic spatial panel model to investigate
the spillover and dynamic effects of energy transition and
economic growth on CO2 emissions for the EU nations
(Ren et al. 2020). Xu et al. used a geographically weighted
regression model to conclude that the heterogeneous impact
on CO2 emissions across provinces and regions in China is
mainly due to the differences in urban real estate and trans-
portation infrastructure investments (Xu and Lin 2021).
Meanwhile, in terms of the non-linear relationship, Zhang
et al. found out that the renewable energy investment in
China got the inverted “U-shaped” relationship with carbon
emissions (Zhang et al. 2021b). And in terms of transport
sector in China, energy efficiency improvement follows a
positive “U-shaped” pattern in relation to CO2 emissions
(Xu and Lin 2015a).

Following the conclusion of Zhang, the characteristics
of carbon emission in the Yangtze River Delta have scale
effects, and regional imbalance always exists (Zhang et al.
2022b). It is of great significance to study the spatial rela-
tion in this region. However, there are few studies that
measure the level of new-type urbanization in this region,
and the nexus between new-type urbanization and carbon
emissions still remains uncertain. Considering the facts
that economic growth, technology research and devel-
oment, and government regulation are the main factors
affecting the spatial carbon emission in this region (Liu
et al. 2022a), this paper aims at measuring the new-type
urbanization in this region, extracting the spatial and non-
linear relations between corresponding variables and
carbon emissions in the Yangtze River Delta to fill the
literature gap existing.

Model specification

Estimation of industrial carbon dioxide emission

The two main sources of industrial CO2 emissions are indus-
trial energy consumption and industrial production. In this
paper, the carbon emission inventory method is used to esti-
mate carbon dioxide emissions (Liu et al. 2015; Shan et al.
2017). The specific emission calculation formula is as follows:

\[ CI = \sum_{i} C_i = \sum_{i} C_i \times NCV_i \times EF_i \times O_i, \]  

where \( CI \) stands for carbon dioxide emissions in industrial
energy consumption, \( C \) stands for energy consumption, and
\( NCV \) stands for its net calorific value. \( EF \) represents its emis-
sion factor, \( O \) represents its oxygenation efficiency, and \( i \)
represents the \( i \)-type of energy.

\[ CP = \sum_{j} CP_j = \sum_{j} C_j \times EF_j, \]  

where \( CP \) stands for carbon dioxide emissions in the indus-
trial process, \( C \) stands for the output product, \( EF \) stands for
the emission factor, and \( j \) represents the \( j \)-type of product.

In summary, the total industrial carbon dioxide emissions
can be expressed as follows:

\[ CE = CI + CP \]  

According to the proportion of energy consumption and
the availability of data sources, the main source of car-
bon dioxide emissions in the product processing raw coal,
natural gas, crude oil, gasoline, electricity, and cement is
selected. Carbon dioxide emission factors, net calorific
values, and oxygenation efficiency were obtained through the
IPCC (The Intergovernmental Panel on Climate Change)
database.

Measurement of new-type urbanization

The “National New-type Urbanization Plan (2014–2020)”
(referred to as the plan) pointed out the transformation
direction of urbanization and the inherent needs. Based
on the characteristics of the new-type urbanization pro-
posed in the plan, this paper formulates an urbanization
evaluation system and proposes the new-type urbaniza-
tion as people-oriented urbanization (POU). This evalua-
tion system contains five specific aspects: economics,
production, population, environment, and transportation
(Table 1).

The specific calculation process of new-type urbanization
is given below (Shang et al. 2018). For the \( j \) index of the \( i \)
city, we mark it as \( x_{ij} \). First, we process the data as follows:

\[ x_{ij}^* = \frac{x_{ij} - \min(x_{ij})}{\max(x_{ij}) - \min(x_{ij})}, i = 1 \ldots 37, j = 1 \ldots 8, \]  

Then, we calculate the sample mean \( \mu_j \) and the sample
standard deviation \( \sigma_j \) of \( x_{ij} \). After that, we obtain the coef-
ficient of variation \( V_j = \frac{\sigma_j}{\mu_j} \). Furthermore, the weight
\( \omega_j \) of each variable can be calculated as follows:

\[ \omega_j = \frac{V_j}{\sum_j V_j}, \]
Finally, the new-type urbanization of the $i$ city is presented as $POU_i = \sum_j x_{ij}^* \times \omega_j$.

