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Threshold Effects of Urban Population Size and Industrial Structure on CO_2 Emissions in China

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Population and industry are closely related to CO_2 emissions in Cities. However, few studies have explored the joint influence of population size and industrial structure on CO_2 emissions. This paper examined the nonlinear influence of population size and industrial structure on CO_2 emissions by using a threshold-STIRPAT model with the latest available data in 2001–2017 from 255 cities in China. Results indicated that the promotion effect of urban population size on CO_2 emissions increased in the first two stages and then decreased in the third stage when the industrial structure exceeded the threshold value of 1.22. Meanwhile, the industrial structure had a positive impact on CO_2 emissions if the urban population was less than 1.38 million. However, the previous promotional effect became an inhibitory effect when the urban population exceeded 1.38 million. According to the above findings, it is necessary to find a reasonable match between urban population size and industrial structure. Specifically, China should formulate differentiated urban population policies in cities with different industrial structures. In addition, for cities with a population size of more than 1.38 million, adjusting the industrial structure to give priority to the tertiary industry will be an effective way to reduce CO_2 emissions.

Keywords: urban population size, industrial structure, CO_2 emissions, threshold-STIRPAT model, threshold effects

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1 INTRODUCTION

The rise of greenhouse gases, especially anthropogenic emissions of CO_2, is the main cause of global climate change (Wang et al., 2019b; Sun et al., 2022). In 2021, global CO_2 emissions from energy consumption and industrial processes rebounded to reach an amount of 36.3 gigatonnes (Gt), the highest ever annual level (IEA, 2022). According to World Economic Forum (WEF), without stronger action, global capacity to mitigate and adapt to climate change will be diminished, eventually leading to a "hot house world scenario" (WEF, 2022).

Cities are responsible for about 75% of the world's consumption of resources (Pacione, 2009). Cities are the gathering place of population and industries (Wang and Wu, 2012; Mori, 2017) and the centers of CO_2 emissions (Grimm et al., 2008; Dhakal, 2009; Glaeser and Kahn, 2010). As the world's largest CO_2 emitter, China's urban area contributed approximately 75.15 and 85% of the total energy consumption and CO_2 emissions (Shan et al., 2018; Tian and Zhou, 2019), both higher than the global average level (Cui et al., 2019). Thus, the urban CO_2 emission reduction and the construction of a low-carbon city have become the strategic goals of China. As scheduled, China achieved the phased goal of carbon intensity reduction in 2020 (Cao and Gao, 2021). As a responsible country, China has promised to reach the peak of its carbon emissions by 2030 and achieve carbon neutrality by 2060. According to the previous studies, the CO_2 emission reduction targets must be eventually decomposed at the city level (Liu et al., 2012; Reuter and Men, 2014). So, cities are the basic units for implementing CO_2 abatement policies in China (Liu et al., 2021).

The rise and fall of cities are always accompanied by the change of population size and the evolution of industrial structure (Yuan et al., 2019). On the one hand, the industrial structure depended on population size and market demand (Abdel-Rahman and Anas, 2004). In other words, population dominates the evolution direction of industrial structure (Ba and Zheng, 2012; He, 2015; Sarkar et al., 2018). On the other hand, the industrial structure gives rise to population size change (Wu, 2012; Han and Li, 2019; Zheng et al., 2021; Guo, 2021). Also, "Regulation population through industrial restructuring" was an important urban population policy in China (Wang and Tong, 2015). The interaction between population size and industrial structure determines the production and consumption patterns (Su and Liao, 2015), which changes the energy efficiency and energy consumption, thus affecting CO_2 emissions (Wang and Wu, 2012; Zhang et al., 2021a). Therefore, the interaction between urban population size and industrial structure cannot be ignored in the study of CO_2 emissions. From the perspective of interactive influence of urban population size and industrial structure, the impacts of both on CO_2 emissions were innovatively explored. The results would help policymakers formulate feasible differentiated policies to achieve CO_2 abatement.

2 LITERATURE REVIEW

The influence of population size on CO_2 emissions is an important issue (Zhou and Wang, 2018; Cui et al., 2019; Tian and Zhou, 2019). With the rapid expansion of urbanization, increasingly urbanized populations and corresponding consumption changes produced more CO_2 emissions (Wiedenhofer et al., 2013; Zhang et al., 2014; Wang et al., 2019b). A great deal of literature confirmed that the population size was an important driving factor of CO_2 emissions (Birdsall, 1992; Dietz and Rosa, 1994; Lonngren and Bai, 2008; Jiang and Hardee, 2011; Wang et al., 2017a; Zhou and Wang, 2018; Jung et al., 2021; Namahoro et al., 2021). Anser et al. (2020) found that the urban population size increased residential CO_2 emissions in South Asian Association for Regional Cooperation (SAARC) member countries (Anser et al., 2020). Some literature found staged heterogeneity in the relationship between population size and CO_2 emissions (Wu, 2012; Chen et al., 2018). According to the size of the urban population, Li et al. (2018) divided 50 cities in China into five kinds and found that the medium-sized cities (population size between 1 million and 2 million) produced the lowest CO_2 emissions (Li et al., 2018). Cui et al. (2019) reported that urban population size in eastern China had a significant double-threshold effect on CO_2 emissions, and the driving effect first decreased and then increased (Cui et al., 2019). Brought the quadratic term of urban population size in the STIRPAT model, Zhang et al. (2021b) found that the impact of the population size on CO_2 emissions per capita presented an inverted U shape (Zhang et al., 2021a). However, only focusing on the impact of urban population size on CO_2 emissions with the change of population size, the above studies failed to reveal the relationship between urban population size and CO_2 emissions comprehensively.