**Stochastic Impacts by Regression on Population, Affluence, and Technology (STIRPAT) model**

As a basic model for investigating the impact on the environment, the IPAT model was proposed by Dietz and Rose to study the effect of population, economic affluence, and technological level on environmental pollution (Dietz and Rosa 1997). The specific expression of the model is shown in Eq. (6):

$$I = aP^bA^cT^d\gamma,$$

(6)

Among them, $I$ represents the pollution of the environment, $P$ represents the population, $A$ represents the wealth of the society, $T$ describes the level of technology, and $\gamma$ is the random error term. In addition, $a$ is the intercept term, and $b$, $c$, and $d$ represent the elastic coefficient of the above variables. And the basic STIRPAT model (7) can be obtained by taking the logarithm of Eq. (6).

$$\ln(I) = \ln(a) + b\ln(P) + c\ln(A) + \ln(\gamma).$$

(7)

In the basic STIRPAT model, $T$ is included in the error term rather than being estimated separately, making it consistent with the IPAT model, where $I$, $P$, $A$ can be balanced by solving for $T$. In this way, we can decompose $T$ by adding additional variables related to the environment. After that, the residual term represents all factors affecting the environment with additional variables deducted (York et al. 2003). In this paper, $P$ and $A$ are represented by the new-type urbanization $POU$ and $GDP$, respectively. $T$ is disaggregated by the low-carbon technology patent applications $LTP$ and the low-carbon pilot city dummy variable $LCC$. The final extended STIRPAT model can be expressed as follows:

$$\lnCE = \lna + b\lnPOU + c\lnGDP + d\lnLTP + eLCC + ln\gamma.$$  

(8)

**Spatial Durbin model and non-parameter additive regression**

In order to extract the spatial correlation between variables, this paper selects the panel data spatial Durbin–fixed effect model. Combining it with the STIRPAT model, the following equation is achieved:

$$\lnCE = a_0 + a_1\lnGDP + a_2\lnPOU + a_3\lnLTP + a_4\lnLTP + a_5\lnPOU + a_6\lnLTP + a_7\lnPOU + a_8\lnLTP + a_9\lnLCC + a_{10}\lnLTP + \mu + \gamma + \epsilon \sim N(0, \sigma^2 \iota_n).$$

(9)

where, $a_0$ is a constant vector. $\mu$ and $\gamma$ represent the spatial fixed effect and time fixed effect, respectively. After estimating Eq. (9), the Wald test will be carried out on the $H_{01} : \beta = 0$ and $H_{02} : \beta + a\lambda = 0$ to verify whether SDM can be reduced to the SAR or SEM, and the likelihood ratio (LR) is applied to reconfirm the outcome. And rejecting both the null hypotheses presents that the SDM satisfies the most over the SAR and SEM models.

In order to investigate the linear and nonlinear relationship between the level of new-type urbanization, low-carbon technology innovation, and carbon dioxide emissions, we utilize the non-parameter additive regression model, as it is a data-driven mathematical model which can fully reflect the relationships between variables. And the specific formulation is in Eq. (10), where $\epsilon$ represents the error term:

$$\lnCE = \lna + b\lnPOU + c\lnGDP + d\lnLTP + eLCC + s(\lnPOU) + s(\lnLTP) + \epsilon.$$  

(10)

**Data source**

The variables involved in the new-type urbanization evaluation system are collected from the corresponding urban statistical yearbooks, except for $X_3$, which is collected from the ecological environment bureau of each city. Due to

| Specific aspects | Indicators | Units |
|-----------------|------------|-------|
| Economic indicator | $x_1$: GDP per capita | Yuan |
|                   | $x_2$: Per capita income of urban residents | Yuan |
|                   | $x_3$: Total social retail products | 100 million yuan |
| Production indicator | $x_4$: The ratio of the secondary industry to GDP | % |
| Population indicator | $x_5$: Urban population (household registration) | Ten thousand |
| Environmental indicator | $x_6$: Urban park and green area per capita | Square meter |
| Environmental indicator | $x_7$: Proportion of days when air quality meets or is better than Grade II standard | % |
| Transportation indicator | $x_8$: Total number of urban public transport passengers | Person |
insufficient data in Xuzhou City, Taizhou City, Lishui City, Lu’an City, and Chizhou City, they were not included in this research.

Based on the CPC-Y02 patent classification system promulgated by EPO (European Patent Office) and USPTO (United States Patent and Trademark Office), we obtained the low-carbon technology patent data in the Incopat Patent Search Database. The data of low-carbon pilot cities were compiled from the relevant policy documents from the National Development and Reform Commission in 2010, 2012, and 2017.

Results and discussions

Estimation results of industrial carbon dioxide emission

The industrial carbon dioxide emissions of 37 cities in the Yangtze River Delta from 2015 to 2019 are illustrated in Fig. 1. The cities with less carbon emissions in the five-year period are Bozhou, Chuzhou, and Tongling, while those with hefty carbon dioxide emissions are Suzhou (Zhejiang) and Nanjing. The carbon emission volume of each city varies considerably, reflecting a certain spatial heterogeneity.

In addition, we also notice that in the five-year period, cities maintaining a downward trend in carbon dioxide emissions are Hangzhou, Shanghai, Huaian, Huaibei, Nantong, and Suqian. The above cities became low-carbon pilot cities in 2010, 2012, 2012, and 2017 (except for Nantong and Suqian), respectively, and Shanghai became a carbon emissions trading pilot city in 2011. To a certain extent, this will help decrease the carbon dioxide emissions. At the same time, the proportion of the tertiary industry in the above-mentioned cities is increasing year by year, which means that the proportion of industry has declined, and thus, industrial carbon emissions have shown a downward trend.

Still, there is a new global dataset on CO₂ emissions for 343 cities compiled by researchers from the Global Project in collaboration with international organizations (Nangini et al. 2019). This dataset contains the Scope-1 CO₂ emissions of 83 cities in China in 2010 provided by Peking University. In order to verify the validity of the carbon dioxide emission we estimate in this paper and to make the data more comparable, we also calculate the carbon emissions of related cities in the Yangtze River Delta in 2010. Taking Shanghai as an example, by Eq. (3), the estimated result is 39.92 million tons, and the Scope-1 carbon emission of Shanghai in dataset is 47.54 million tons. The gap is mainly due to the fact that Scope-1 emissions contain six aspects: (1) agriculture, forestry, and other land use; (2) industrial processes and product use; (3) in-boundary waste and wastewater; (4) stationary fuel combustion; (5) in-boundary transportation; and (6) grid-supplied energy, while the estimated scope of this paper covers industrial process only. The proportion of carbon dioxide emissions in industrial processes is 70% to 80%, which confirms the effectiveness of the carbon dioxide emissions estimation in this paper to a certain extent.

Estimation results of new-type urbanization

Because the traditional indicators cannot fully reflect the depth of the development level of cities, the article calculates the new-type urbanization level (POU) of 37 cities in the
Yangtze River Delta from 2015 to 2019. The weights of the corresponding indicators in each year are given (Table 2).

From Table 2, we can find that the changes in the weights of each indicator from 2015 to 2019 are comparatively slight, which demonstrates that the development of the economy, production, population, environment, and transportation in the region has been relatively stable in recent years. On the whole, the weight of \( x_5 \) (the ratio of urban population) ranks high, which shows that in the evaluation system, the traditional method is still playing an important role. In addition, the values of \( x_3, x_8 \) imply that there are still large gaps of each city in consumption level and transportation convenience.

From Fig. 2, we can see that most cities showed an increasing trend in new-type urbanization from 2015 to 2019. Shanghai is far ahead with a score over 90. This reflects that Shanghai, as an economic and a financial center, is particularly outstanding in economy, technology, and environment. In 2019, the new-type urbanization levels of the three provincial capitals Hefei, Hangzhou, and Nanjing were 17.79, 34.92, and 52.79, respectively. It is worth noting that, the new-type urbanization level of all prefecture-level cities in Anhui Province is comparatively moderate, with an average level of 10 points. This indicates that the development level of each region in the Yangtze River Delta is quite distinct, and there is a certain regional incompatibility problem. The possible reason is that, except for Anhui Province, the rest of the provinces (including municipality) are located in the coastal areas, which enjoy more dynamic economic development and trade. Nonetheless, Anhui Province is inland and does not have certain location advantages, which leads to particular backwardness.