With the evolution of industrial structure, the proportion of services gradually increased while manufacturing decreased (Kolko, 1999; He and Mao, 2016). But the demands and structures of energy consumption brought by the primary, secondary, and tertiary industries were quite different, leading to different impacts of the three industries on CO_2 emissions (Li and Zhou, 2021). Thus, the industrial structure was used as a "monitor" of energy efficiency (Lu et al., 2021). A large body of studies considered that the adjustment in industrial structure played a key role in CO_2 emission mitigation (Zhang et al., 2019b; Chuai and Feng, 2019). Some studies concluded that by shrinking the scale of the secondary industry but vigorously developing the tertiary industry, China could maintain economic development and reduce CO_2 emissions (Zhixin and Qiao, 2011; Yu et al., 2018; Zhu and Shan, 2020; Lin and Wang, 2021). It is widely acknowledged that the optimal population size has a dependence on industrial structure (Au and Henderson, 2006; Wang et al., 2017b). Based on the STIRPAT model, Wang (2018) analyzed 9 cities in Fujian and found that the relationship between urban population density and per capita CO_2 emissions was U-shaped in cities with different industrial structures, but cities with a higher proportion of secondary industry accelerated the arrival of the turning point (Wang, 2018). Owing to the vastness of its territory, China's regional resource endowments differed greatly, leading to the differences in industrial structure between cities (Cao et al., 2017). However, whether the influence of urban population size on CO_2 emissions varied at different stages of industrial structure was not discussed yet. Given this, the nonlinear influence of urban population size on CO_2 emissions in cities with different industrial structures was studied in this paper so as to help policymakers formulate differentiated policies in cities at different stages of industrial structure.

Some studies found that the adjustment in industrial structure did not always achieve CO_2 abatement. Using the panel data of 281 cities in China, Zhang and song (2020) found that the industrial restructuring to the tertiary industry had no significant effect on CO_2 emission mitigation (Zhang and song, 2020). A new puzzle emerged, recklessly rushing to services sometimes failed to achieve CO_2 emission mitigation (Zhang and Song, 2020; Zheng et al., 2020). It was found that cities with a population below a specific size could not simultaneously realize the linkage effect of upstream-downstream industries, so the growth of the proportion of services in these cities did not help improve economic efficiency (Ke and Zhao, 2014). Cities in China are diverse, and the industrial restructuring needs to adapt to the characteristics of cities. Significantly, the industrial structure should reasonably match the size of the urban population. It was found that the elasticity of CO_2 emission to industrial structure was more than 0.8 in large cities, while it was not significant in small and medium-sized cities (Chen et al., 2018).

Then, were there reasonable industrial structures in the cities with different population sizes? So, in the cities with varying population sizes, the nonlinear effects of the industrial structure on CO_2 emissions were studied in this paper, which could provide a solution to the question.

In summary, the impacts of urban population size and industrial structure on CO_2 emissions were generally uncertain. The nonlinear impacts of urban population size and industrial structure on CO_2 emissions were not fully revealed in the existing literature. There was a linear effect in a specific sample or in a specific period, but it was often nonlinear when the sample was large enough and the investigation period was long enough. Considering the great changes of urban population size and industrial structure in the past 20 years in China, it was reasonable to assume that the influences were nonlinear. Moreover, the nonlinear impacts remained to be further tested in this paper. In addition, previous studies ignored the interaction between urban population size and industrial structure, which may also affect the applicability of the conclusions obtained. To investigate the nonlinear impacts of urban population size and industrial structure on CO_2 emissions, it was necessary to divide the urban population size and industrial structure stages. The combination of the threshold model and the STIRPAT model, namely the threshold-STIRPAT model, was widely used to estimate thresholds of variables affecting CO_2 emissions (Wang, 2016; Wang et al., 2019a; Huo et al., 2021). By dividing variable stages using a strict statistical inference method, the threshold-STIRPAT model avoided the estimation bias brought by the methods such as by adding a quadratic term, an interactive term, and empirically judged in previous studies (Li and Lin, 2015; Cui et al., 2019; Dong et al., 2019).