Cross-sectional dependency and stationary test

However, before establishing the corresponding models, for panel data, it is necessary to check the cross-sectional dependency because it may be biased if the statistically significant CD is ignored in analyses. We followed (Yasin et al. 2022) to carry out the Pesaran cross-sectional dependency test (Pesaran 2014) with the null hypothesis of cross-sectional independency. The outcomes in Table 3 show that the panel data suffers the CD concerns. Under such circumstances, the traditional first-generation unit root test cannot be applied. Specifically, we applied the cross-sectional adjusted Im-Pesaran-Shin (CIPS) test (Pesaran 2007) with the null hypothesis of the existence of unit root which

### Table 2: Indicator weights

| Variables | 2015    | 2016    | 2017    | 2018    | 2019    |
|-----------|---------|---------|---------|---------|---------|
| \( x_1 \) | 0.0994  | 0.0969  | 0.0978  | 0.0916  | 0.0916  |
| \( x_2 \) | 0.0544  | 0.0519  | 0.0524  | 0.0527  | 0.0556  |
| \( x_3 \) | 0.2483  | 0.2360  | 0.2337  | 0.2374  | 0.2373  |
| \( x_4 \) | 0.0125  | 0.0111  | 0.0102  | 0.0124  | 0.0128  |
| \( x_5 \) | 0.1598  | 0.1528  | 0.1500  | 0.1493  | 0.1494  |
| \( x_6 \) | 0.0374  | 0.0428  | 0.0426  | 0.0441  | 0.0396  |
| \( x_7 \) | 0.0212  | 0.0231  | 0.0357  | 0.0274  | 0.0288  |
| \( x_8 \) | 0.3674  | 0.3855  | 0.3776  | 0.3851  | 0.3850  |

### Table 3: The cross-sectional dependency test and panel unit root analysis

|                | lnCE    | lnGDP   | lnPOU    | lnLTP   |
|----------------|---------|---------|----------|---------|
| Pesaran CD test| 4.1430***| 55.9860***| 32.7460***| 29.8240***|
| CIPS test     | -1.9100***| -1.5700** | -1.3440** | -1.4550* |

*: p value < 0.1; **: p value < 0.05; ***: p value < 0.01
overcomes the limitation of the first-generation unadjusted Im-Perasan-Shin (IPS) test. The results show that the panel variables are stationary, and the panel cointegration analysis is avoided (Table 3).

**The spatial effects**

After estimating the industrial carbon dioxide emissions in the Yangtze River Delta from 2015 to 2019, the spatial relationship can be further investigated. We take the binary adjacency matrix as the spatial weight matrix to get the Moran I index of carbon emissions (Table 4). The value range of the Moran I index is \((-1, 1)\). It can be seen from Table 4 that the value of Moran I index is positive, indicating that there is a certain positive spatial correlation of industrial carbon dioxide emissions.

As for Moran scatter plot, the first quadrant (HH type) and the third quadrant (LL type) demonstrate that there is a positive spatial correlation between observations, while the second quadrant (LH type) and the fourth quadrant (HL type) indicate negative spatial correlation. The first quadrant represents cities with high observations surrounded by cities with high observations, such as Hefei, Shanghai, and Suzhou (Jiangsu). The second quadrant indicates that cities with low observations are surrounded by cities with high observations, such as Huzhou and Chuzhou. The third quadrant implies that the cities with low observation values are surrounded by cities with low observation values, such as Jinhua and Lishui (Table 5). This shows that Jiangsu Province and Shanghai with high economic levels have formed an area with high carbon emission concentration, while Anhui Province with a comparatively low economic level is an area with low carbon emission concentration.

Utilizing Moran I along with Moran scatter plot to test the spatial effects among variables is not enough. Hence, before carrying out spatial analysis, we established pooled OLS regression and panel FE models to tell if there are spatial autocorrelations by the Lagrange Multiplier test and its robust versions (Mahmood 2022). If the spatial autocorrelation is valid in model, the carbon emissions in the Yangtze River Delta could have spillovers on neighbors, which enables us to use the spatial Dubin model to measure the spillover relationships. The outcomes are shown in Table 6. For the spatial lag and error results, both LM tests verify the existence of spatial dependency in the models and indicate that we can move forward to the spatial relationship.

### Table 4 Moran I index of industrial carbon emissions

| Year | 2015 | 2016 | 2017 | 2018 | 2019 |
|------|------|------|------|------|------|
| Moran I | 0.040 | 0.133 | 0.042 | 0.045 | 0.054 |

### Table 5 Spatial distribution in four quadrants of Moran I scatterplot

| HH type | Shaoxing, Jiaxing, and Mananshan | Ningbo, Shaoxing, and Jiaxing |
|---------|----------------------------------|--------------------------------|
|         | Hefei, Fuyang, Shanghai, Wuxi, Changzhou, and Zhenjiang | Zhousing, Hefei, Maanshan, Shanghai, Wuxi, and Changzhou |
|         | Suzhou (Jiangsu) and Nantong | Suzhou (Jiangsu) and Nantong |
|         | Yancheng and Yangzhou | Yancheng, Yangzhou, and Zhenjiang |
| LH type | Huzhou, Zhoushan, Tongling, Chuzhou, Xuancheng, and Bozhou | Huzhou, Tongling, Fuyang, Chuzhou, Xuancheng, and Bozhou |
| LL type | Jinhua, Quzhou, and Taizhou | Jinhua, Quzhou, Lishui, and Bengbu |
|         | Lishui, Bengbu, and Huangshan | Huangshan, Suzhou (Anhui), and Suqian |
|         | Suzhou (Anhui), Suqian | |
| HL type | Hangzhou, Ningbo, and Wenzhou | Hangzhou, Wenzhou, and Taizhou |
|         | Wuhu, Huainan, and Huaiabei | Wuhu, Huainan, and Huaiabei |
|         | Anqing, Lianyungang, and Hainan | Anqing, Nanjing, and Lianyungang |

*: p value < 0.1; **: p value < 0.05; ***: p value < 0.01
of each variable from neighboring cities on local carbon emissions. Meanwhile, the estimated indirect effects can represent the spillover relationship to a certain extent.

The coefficients of $lnGDP$ are positive and significant in point, direct, indirect, and total estimates. What’s more, every unit increase in economic level in neighboring will generate an increase of 1.8434 units in local carbon emissions when other conditions remain unchanged. Therefore, we can get the conclusion that both local economic growth and neighboring economic growth cause the increase in carbon dioxide emissions. The outcomes are similar with the study results of Wang who holds the idea that the promotion effect of economic development on carbon emissions in the Yangtze River Delta was greater than the inhibitory effect (Wang et al. 2022b). We believe that the main reason for this result is an investment, and the flow of resource caused by investment is not limited to one city, but circulates within the entire region, resulting in a certain spatial effect. Investment, as one of the three major drivers of economic growth (Xu and Lin 2016b), has huge scales in the long run. In 2017, the total fixed asset investment in Shanghai, Anhui, Zhejiang, and Jiangsu provinces is relatively high, reaching 724.66 billion yuan, 2918.596 billion yuan, 3112.599 billion yuan, and 5300 billion yuan, respectively. Consequently, the investment of government and enterprises in infrastructure construction will expand the consumption of high-carbon emission resources such as steel, cement, energy, and electricity. At this point, the production of these products will consume more fossil energy, resulting in higher carbon emissions.

The impact of $lnPOU$ on industrial carbon dioxide emissions is significant, and the coefficients are negative in point, direct, indirect, and total estimates, indicating that the higher the level of new-type urbanization, the lower the volume of its industrial carbon dioxide emissions. And each unit increase in the new-type urbanization will contribute to a reduction of 0.6119 units of industrial carbon dioxide emissions. The coefficient of spatial term $WinPOU$ is $-2.3194$ and is significant at the level of 0.05, which demonstrates that there is a negative spatial spillover effect in new-type urbanization. We can conclude that the improvements of both local and neighboring new-type urbanization have pleasant environmental effects in reducing carbon emissions. We believe that the main reason is that the development of new-type urbanization has brought about information sharing, transformation convenience, and the upgrading of the industrial structure, which in turn promote the green growth of the economy and reduce carbon dioxide emission to a certain extent (Dong et al. 2020). Moreover, the new-type urbanization has a significant effect on reducing energy intensity (Wang et al. 2021). Hence, the improvement of new-type urbanization is backed up by the efficient use of energy.
and technological innovation (Wang et al. 2019; He et al. 2017). When the level of new-type urbanization progresses to a certain extent, it will lead to a certain aggregation effect and scale effect in its adjacent areas (Liu et al. 2017). Thus, the improvement of new-type urbanization not only decreases its own carbon emissions, but also reduces the carbon emissions of its surrounding areas.