Thus, based on the available data from 2001 to 2017 in China's 255 cities, this paper used the threshold-STIRPAT model to investigate the nonlinear influence of the urban population size and industrial structure on CO_2 emissions. The contributions of this paper were three folded. First, the staged effects of urban population size on CO_2 emissions in different stages of population size were studied. Secondly, the effects of population size in cities at different stages of industrial structure on CO_2 emissions were discussed. Thirdly, the phased effects of industrial structure on CO_2 emissions in cities with different population sizes were analyzed.

3 METHODS AND DATA

3.1 Threshold-STIRPAT Model

STIRPAT model, one of the most representative methods in environmental impact assessment, is widely used to study CO_2 emissions and the influencing factors (Li et al., 2016; Yi et al., 2019; Yue et al., 2022; Ziyuan et al., 2022). STIRPAT model overcomes the limitations of single elasticity in the IPAT model (Dietz and Rosa, 1994; Huo et al., 2021). Compared with the LMDI method, the STIRPAT model allows estimating the impact of each factor as a parameter, which makes up for the deficiency that the LMDI model cannot measure elasticity (Cai et al., 2017; Chen et al., 2018). The STIRPAT model is as follows:

$$I_{it} = \alpha P_{it}^{b} \times A_{it}^{c} \times T_{it}^{d} \times e_{it} \tag{1}$$

Where I represents environmental impact; P denotes population; A represents affluence level; T represents technical level; a, b, c, and d are the parameters. e is the random disturbance. The logarithmic form of the model is:

$$\ln I_{it} = \alpha + b\ln(P_{it}) + c\ln(A_{it}) + d\ln(T_{it}) + e_{it} \tag{2}$$

The fixed-effect panel threshold model is proposed by Hansen, (1999), which is used to describe the jumping character or structural break in the relationship between variables (Hansen, 1999; Hansen, 2000). The setting of the single-threshold model is as follows:

$$y_{it} = \mu_i + \beta_1 x_{it} I(q_{it} \le \gamma) + \beta_2 x_{it} I(q_{it} > \gamma) + e_{it} \tag{3}$$

Where i and t represents cities and years. y_{it} is the dependent variable; x_{it} is the explanatory variable; q_{it} is the threshold variable; μ_i is the individual effect; $e_{it} \sim iid(0, \delta^2)$ is the random disturbance. $I(\cdot)$ is the indicator function. The γ is a specific threshold value. β_1 and β_2 are the parameters to be estimated, respectively.

In this study, the extended STIRPAT model, including the urban population size, industrial structure, technical level, per capita GDP, and foreign direct investment, are used to investigate their effects on CO_2 emissions. By choosing the urban population size and industrial structure as the threshold variables, respectively, the threshold-STIPPAT models are as follows:

$$\begin{aligned} \ln(co_2)_{it} = \mu_i + \lambda Z_{it} + \beta_1 \ln(scale_{it}) I(scale_{it} \le \gamma) \\ + \beta_2 \ln(scale_{it}) I(scale_{it} > \gamma) + e_{it} \end{aligned} \tag{4}$$

$$\begin{aligned} \ln(co_2)_{it} = \mu_i + \lambda Z_{it} + \beta_1 \ln(scale_{it}) I(\ln(is)_{it} \le \theta) \\ + \beta_2 \ln(scale_{it}) I(\ln(is)_{it} > \theta) + e_{it} \end{aligned} \tag{5}$$

$$\begin{aligned} \ln(co_2)_{it} = \mu_i + \lambda Z_{it} + \beta_1 \ln(is)_{it} I(scale_{it} \le \xi) \\ + \beta_2 \ln(is)_{it} I(scale_{it} > \xi) + e_{it} \end{aligned} \tag{6}$$

Where γ, θ, and ξ denote the threshold values. $\ln(co_2)_{it}$ represents the logarithm of CO_2 emissions; $\ln(scale_{it})$ is the logarithm of the urban population size; $\ln(is)_{it}$ is the logarithm of industrial structure. Z_{it} is a set of control variables, including technical factor $\ln(rd)_{it}$, per capita GDP $\ln(gdp)_{it}$, and foreign direct investment $\ln(fdi)_{it}$. **Eq. 4** investigates the staged effect of urban population size on CO_2 emissions with urban population size as a threshold variable. **Eq. 5** examines the phased effect of population size on CO_2 emissions with industrial structure as a threshold variable. **Eq. 6** investigates the staged impact of industrial structure on CO_2 emissions with urban population size as the threshold variable.

3.2 Two-Way Fixed Effects Panel Model

To investigate whether the influence of urban population size on CO_2 emissions presented U shape obtained in previous studies, this paper adds the quadratic term of urban population size to construct the following two-way fixed effects panel model:

$$\begin{aligned} \ln(co_2)_{it} = \phi_0 + \phi_1 \ln(scale_{it}) + \phi_2 [\ln(scale_{it})]^2 + \phi_3 \ln(is)_{it} \\ + \lambda Z_{it} + \mu_i + \eta_t + \varepsilon_{it} \end{aligned} \tag{7}$$

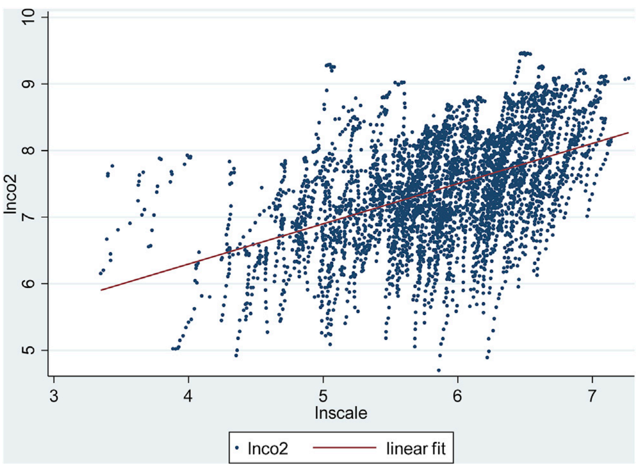

FIGURE 1 | Scatter plot of urban population size and CO2 emissions in 255 cities.

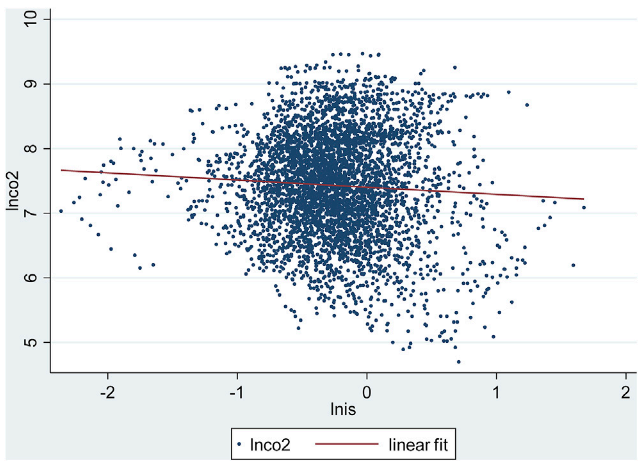

FIGURE 2 | Scatter plot of industrial structure and CO2 emissions in 255 cities.

Where, μ_i is the individual effect; η_t is the time effect; and ε_{it} the disturbance. The control variables are consistent with **Eqs. 4–6**. As reference, **Eq. 7** without the quadratic term of urban population size is expressed by Model 1. **Eq. 7** is denoted by Model2. In Model 2, the mean center processing was conducted on the urban population size, then the residual-centralization program (Zhang and Rajagopalan, 2010; Geng et al., 2012; Yu and Tao, 2015) was used to eliminated the multicollinearity of $\ln(scale_{it})$ and $[\ln(scale_{it})]^2$.

3.3 Variable Description and Data Sources

3.3.1 Dependent Variable

CO_2 emissions (co_2). By using a particle swarm optimization-back propagation (PSO-BP) algorithm to unify the scale of DMSP/OLS and NPP/VIIRS satellite imagery, China emission accounts, and datasets (CEADs) estimated the county-level CO_2 emissions of China (Chen et al., 2020). Based on the data provided by CEADs, this paper summed up the county-level CO_2 emissions to obtain the city-level CO_2 emissions in China from 2001 to 2017.

3.3.2 Core Explanatory Variables

Urban population size (*scale*). According to the previous studies (Zhang et al., 2021a; Tang and Guo, 2021), the year-end population in the city was used to represent the urban population size.

Industrial structure (*is*). According to the previous literature (Gan et al., 2011; Sun and Zhou, 2016; Zhang et al., 2019a; Zhang and Song, 2020), this study used the ratio of the output value in the tertiary industry to the output value in the secondary industry to denote the industrial structure.

3.3.3 Control Variables

The control variables were technical level, per capita GDP, and foreign direct investment. The technical factor $\ln(rd)$, was represented by fiscal expenditures on science and technology (Ma et al., 2013a). $\ln(gdp)$ denoted the per capita GDP of a city. The actual utilization of foreign investment in the city, denoted by $\ln(fdi)$, was used to test whether the pollution haven hypothesis existed.

TABLE 1 | Impact of urban population size on CO_2 emissions.