The coefficient of $lnLTP$ is positive in point, direct, indirect, and total estimates, which indicates that the level of low-carbon technological innovation cannot suppress carbon dioxide emissions. The possible reasons are the low-level low-carbon technology innovation in China and the problem of uncoordinated development between regions. China’s low-carbon technology patent applications are mainly concentrated in universities, and the corresponding results have not been effectively transferred into enterprises. The proportion of low-carbon technology patents owned by enterprises is relatively small, and there is plenty of room for improvement in the technology of capturing, storing, or processing greenhouse gasses (Huang and Mauerhofer 2016). Therefore, factors such as uneven regional distribution of low-carbon technology patents, single technology, and insufficient high-end technology have led to the fact that the current low-carbon technology is insufficient to reduce carbon dioxide emission.

The coefficients of $LCC$ are negative in point and direct estimates, indicating that being the low-carbon pilot city is more conducive to reducing carbon dioxide emissions. However, this negative effect is not significant, which may be due to the fact that among the 37 cities, 21 cities are not low-carbon pilot cities, and 9 cities became pilot cities since 2017. Thus, the effects are not obvious. On the other hand, the coefficient of $WLCC$ is negative and significant at the level of 0.001, and the coefficients of the $LCC$ are negative and significant in indirect and total estimates which reveals that cities bordering with the low-carbon pilot city are more likely to achieve carbon dioxide emission reduction than cities with no low-carbon pilot city at the border. The outcome of LCC is similar with the research of DU et al. which agree with the opinion that the policy has spatial spillover and has a positive impact on the neighboring cities (Du et al. 2022). We believe that the possible reason is that the implementation of the low-carbon pilot policy has brought resource input and technical leverage to a certain extent (Fu et al. 2021), which is conducive to the reduction and the improvement of carbon emission efficiency in the short-term and long-term (Li et al. 2021b).

**Results of non-linear relationships**

Before establishing the non-parameter additive regression model, it is of great significance to check the relationships between variables. For this purpose, we apply the scatter plots to represent the nexus between new-type urbanization and carbon emission (Fig. 3A) and the nexus between low-carbon technology patents and carbon emission (Fig. 3B). In Fig. 3A, all the points may be separated into two parts, upper and down on the horizontal line $y = 17$. With the points upper on the line $y = 17$, the relationship between $lnPOU$ and $lnCE$ is an inverted “N-shaped” type. With the points down on the line, the linkages between the two variables may be a regression model with a negative slope.

![Fig. 3](image_url) The nonlinear relationship scatter plot (A relationship between $lnPOU$ and $lnCE$. B Relationship between $lnLTP$ and $lnCE$)
Hence, we can see that the relationship between \( \ln POU \) and \( \ln CE \) is mixed with linear and non-linear parts, so it is suitable to use the non-parameter additive regression model. As for the nexus between \( \ln LTP \) and \( \ln CE \), there is a clear inverted “U-shaped” relationship in Fig. 3B, and the rest points may form a linear relationship. So, we can see that the nexus between \( \ln LTP \) and \( \ln CE \) is mixed with linear and non-linear parts. Consequently, it is necessary to choose this data-driven model.

The following part analyzes the nonlinear impact of new-type urbanization and low-carbon technological innovation on industrial carbon dioxide emissions. We can see that there is an “N”-type relationship between \( \ln POU \) and \( \ln CE \) (Fig. 4A), which is consistent with the findings of Zhao (Zhao et al. 2020). This illustrates that in the early stage of development, the new-type urbanization has played a restraining role in carbon dioxide emissions. The main reasons are as follows: In the initial stage, the development of the new-type urbanization not only improved the utilization rate of public facilities and transportation, but also increased the degree of industrial agglomeration and thus reduced the corresponding environmental treatment costs (Wu et al. 2021), and thereby reduced carbon dioxide emissions. Nevertheless, the middle and late stages show an obvious inverted “U”-shaped relationship, which is consistent with the research results of Huang (Huang and Matsumoto 2021). This is mainly due to the fact that further development of urbanization means the influx of population and the expansion of land, which requires a lot of construction of housing, infrastructure, roads, bridges, etc., and that will bring about the expansion of demand for steel, cement, and fossil energy (Xu and Lin 2015b). In addition, the increase in population will further rise the demand for transportation and household energy, which will bring about the carbon dioxide emissions (Xu and Lin 2016a). In the later stage, the impact of the new-type urbanization is inhibitory. The main reasons are as follows: The later stage is with a sound public transportation network and the green development of the environment, which will reduce carbon dioxide emissions. Additionally, under the long-term implementation of harmony and coordination without sacrificing resources and the environment, it will further improve the efficiency of emission reduction (Chen et al. 2019).