Variables	CO_2 emissions	CO_2 emissions
	Model 1	**Model 2**
lnscale	0.1479*** (0.0352)	0.1459*** (0.0328)
$(\text{lnscale})^2$		−0.0100 (0.0209)
lnis	−0.0233** (0.0101)	−0.0232** (0.0101)
lnrd	0.0201*** (0.0036)	0.0200*** (0.0037)
lngdp	0.1476** (0.0320)	0.1480*** (0.0319)
lnfdi	−0.0038*** (0.0014)	−0.0038** (0.0014)
Cons	4.4281*** (0.3853)	5.2949*** (0.2988)
Wooldridge test	1066.76***	1067.14***
Wald test	46595.31***	45309.66***
F test	399.48***	399.41***
LM test	27607.67***	27607.30***
Hausman test	242.55***	242.42***

*Note: *, **, and *** represent the significant levels at 10, 5, and 1%, respectively; values in parentheses are the Driscoll-Kraay standard error.*

3.3.4 Data Sources

CO_2 emissions data were collected from CEADs (https://www.ceads.net.cn/). By removing those cities with incomplete statistical data (the Statistical Yearbooks lacked statistics data of certain indicators), 255 prefecture-level cities with different types were selected as research samples (there were 265 prefecture-level cities in China whose administrative divisions was not adjusted over the period 2001–2017), which made the data entire and coherent to ensure the comprehensiveness of the research. The data of other variables were collected from the China City Statistical Yearbooks (2002–2018)and the China National Bureau of Statistics.

TABLE 2 | Results of threshold effect test.

Threshold variable	H_0	H_1	Threshold effect	F statistic	*p* value
lnscale	$\beta_1 = \beta_2$	$\beta_1 \neq \beta_2$	Single threshold	86.30	0.1110

Note: The threshold variable and the threshold dependent variable are both the urban population size.

TABLE 3 | Results of threshold effect test.

Threshold variable	H_0	H_1	Threshold effect	F statistic	*p* value
lnis	Linear model	Single-threshold	Single threshold	52.04	0.0100
	Single-threshold	Double threshold	Double threshold	34.51	0.0410
	Double threshold	Triple threshold	Triple threshold	21.31	0.4580

Note: The threshold variable is industrial structure, and the threshold dependent variable is urban population size.

3.4 Descriptive Statistics

Figure 1 and **Figure 2** show the scatter plots of urban population size and CO_2 emissions, industrial structure, and CO_2 emissions, respectively.

As shown in **Figure 1**, CO_2 emission increased markedly with the growth of urban population size. As shown in **Figure 2**, in the process of industrial structure adjustment, the proportion of the secondary industry with high energy consumption decreased, and the proportion of the tertiary industry dominated by services, emerging industry, and low-carbon industry increased, the CO_2 emissions gradually decreased.

However, the scatter plot and linear regression were difficult to show the staged heterogeneity of the influence of urban population size and industrial structure on CO_2 emissions. Therefore, it was necessary to use the threshold-STIRPAT model to study the phased effects of urban population size and industrial structure on CO_2 emissions.

4 RESULTS AND DISCUSSION

4.1 Impact of Urban Population Size on CO_2 Emissions

For the sake of analyzing the impact of urban population size on CO_2 emissions, the xtscc command in the Stata software was used to estimate the two-way fixed effects panel model. The results are listed in **Table 1**.

As shown in **Table 1**, Model 1 showed that the impact of urban population size on CO_2 emissions was positive. The variance inflation factor (VIF) was 2.26 in Model 2, indicating no severe multicollinearity. In Model 2, the coefficient of the quadratic term of the urban population size was negative, but it was not statistically significant. The coefficient of urban population size was significantly positive, indicating the relationship between urban population size and CO_2 emissions was linear.

At the same time, using the urban population size as the threshold variable, **Eq. 4** examined whether the impact of urban population size on CO_2 emissions differed with the change of urban population size. In the process of threshold estimation, two tests are needed (Huang et al., 2018). The first is whether there is a threshold, and the second is whether the estimated threshold value is equal to the actual threshold value. The existence of the urban population size threshold was tested by using the Bootstrap method. The test's F statistic and *p* value are shown in **Table 2**.

TABLE 4 | Influence of urban population size on CO_2 emissions at different thresholds of industrial structure.

Variables	Threshold-STIRPAT model (5)
lnrd	0.0205*** (0.0021)
lngdp	0.1571*** (0.0080)
lnfdi	−0.0037*** (0.0010)
Interval 1: lnscale (lnis ≤ -1.3774)	0.1332*** (0.0228)
Interval 2: lnscale (−1.3774 < lnis≤0.1992)	0.1566*** (0.0226)
Interval 3: lnscale (lnis > 0.1992)	0.1495*** (0.0026)
Cons	4.3001*** (0.1556)

*Note: *, **, and *** denote significance levels at 10, 5, and 1%, respectively.*

As shown in **Table 2**, the *p* value of the single threshold was 0.1110, failing to pass the significant test. Thus, the null hypothesis H_0 that there was no single threshold effect was accepted. In other words, urban population size had a significantly positive effect on CO_2 emissions, and there was no staged heterogeneity in such effect.