The relationship between low-carbon technology and industrial carbon dioxide emissions is an inverted “U” shape (Fig. 4B), which means that in the early stage, it has a positive effect on carbon emissions and a negative effect in the later stage, which is consistent with the findings of Shao (Huang and Matsumoto 2021). This is primarily because in the initial stage, as mentioned in “Results of the spatial relationships,” the development of low-carbon technology is limited by the level of economic development and productivity, and the technologies newly applied cannot be transferred swiftly and effectively into productions in enterprises, thereby failing to decrease carbon emissions. Furthermore, the promotion of high-level low-carbon methods requires the deployment of funds, time, manpower, and material resources and cannot promptly play a role in curbing carbon emissions.

**Fig. 4** Nonlinear effects (A the inverted “N-shaped” relationship between \( \ln POU \) and \( \ln CE \). B The inverted “U-shaped” relationship between \( \ln LTP \) and \( \ln CE \))
emissions. Nonetheless, when the level of low-carbon technology develops into a certain stage, it brings changes in production methods and improvements in energy efficiency. And the traditional methods with high environmental pollution will be replaced by production methods with high technology content and output efficiency. This will greatly reduce the carbon dioxide emissions.

Conclusions and policy implications

This paper utilizes panel data of 37 cities in the Yangtze River Delta region to estimate the industrial carbon dioxide emissions from 2015 to 2019. Subsequently, the new-type urbanization is measured, and the impact of economy level, new-type urbanization, low-carbon technological innovation, and low-carbon pilot city policy on carbon dioxide emission is explored. At last, the spatial Durbin model and non-parameter additive regression model are utilized to extract the spatial and nonlinear relationships of the impact. Based on the research above, we obtained the following findings.

First, we discovered that the economic growth will lead to an increase in the carbon dioxide emissions of the city and its neighbors, while the development of new-type urbanization will significantly decrease the carbon dioxide emissions of the city and its neighbors. Second, the current low-carbon technology level is not sufficient to curb carbon dioxide emissions. Third, to a certain extent, low-carbon pilot policy can reduce carbon dioxide emission. Finally, the relationship between the new-type urbanization and carbon emission is an inverted “N”-shaped curve, while the low-carbon technology shows a particular inverted “U”-shaped relationship with carbon emission. Based on these findings, relevant proposals are offered as follows.

We believe that in order to reduce carbon dioxide emissions, we should improve the level of new-type urbanization and technological innovation. From the perspective of new-type urbanization, cities should pay attention to the important areas of it, such as population urbanization and environmental friendliness. In terms of population urbanization, the government should consider formulating corresponding talent introduction policies, since the talents can help with technological innovation. As for low-carbon technology, it is necessary to improve the individual types of application and increase financial allocation as much as possible to promote the development of high-level low-carbon technologies such as carbon capture, carbon sequestration, and carbon absorption. In addition, relative authorities should increase the funding allocation for colleges to a certain extent as they are the key low-carbon patent application entities. Under the circumstance that the low-carbon pilot city policy is conducive to reducing carbon emissions, this policy should be further promoted. Relevant government departments should expand relevant emission reduction policies, such as the carbon emission trading, and study the feasibility of the carbon tax in China.

The limitations of this paper lie mainly in two aspects. First, the sample is restricted in the Yangtze River Delta Region, and consequently, neighborhood effects can only be modeled to a limited extent. Hence, the research object can be further extended and refined, and microdata can be utilized as much as possible to avoid such limitation. Second, this paper focuses on the econometric model. Nevertheless, the combination of traditional econometric models and artificial intelligence methods can be considered. If the above-mentioned shortcomings can be overcome, the subject of this paper is still worthy of further study.

Author contribution All authors contributed to the study’s conception and design. Material preparation, data collection, and analysis were performed by Yazhen Zhang and Xiaoping Chen. The first draft of the manuscript was written by Yazhen Zhang, and all authors commented on previous versions of the manuscript. All authors read and approved the final manuscript.

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

Declarations

Ethics approval and consent to participate Not applicable.

Consent for publication Not applicable.

Conflict of interest The authors declare no competing interests.

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