Model 1 indicated that a 1% rise in urban population size could increase the CO_2 emissions by 0.1479%. The impact of industrial structure on CO_2 emissions was significantly negative. Increasing the proportion of the tertiary industry reduced CO_2 emissions significantly, which was consistent with the previous conclusion (Shan et al., 2017). Overall, the high-carbon development mode can be avoided by guiding the adjustment in the industrial structure to the tertiary industry with high added value and low energy consumption.

The influence of technical factors on CO_2 emissions was positive, inconsistent with previous literature (Sheng et al., 2019). Compared with the developed countries, technological innovation in most developing countries increased CO_2 emissions (Kumar and Managi, 2009). As the world's largest developing country, China's research and development spending focused on technology that facilitated production rather than reduced energy consumption and CO_2 emissions (Yu and Du,

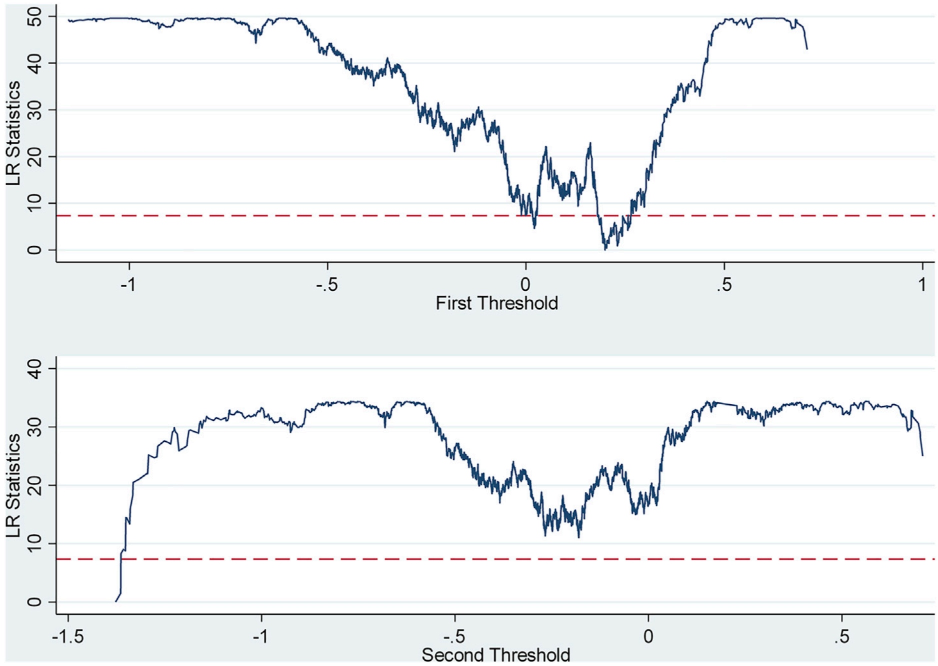

FIGURE 3 | LR diagram with the threshold variable industrial structure.

2019; Lin and Wang, 2021). As such, China's technical factor tended to increase CO_2 emissions, which was confirmed in this study.

A 1% increase in per capita GDP could bring the rise of CO_2 emissions by 0.1476%. A 1% increase in foreign direct investment led to a 0.0038% reduction in CO_2 emissions. The pollution paradise was not confirmed in this study, which was consistent with the viewpoints of other studies (Yi et al., 2019; Yu and Du, 2019).

4.2 The Relationship Between Urban Population Size and CO_2 Emissions at Different Thresholds of Industrial Structure

Using **Eq. 5**, the phased effects of urban population size on CO_2 emissions at different stages of industrial structure were investigated. The results of the industrial structure threshold test are shown in **Table 3**.

As shown in **Table 3**, the number of thresholds was determined. From the p value in **Table 3**, the single threshold test of industrial structure rejected the original hypothesis of linear model ($\beta_1 = \beta_2$) at the significance level of 1%. And the double threshold test rejected the null hypothesis (H_0) of a single threshold at the significance level of 5%. However, the p value of the third threshold was 0.458, indicating it accepted the null hypothesis of no three-threshold effect.

As shown in **Table 4**, the industrial structures in different cities were divided into three intervals by two threshold values: interval 1 (lnis ≤ -1.3774), interval 2 ($-1.3774 <$ lnis ≤ 0.1992), and interval 3 (lnis > 0.1992).

Table 4 indicated that the impact of urban population size on CO_2 emissions had nonlinear characteristics at different stages of industrial structure.

Then, the likelihood ratio (LR) statistic was used to test whether the estimated threshold value was equal to the actual value.

As shown in **Figure 3**, the LR statistics of the two threshold values were both significantly less than the critical value of 7.35 (marked with red dotted line in the figure). In other words, the threshold estimator for the industrial structure was true and effective.

In the three stages of industrial structure, the driving effect of urban population size on CO_2 emissions first increased and then decreased. When the industrial structure was below the threshold of 0.25 (i.e., lnis ≤ -1.3774), the coefficient was 0.1332; When the industrial structure was between 0.25 and 1.22 (i.e., $-1.3774 <$ lnis $\leq$ 0.1992), the coefficient was 0.1566; When the industrial structure was higher than the threshold value of 1.22 (i.e., lnis > 0.1992), the coefficient was 0.1495. Most of the cities in the sample were in the second stage (i.e., $-1.3774 <$ lnis ≤ 0.1992), where the secondary industry led the economy. And most of the heavy industries in the secondary industry were energy-intensive industries (Hao et al., 2020; Li and Zhou, 2021). The expansion of urban population size in this stage provided human capital for industrial division, which would lead to further increase in energy consumption. In the third stage (i.e., lnis > 0.1992), the tertiary industry with low energy consumption and high added value led the economy. The service industries such as information, tourism, finance and logistics in the tertiary industry consumed less energy (Zhang et al., 2019b; Zheng et al., 2020; Yuan and Zhou, 2021). Taking Taiyuan as an example, its industrial structure exceeded

TABLE 5 | Results of threshold effect test.

Threshold effect	F statistic	*p* value	1% Threshold	5% Threshold	10% Threshold
Single threshold	209.33	0.0000	72.7599	53.3542	46.1712
Double threshold	8.77	0.99	87.1585	54.4877	46.065

Note: The threshold variable is the urban population size, and the threshold dependent variable is the industrial structure.

TABLE 6 | Influence of industrial structure on CO_2 emissions at different thresholds of urban population size.

Variables	Threshold-STIRPAT model (6)
lnrd	0.0223*** (0.0021)
lngdp	0.1440*** (0.0085)
lnfdi	−0.0042*** (0.0010)
lnis (scale ≤ 138.35)	0.1567*** (0.0150)<
lnis (scale > 138.35)	−0.0527*** (0.0076)
Cons	5.3122*** (0.0736)

*Note: *, **, and*** represent the significance level of 10, 5, and 1%, respectively.*

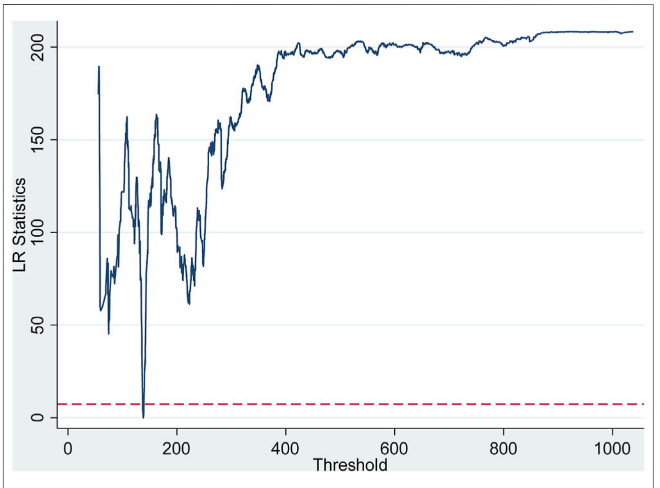

FIGURE 4 | LR diagram with the threshold variable urban population size.

1.22 since 2012. From 2012 to 2017, the increase of Taiyuan's population size did not lead to a significant increase in CO_2 emissions.

The actual situations in Anyang and Haikou were also consistent with the results. The industrial structure of Anyang was between 0.25 and 1.22, while the industrial structure of Haikou was higher than 1.22 over the period 2001–2017. Moreover, the increment difference of the two cities' population size was relatively small (an increase of 1.02 million people in Anyang and an increase of 1.11 million people in Haikou). Over the period, Anyang's CO_2 emissions increased by 24.25 million tons, while Haikou's CO_2 emissions increased by just 9.57 million tons. The effects of urban population size change on CO_2 emissions were quite different in the two cities. The same increase of urban population size brought higher CO_2 emissions when the city's industrial structure was in the second stage.

4.3 The Relationship Between Industrial Structure and CO_2 Emissions at Different Thresholds of Urban Population Size

In **Eq. 6**, the urban population size was selected as the threshold variable to examine whether the impact of industrial structure on CO_2 emissions had a population size threshold effect. **Table 5** displayed the results of the threshold effect test.

As shown in **Table 5**, there was a single threshold effect. The estimated results of **Eq. 6** are listed in **Table 6**.

Table 6 showed that the threshold value was 1.3835 million people. Urban population sizes were divided into two stages and the influence coefficients of industrial structure on CO_2 emissions were 0.1567 and −0.0527, respectively.

From **Figure 4**, it could be seen that the threshold value of urban population size was true and effective.

The influence of industrial structure on CO_2 emissions was opposite when it exceeded the threshold, first promoting and then restraining. When the urban population size was below the threshold value of 1.3835 million people, an increase in the ratio of the tertiary industry to the secondary industry failed to achieve CO_2 emission reduction. The results also answered why industrial restructuring towards tertiary industry sometimes failed to achieve CO_2 emission reduction.

When the urban population size exceeded 1.3835 million people, the influence coefficient of industrial structure on CO_2 emissions was significantly negative. Such as Maanshan, a city dominated by secondary industry, exceeded the threshold value of 1.3835 million people in 2011. Moreover, its population size barely changed in 2011–2017. However, the ratio of the tertiary industry to the secondary industry increased rapidly (from 0.38 in 2011 to 0.83 in 2017). We found that its CO_2 emissions declined from 15.66 million tons in 2011 to 14.33 million tons in 2017. Similar for Daqing, with a population size more than 1.3835 million people in 2001–2017, its tertiary industry increased significantly from 2014, which was helpful to reduce CO_2 emissions. In cities with a population size larger than 1.3835 million people, adjusting the industrial structure to increase the tertiary industry and decrease the secondary industry was helpful to reduce CO_2 emissions.

This conclusion was consistent with the viewpoints of the previous studies from the perspectives of CO_2 emission intensity and economic performance. It was found that the inhibition effect of industrial structure on CO_2 emission intensity was enhanced when the urbanization level was improved (Yu et al., 2022). By introducing the corss term of urban population size and industrial agglomeration, Zhang et al. (2021a) found that the cities with a population more than 1.52 million was conducive to play the CO_2 emission reduction effect brought by industrial agglomeration (Zhang et al., 2021a). Cao (2017) deliberated the panel data of 277 cities and concluded that diversification in industry development patterns enhanced economic performance only when the population size exceeded 1.27 million people (Cao, 2017). From the perspective of CO_2 emission reduction, this paper concluded that the industrial structure should be adjusted according to the urban population size. The threshold value of 1.3835 million people was almost consistent with the previous literature.

5 CONCLUSION AND POLICY RECOMMENDATIONS

In this study, the threshold-STIRPAT method was applied to investigate the nonlinear influence of urban population size and industrial structure on CO_2 emissions in China's 255 cities over the period of 2001–2017. The main findings were as follows: Urban population size positively affected CO_2 emissions. Such driving effects did not vary with the change of urban population size but varied across different industrial structure stages. And the degree of the driving effects first increased when industrial structure exceeded the threshold value of 0.25, then decreased when industrial structure exceeded the threshold value of 1.22.

Furthermore, the impact of industrial structure on CO_2 emissions was heterogeneous in different stages of urban population size. When the urban population exceeded 1.3835 million people, the industrial adjustment by expanding the tertiary industry and reducing the secondary industry was conducive to reducing CO_2 emissions. However, when the urban population has not yet crossed 1.3835 million people, the above industrial restructuring strategies failed to produce lower CO_2 emissions.

In the progress toward "carbon peak and carbon neutrality", China should more scientifically coordinate population development and industrial development. From the perspective of population, a sound green consumption system should be established. By advocating and promoting a low-carbon lifestyle, the promoting effect of the urban population size on CO_2 emissions will be gradually reduced. From the perspective of industry, most Chinese cities' industrial structures are in the second stage, so the government should give priority to the tertiary industry while reducing the industrial CO_2 emission intensity.

From the perspective of cities, the industrial structure and the urban population should be reasonably matched. The population development and the adjustment of industrial structure in cities should be differentiated. According to the conclusions obtained in this paper, it is necessary to explore the differential CO_2 emission reduction paths in accordance with the size of urban population and heterogeneous industrial structure. For cities with industrial structure lower than the threshold value of 0.25 and higher than the threshold value of 1.22, the local government should appropriately expand urban population size to achieve economies of scale, which will be a helpful way to mitigate CO_2 emissions. However, for cities with industrial structure between 0.25 and 1.22, the local government should implement a compact development mode to mitigate CO_2 emissions.

In addition, the local government should formulate industrial adjustment policies according to the population size. In cities with a population larger than 1.38 million, adjusting industrial structure and prioritizing tertiary development will effectively reduce CO_2 emissions. However, for cities with a population lower than 1.38 million, recklessly running to the tertiary will increase CO_2 emissions. For these cities, strengthening the research and development of low-carbon technologies and introducing foreign advanced technologies to improve energy efficiency can be helpful to reduce CO_2 emissions.

DATA AVAILABILITY STATEMENT

The raw data supporting the conclusion of this article will be made available by the authors, without undue reservation.

AUTHOR CONTRIBUTIONS

XZ: Conceptualization, Methodology, Writing-review and editing. YX: Conceptualization, Data curation, and Formal analysis.

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